附件一

行政院國家科學委員會補助專題研究計畫 ■成果報告 □期中進度報告

總計畫-協力式感知無線網路之研究

子計畫五-協力式感知無線網路之頻譜偵測及接收機設計

計畫類別：□個別型計畫　■整合型計畫
計畫編號：NSC　97－2221－E－009－101－MY3
執行期間：99 年 8 月 1 日至　100 年 7 月 31 日

執行機構及系所：國立交通大學 電信工程研究所

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成果報告類型(依經費核定清單規定繳交)：□精簡報告　■完整報告

本計畫除繳交成果報告外，另須繳交以下出國心得報告：
□赴國外出差或研習心得報告
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□出席國際學術會議心得報告
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中　華　民　國　100 年 10 月 28 日

前言

本三年期計劃主要是針對下世代協力式感知無線網路開發出一系列的高效能基頻信號處理演算法。這三年中計劃執行的成果甚為豐碩,其中針對以下數個研究主題都有具體的研究成果發表於頂尖 IEEE 國際期刊與指標型 IEEE 國際研討會：

- 針對具多封包接收能力通道之協力式網路資源存取之通訊協定技術
- 針對放大傳遞(Amplify-and-Forward)多天線協力式通訊系統之訊源端／中繼端前置編碼設計
- 針對多輸入多輸出單載波區塊式傳輸系統於時變通道估計誤差下的強健式接收機設計
- 於局部感測器偵測機率未知的環境下具通道感知能力之決策融合技術
- 基於前置編碼之盲蔽式通道判別系統於單載波區塊式傳輸系統之通道容量分析
- 基於能量偵測器之頻譜偵測機制於主要用戶信號時間延遲下之效能分析
- 基於審查（Censoring）機制下的節能分散式信號偵測技術
- 於感測雜訊參數誤差下的強健節能分散式參數估計技術
- 針對多輸入多輸出廣播系統利用零點強制接收機於通道估計誤差下的效能分析

以下將就上列數個研究主題作更詳細的說明。

主題一：

針對具多封包接收能力通道之協力式網路資源存取之通訊協定技術

摘要

協力式網路中的媒體存取控制（MAC）協定設計在多封包接收（MPR）通道是一個富挑戰性的題目，但是尚未有文獻發表。本計畫提出一個利用合作差異（cooperation diversity）的媒體存取控制協定來改進多封包接收通道的吞吐量（throughput）。本計畫提出的方法可以有效率地利用使用者沒有封包傳送的空檔，因此降低了一般中繼階段可能產生的吞吐量損失。透過馬可夫鏈（Markov Chain）模型，我們做了最壞狀況的吞吐量數學分析。並且得到 (1) 因同時傳輸的中繼封包干涉對直接鏈結造成的吞吐量損失的封閉式上界; (2) 傳送失敗的使用者因協力式中繼傳輸所獲得吞吐量增益的封閉式下界。分析的結果讓我們可以直接根據多封包接收通道系數檢視所提出協定的吞吐量性能。模擬結果不但顯示了提出方法在系統吞吐量的優點，也驗證了分析的正確性。

關鍵字：多封包接收、媒體存取控制、跨層設計、協力式通訊。

Abstract

Medium access control (MAC) protocol design for cooperative networks over multi-packet reception (MPR) channels is a challenging topic, but has not been addressed in the literature yet. In this project, we propose a MAC protocol to exploit the cooperation diversity for throughput enhancement over MPR channels. The proposed approach can efficiently utilize the idle periods for packet relaying, and can thus effectively limit the throughput loss resulting from the relay phase. By means of a Markov chain model, the worst-case throughput analysis is conducted. Specifically, we derive (i) a closed-form upper bound for the throughput penalty of the direct link that is caused by the interference of concurrent packet relay transmission; (ii) a closed-form lower bound for the throughput gain that a user with packet transmission failure can benefit thanks to cooperative packet relaying. The results allow us to investigate the throughput performance of the proposed protocol directly in terms of the MPR channel coefficients. Simulation results confirm the system-wide throughput advantage achieved by the proposed scheme, and also validate the analytic results.

Keywords: Multi-Packet Reception; Medium Access Control; Cross-Layer Design; Cooperative Communications.

前言

為滿足高品質、高速率的多媒體通訊需求以及增加通訊使用者用戶，無線通訊設計著重於如何增加通訊系統的頻譜使用率及如何提高通訊的鏈結品質與通訊容量。因此如何針對無線通訊的特性，設計合乎系統需求的通訊技術一直是新一代通訊標準所追求的目標。近年來協力式通訊於感知無線網路系統中的應用已被廣泛地探討研究，其主要概念為利用中繼節點幫忙傳送信號，使得系統能有較多且獨立鏈結路徑，藉以實現多輸入多輸出的系統概念，因此，這種系統也稱為虛擬多輸入多輸出系統。本計劃針對協力式無線通訊系統做深入的分析研究，並提出新穎的協力式多群優先佇列協定，以滿足未來無線通訊高品質、高速率的需求。

研究目的

有效的媒體存取控制機制是達成高吞吐量、低延遲、及品質服務的關鍵。傳統的媒體存取控制協定設計都是基於碰撞通道模型，因此忽略了實體層多封包接收的能力。從[1]到[4]可以發現一些開發多封包接收媒體存取協定的設計。這些協定需要動態調整存取通道的使用者數目來發揮多封包接收的優點，不管是藉由整個網路交通狀態的徹底搜尋或是某種通道預約的機制。而協力式通訊已廣為人知是一個開發多用戶差異的重要的技術。在媒體存取控制層，不同的協力式協定已見諸文獻，然而都是以單封包接收的情境作推導。

協力式的多封包接收媒體存取控制協定設計同時有下列的限制而更具挑戰性。首先，中央控制器必須知道所有鏈結的多封包通道狀況來決定存取集合。但是如此將導致額外的通訊負擔並且惡化系統整體的吞吐量，特別是在大規模的行動網路上。其次，當封包接收因為碰撞導致失敗時，部分使用者必須擔任中繼負責封包的重傳。如果沒有適當設計的媒體存取控制協定來實現協力傳輸的優點，勢必加大整體吞吐量的惡化程度。就我們所知，尚未有協力式的多封包接收媒體存取控制協定在文獻上發表。

文獻探討

最初反應實體層多封包接收能力的研究可以回溯至經由成功接收機率描述捕捉效應的通道模型。捕捉效應對各種現存媒體存取控制協定，例如 ALOHA 和 FCFS 的影響，則在[5]-[7]被探討。然而，捕捉效應整體而言仍然停留在實際通道特性的簡化表示而無法確切描述其多封包接收能力。因此也促使更實際的多封包接收通道模型的發展[1]，隨後陸續有媒體存取控制協定基於此模型被提出[2]-[4]。協力式通訊則是近年來吸引各界目光的另一個研究領域。協力差異可以被利用在實體層和媒體存取控制層改善系統性能。在實體層，許多基於放大-轉送和解碼-轉送的變形技術被提出。而在媒體存取控制層，特殊的協力式媒體存取控制協定像是協力式多重存取（Cooperative Multiple Access）[8]、協力媒體存取控制（CoopMAC）[9]、和網路中經由合作和節省能量允許改善存取（ALLow Improved Access in the Network via Cooperation and Energy Savings）協定[10]也陸續被提出。儘管如此，封包接收能力和協力差異卻尚未被結合來設計媒體存取控制。一方面要把多封包接收能力放進以單封包接收設計的協力式存取控制協定非常困難，除非是加諸某種假設，例如[11]中的分離通道（Separate Channels）。另一方面，現有的非協力式多封包接收媒體存取控制協定已經太複雜而無法再將協力機制包含進來分析。直到最近有一個藉由簡單的旗標位元機制和多群優先佇列的多封包媒體存取控制協定發表[12]。多群優先佇列有幾項特色成為協力式多封包接收媒體存取控制的潛力。一是多群優先佇列根據預定的優先順序排定使用者存取通道的順序，因此不需要透過對通道狀態及交通狀況的徹底搜尋來作活動使用者的選擇。如此將大量減輕在稠密協力網路的通訊負擔。第二，旗標位元可以提供中央控制器有關每一個使用者緩衝器的狀態。與多群優先順序結合後，通道存取將可在直接傳輸與中繼傳輸之間

取得較佳的平衡，因此在高碰撞環境中，由於中繼傳輸造成的吞吐量損失可以大量降低。為了達成上述優點，我們延伸原本的多群優先佇列法成為適用於協力式多封包接收網路的媒體存取控制協定。

研究方法

我們首先將傳統的多封包接收矩陣一般化，以符合每一個使用者通道都不相同的實際狀況。假設使用者數目是M，令U是使用者 ID 的排列組合，則多封包接收矩陣可以寫成

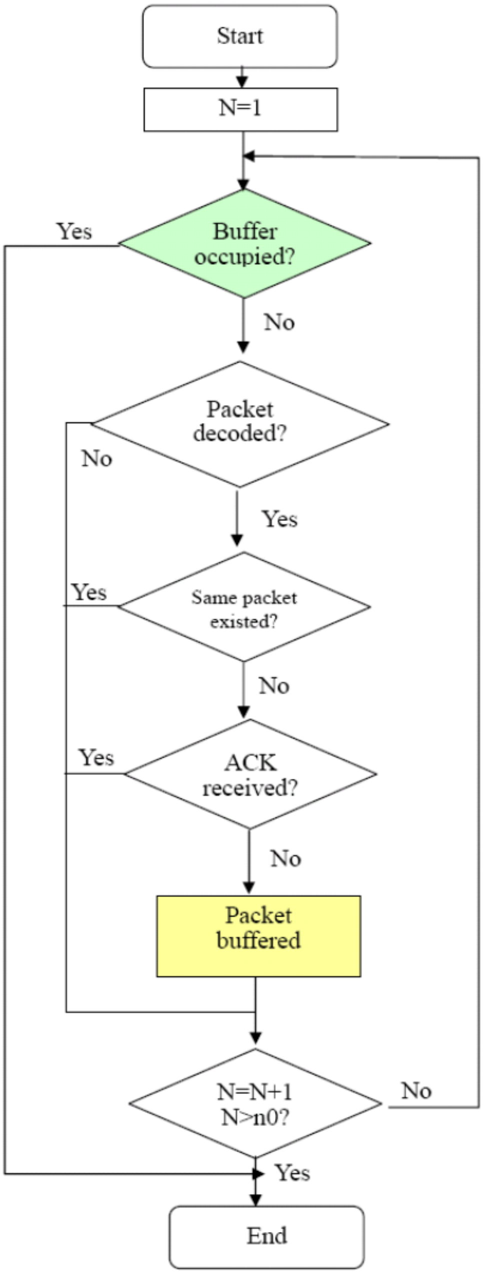
$$\mathbf{C}(U) \triangleq \begin{bmatrix} C_{1,0}(U) & C_{1,1}(U) & & & \\ C_{2,0}(U) & C_{2,1}(U) & C_{2,2}(U) & & \\ \vdots & \vdots & \vdots & & \\ C_{M,0}(U) & C_{M,1}(U) & C_{M,2}(U) & \cdots & C_{M,M}(U) \end{bmatrix}. \quad (1)$$

其中$C_{n,k}(U) = \Pr\{k$個封包被成功接收 ｜ U的前面n個封包被傳送$\}$。值得注意的是，由(1)可以看出不同的使用者排列組合順序將會有不同的多封包接收矩陣。$C_n(U) \triangleq \sum_{k=1}^{n} kC_{n,k}(U)$代表傳送$n$個封包時可以正確收到的封包數期望值，而對應的多封包接收通道的容量定義成$\eta(U) = \max_{n=1,\cdots,M} C_n(U)$。由於達成上述多封包接收通道容量的$n$不一定是唯一的，因此令

$$n_0(U) \triangleq \min\left\{\arg\max_{n=1,\cdots,M} C_n(U)\right\} \quad (2)$$

為達成多封包接收通道容量的最小n值。一方面小於n_0的n值無法達到通道容量，而大於n_0的n值即使可以達到通道容量，卻浪費了傳輸功率。

假設使用者i被允許存取通道，並且如同多群優先佇列一樣有旗標位元加在每一個傳送封包的末端。旗標位元只有在第二個緩衝器的封包是自己的時候才會開啟，而當二個緩衝器是空的或是來自別的使用者時則關閉。當某一個封包被成功接收時，中央控制器會依據它的旗標位元做如同多群優先佇列的排程。當封包接收失敗，而另一個使用者k有空的緩衝器並成功接收該封包時，便可以在接下來存取通道的時候擔任中繼的角色，如圖一所示。



圖一：使用者擔任中繼時的運作流程圖。

如果沒有任何使用者可以擔任中繼，也就是其它使用者的緩衝器都是滿的或沒有其它使用者成功接收該封包，使用者i將在自己下一個存取通道的時後重傳該封包。上述協定可以整理出幾項特點：

1) 旗標位元的設置提供中央控制器一個內建機制去區別直接傳輸與中繼-空閒鏈結。旗標位元開啟的使用者為直接傳輸，將被排進 ACTIVE 或 PREM 群組而擁有較高的通道存取優先權。如此將可避免碰狀發生時經常性的中繼傳輸造成吞吐量的下降。

2) 歸功於 PREM 的機制，當使用者等待超過一定期間S時，將被授予最高的通道使用權。如此將限制中繼傳輸的延遲時間以滿足品質服務的需求。

3) 在本協定中，中央控制器依據旗標位元與S對每一個使用者排程，並不需要另外對使用者做活動的估算，因此運算複雜度可以大幅降低。

由於本協定是利用使用者的空閒時間做中繼傳輸，因此相對於多群優先佇列協定勢必會增加同時傳送的封包數量。即使中繼傳輸可以補償原本封包接收失敗的吞吐量損失，也會對同時傳輸的其它封包造成額外的干擾。由此中繼傳輸造成的額外干擾將是種整體系統吞吐量性能的主要限制因素。利用多群優先佇列協定可達到的吞吐量作為比較基準，我們提出最差狀況的分析，也就是 n_0 個同時傳輸中只有一個直接傳輸，其餘 n_0-1 個都是中繼傳輸。儘管如此的分析相對保守，卻可以直接經由多封包接收矩陣算出吞吐量增益的下界與損失上界。

透過有限狀態的生死過程[13]來描述緩衝器的狀態，我們可以推導出下列定理。

定理一： 假設多群優先佇列協定中，使用者 u_1 的封包阻絕機率 $p_{u_1}^B$ 小於某個正數 δ，也就是 $p_{u_1}^B \le \delta$。則協力式多群優先佇列協定中的直接鏈結使用者 u_1 遭受的吞吐量損失 $\Delta_{u_1}^p$ 會小於某個上界

$$\Delta_{u_1}^p \le \Delta_{u_1} + \frac{\delta\left(A_{u_1} + B_{u_1}\right)}{A_{u_1} + \delta B_{u_1}}, \tag{3}$$

其中
$$\Delta_{u_1} = C_1\left(\{u_1\}\right) - C_{n_0(U)}\left(U\right) + C_{n_0(U)-1}\left(U \setminus \{u_1\}\right), \tag{4}$$

A_{u_1} 和 B_{u_1} 為封包產生機率和封包成功接收機率的函數。

定理二： 假設使用者 u_j（$u_j \in U \setminus \left\{u_2,\cdots,u_{n_0(U)}\right\}$）傳輸失敗. 從中繼使用者 $u_k \in \left\{u_2,\cdots,u_{n_0(U)}\right\}$ 所獲得的吞吐量增益為 $\Delta_{u_j}^g$，則

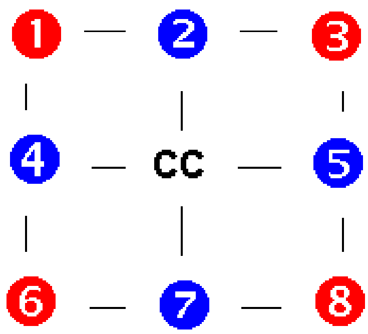
$$\Delta_{u_j}^g \ge p\left(C_{n_0(U)}\left(U\right) - \min_{u_k \in \left\{u_2,\cdots,u_{n_0}\right\}} C_{n_0(U)-1}\left(U \setminus \{u_k\}\right)\right), \tag{5}$$

其中 p 是封包產生機率。

由以上定理可知，即使中繼傳輸會造成直接傳輸的干擾，只要式(5)大於式（3），協力式多群優先佇列協定整體獲得的增益還是大於損失。

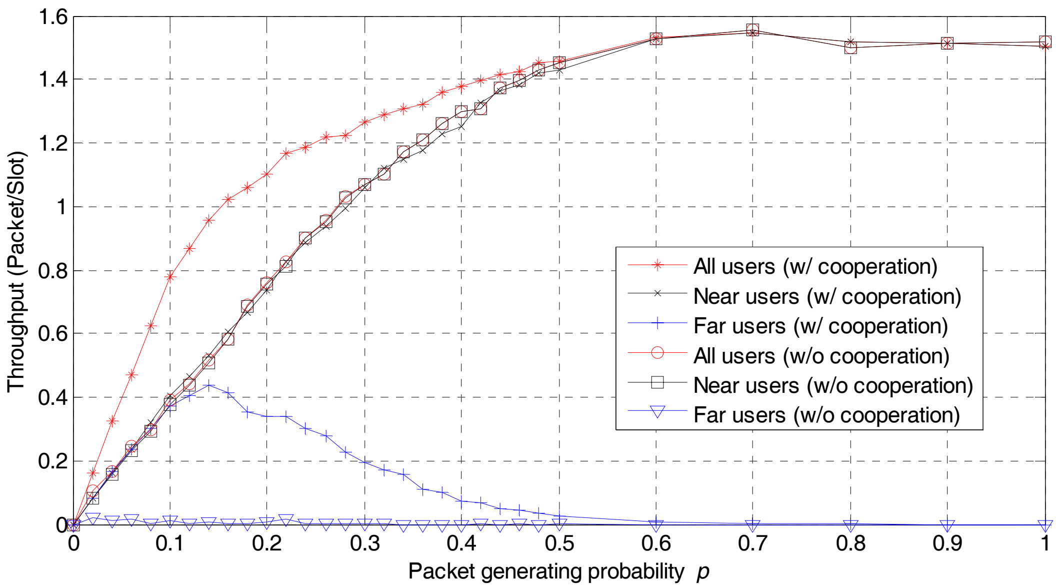
結果與討論

我們考慮一個隨機展頻碼的 CDMA 網路來計算相對應的一般化多封包接收矩陣通道模型。封包長度、展頻增益、可修正錯誤位元數和[12]一樣分別是 200、6、和 2。總共有 8 個使用者如圖二作網狀分佈，其中近距離使用者（2、4、5、7）距離中央控制器 L，其對應接收的訊號雜訊比為 10dB；遠距離使用者（1、3、6、8）距離中央控制器 $\sqrt{2}L$。由於增加的旗標位元僅造成 1/200 = 0.005 的額外負擔，因此在以下的性能比較中可以忽略不計。



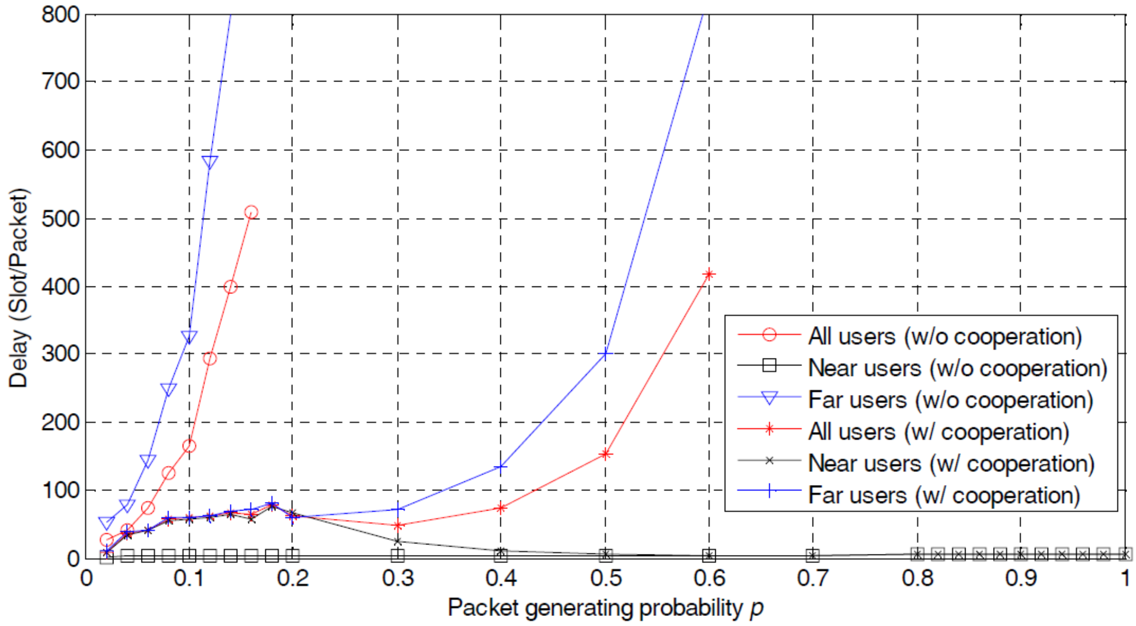
圖二：模擬中 8 個使用者的網狀分佈。

圖三比較了提出的方法與既有文獻[12]的吞吐量性能。從圖中可以看出遠距離使用者們在沒有近距離使用者們合作的情況下吞吐量幾乎是零。一旦有了近距離使用者的合作，在低交通量的情況下，遠距離使用者們的平均吞吐量便可以獲得改善。更重要的是，這樣的合作並不會造成近距離使用者吞吐量性能的下降，因為中繼傳輸只有在他們空閒的時候才會發生。基於這樣的協力式機制，協力增益會隨著交通量的逐漸增加而減小。



圖三：本計劃所提出的協力式機制吞吐量效能比較。

圖四為延遲性能的比較。如圖所示，遠距離使用者無限延遲發生時的交通量有效的往右偏移，從低交通量變成中交通量。相對付出的代價則是近距離使用者的延遲稍微的增加。



圖四：本計劃所提出的協力式機制延遲效能比較。

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主題二：

基於前置編碼之盲蔽式通道判別系統於單載波區塊式傳輸系統之通道容量分析

摘要

在接收端要作盲蔽式的通道估測時，傳送端前置編碼的傳送是一個重要的技術。在以往的文獻中，前置編碼對通道容量(capacity)的影響很少被討論到。在本研究中，我們考慮基於循環字首(cyclic prefix)單載波區塊傳輸系統(single carrier block transmission)的傳輸方式，並於傳送端使用非冗餘(non redundant)的對角前置編碼；而在接收端採用近來提出的共變數匹配(covariance-matching)之盲蔽式通道估測。吾人證明了當接收端擁有完整的通道的資訊時，最佳雜訊抵抗性的前置編碼技術會造成較差的通道容量(capacity)。而當同調區間(coherent time)有限時，會因為共變數矩陣的有限的取樣估計誤差(finite-sample estimation error)，而使得估測通道跟實際通道不批配。在前置編碼的技術中，同調區間的大小會直接影響到通道估測的準確度。因此以達到最大通道容量為前提下，決定該使用多少的同調區間作前置編碼來確保通道估測的準確度為重要的考量。為此，我們採用 training based capacity performance 為衡量基準；利用矩陣擾動定理，可以得到一個通道容量下界的近似解，以此用來衡量盲蔽式估測通道與真實通道的匹配度。此外，藉由這個通道容量下界的近似解，也可以得到為達通道容量最大化所需前置編碼時間的近似值。提出的分析研究也可以由數值模擬結果得到證明。

關鍵字： 盲蔽式通道估測; 通道容量; 前置編碼; 單載波區塊傳輸; 循環字首; 矩陣擾動分析; 取樣共變數矩陣; 循環矩陣.

Abstract

Transmit precoding is a key technique for facilitating blind channel estimation at the receiver but the impact due to precoding on the channel capacity is scarcely addressed in the literature. In this paper we consider the single-carrier block transmission with cyclic prefix, in which the transmitter adopts non-redundant diagonal precoding, and at the receiver the channel information is acquired through a recently proposed covariance-matching blind channel estimation scheme. It is shown that, when perfect channel knowledge is available at the receiver, the optimal noise resistant precoder incurs the worst-case capacity penalty. When the coherent interval is finite, channel mismatch occurs due to finite-sample covariance matrix estimation. Thus, we aim to determine how much of the coherent time should be dedicated to precoding in order to trade channel estimation accuracy for the maximal capacity. Toward this end, the so-called training based capacity is used as the performance measure. By leveraging the matrix perturbation theory, we derive a closed-form capacity lower bound which takes channel mismatch in the considered blind estimation scheme into account. Based on an approximate formula for the lower bound, a closed-form estimate of the capacity-maximizing precoding period is given. Numerical simulations are used for evidencing the proposed analytic study.

Keywords: Blind channel estimation; channel capacity; precoding; single-carrier block transmission; cyclic prefix; matrix perturbation analysis; sample covariance matrix; circulant matrix.

研究目的與文獻探討

盲蔽式通道估測被視為是替代 training scheme 且得以保有頻寬效率的方法［5］。在現存的盲蔽式估測方法中，傳送前置編碼的方式近幾年被廣為採用［5]，[8]，[9]。傳送端的前置編碼信號雖然會幫助盲蔽式通道的估測，但也會對通道容量有根本的影響［2］。在完美通道資訊的假設下，通道容量的效能在［2］中分別由各種有冗元和沒有冗元(non redundant)的前置編碼來分析。而前置編碼方式下產生的通道估測錯誤主要是因為只能在有限的取樣量，經過計算和統計時造成的［5］。在現有文獻中都還尚未提出為深入的探討：以前置編碼方式所作的盲蔽式估測通道的準確度為考量，並依此分析系統通道容量可達的上限。

在這篇論文中我們考慮傳送端使用了一個沒有冗元(non redundant)的對角前置編碼—單載波循環字首傳送［4］，而在接收端以共變數匹配的方式(covariance matching scheme)得到通道的資訊[9]。這篇論文的主要目的是由通道容量的觀點出發，找出最佳的抵抗雜訊程度，也就是最高的通道估測準確度。進而在通道容量和通道估測的準確性之間作權衡考量[9]。更明確的來說，當接收端的訊號共變數矩陣可以完全的知悉，也就是通道估測完全正確，此時只能達到最小的通道容量。因此假設我們採用前置編碼來改善通道估測的準確度，則會犧牲訊息的傳送率。我們接著轉而考慮現實的區塊衰減(block fading)環境［6］。很明顯的，如果所有的訊號區塊在同調範圍內做前置編碼，且接收端使用所有的可靠數據區塊來形成共變數矩陣，則會得到最精確的通道估測，因為共變數矩陣會盡可能保持很小的估測錯誤。然而這樣的好處必須犧牲通道容量來達成。相反的，假如只有同調時間的某部分用來做前置編碼，則通道估測的品質會相對的較差，然而通道容量的損耗也會減少。因此很自然的衍生一個問題：該使用多少的同調區間作前置編碼，以達到通道估測準確度和系統通道容量之間最佳的平衡?

我們藉由通道容量的測度來衡量以上的問題[1]，[6]，[7]。藉由矩陣擾動(matrix perturbation)定理[11]，在盲蔽式估測的架構下，根據不同的通道估測準確度可以得到不同的通道容量下限。為了簡化分析，經由下面三個手法可以得到通道容量下限的近似值。首先，在盲蔽式通道估測下，可以用數據描述通道容量的損失。第二，藉由這個結果，可以簡單的分析所需的前置編碼時間和最大通道容量。第三，看似不利的部分經過適當的解釋可以對分析有所助益。在數值模擬上證實了以上方法所分析出的通道容量。

研究方法

基於對角化前置編碼的盲蔽式通道估計

A. 通道估計演算法

我們考慮一個作用於 L-階頻率選擇衰減（frequency-selective fading）通道上的系統，此系統對單載波循環字首（single-carrier cyclic prefix）做前置編碼，描述如下［27］：

$$\mathbf{y}_k = \mathbf{G}\mathbf{P}\mathbf{s}_k + \mathbf{v}_k,\ k \geq 0, \tag{2.1}$$

其中 $\mathbf{s}_k \in \mathbb{C}^N$ 及 $\mathbf{y}_k \in \mathbb{C}^N$ 分別為信號源訊號及接收訊號，而 $\mathbf{v}_k \in \mathbb{C}^N$ 則為雜訊向量，

$$\mathbf{P} := diag\left[p(0)\cdots p(N-1)\right] \in \mathbb{R}^N, p(n) \in \mathbb{R}, \tag{2.2}$$

為一對角化前置編碼矩陣，且 $\mathbf{G} \in \mathbb{C}^{N\times N}$ 為循環通道矩陣，且其第一行如以下所示：

$$\mathbf{g} := [h(0) \quad \cdots \quad h(L) \quad 0 \quad \cdots \quad 0]^T \in \mathbb{C}^N, \tag{2.3}$$

其中 $h(n)$ 為第 n 個通道之通道值，$0 \le n \le L$。對角化前置編碼的目的在於有意識地使發射功率變化以便於在接收端採取盲蔽式通道估計。[27]的方法利用了通道矩陣 $\mathbf{G}$ 的循環架構以及因應 $\mathbf{G}$ 而設定的共變數匹配(covariance-matching) 通道估計。更精確地講，因為 $\mathbf{G}$ 為循環矩陣，所以整個矩陣可用第一列來表示，如[28]

$$\mathbf{G} = \left[\mathbf{g} \quad \mathbf{Jg} \quad \cdots \quad \mathbf{J}^{N-2}\mathbf{g} \quad \mathbf{J}^{N-1}\mathbf{g}\right], \tag{2.4}$$

其中 $\mathbf{J}$ 為一 $N \times N$ 之置換(permutation)矩陣。根據(2.4)式並且在[29]及[30]一般性的假設下，

(一) $E\{\mathbf{s}_k\} = \mathbf{0}$ 且 $E\{\mathbf{s}_k\mathbf{s}_k^H\} = \mathbf{I}$

(二)雜訊向量 $\mathbf{v}_k$ 為一白複數循環高斯(white complex circularly Gaussian)分布，且期望值為 0，共變數矩陣為$\sigma_v^2\mathbf{I}$，並與來源訊號$\mathbf{s}_k$互為獨立。因此，接收訊號(2.1)的共變數矩陣為

$$\mathbf{R}_\mathbf{y} = E\mathbf{y}_k\mathbf{y}_k^H = \sum_{n=0}^{N-1} p(n)^2 \mathbf{J}^n \mathbf{g}\mathbf{g}^H \left(\mathbf{J}^T\right)^n + \sigma_v^2\mathbf{I}. \tag{2.5}$$

由上可見，對一個給定的 $\mathbf{R}_\mathbf{y}$ ，(2.5)式定義了一組線性方程式，且其通道係數乘積$h(k)h(l)^*$(亦即 $\mathbf{g}\mathbf{g}^H$ 中之元素)為未知。藉由引入 $vec(\cdot)$這個函數，(2.5)式可被重新整理成以下形式(見[27])

$$vec(\mathbf{R}_\mathbf{y}) = \tilde{\mathbf{Q}}vec(\mathbf{h}\mathbf{h}^H) + \sigma_v^2 vec\left(\mathbf{I}\right), \quad \tilde{\mathbf{Q}} := \mathbf{Q}\mathbf{J}_1 \tag{2.6}$$

其中 $\mathbf{Q}$ 為一 $N^2 \times N^2$ 塊循環伴隨循環塊矩陣(block-circulant-with-circulant block, BCCB)[28]，且其第一列為

$$\left[p(0)^2\mathbf{I} \quad p(N-1)^2\mathbf{J}^{N-1} \quad \cdots \quad p(1)^2\mathbf{J}\right] \tag{2.7}$$

而 $\mathbf{J}_1 \in \mathbb{R}^{N\times(L+1)^2}$ 為某一置換矩陣。假設矩陣 $\tilde{\mathbf{Q}}$ 為行滿秩，[27, 定理 4.1]提空了一個方程式(2.6)有解的充分條件。如此一來，給定了接收資料 $\mathbf{R}_\mathbf{y}$ 後，通道係數乘積向量可推導成以下形式

$$vec(\mathbf{h}\mathbf{h}^H) = \left(\tilde{\mathbf{Q}}^T\tilde{\mathbf{Q}}\right)^{-1}\tilde{\mathbf{Q}}^T vec\left(\mathbf{R}_\mathbf{y}\right). \tag{2.8}$$

一旦得知了 $vec(\mathbf{hh}^H)$ 以後，我們接著寫出以下之秩為一的矩陣

$$\mathbf{H} := \mathbf{hh}^H = \left[h(k)h(l)^*\right]_{0\le k,l\le L}. \tag{2.9}$$

接著藉由計算出矩陣 $\mathbf{H}$ 的主要特徵向量，便可建立通道脈衝響應向量 $\mathbf{h}$，但伴隨一個長數的不確定值。

B. 最佳抗雜訊前置編碼

在(2.6)式中我們認為通道係數乘積 $vec(\mathbf{hh}^H)$ 是值得探討的訊號， $\tilde{\mathbf{Q}}$ 的行空間定義了此訊號的子空間，且白雜訊擾動 $vec\ \mathbf{I}$ 生成了雜訊子空間。我們注意到 $\tilde{\mathbf{Q}}$ 主要受各個前置編碼係數 $p\ n$ 影響。為了減輕雜訊對估計通道的影響，一個直覺的方法是設計 $p(n)$ 使得訊號和雜訊子空間盡可能接近正交。在［27］中，設計前置編碼器的難題在於：如何最小化雜訊 $vec\ \mathbf{I}$ 和矩陣 $\tilde{\mathbf{Q}}$ 的各行之間最大之相關指數，且受限於兩個限制式為

$$\sum_{n=0}^{N-1} p(n)^2 = N, \text{ and } p(n)^2 \ge \delta > 0, \ \forall\ 0 \le n \le N-1. \tag{2.10}$$

最佳抗雜訊前置編碼器允許了以下的二級脈衝形式（見［27, p–1121］）：對一個固定但是任意的 $0 \le m \le N-1$，

$$p(m)^2 = N(1-\delta) + \delta \text{ and } p(n)^2 = \delta \text{ for } n \ne m. \tag{2.11}$$

基於精確通道資訊的容量效能

假設接收端得知完整的通道資訊，並忽略掉循環字首產生的冗餘（overhead）， 則眾所周知的，系統(2.1）的各態歷經的（ergodic）容量（每傳送方塊包含的位元數)可表示成

$$I = E \log\det\ \mathbf{I} + \sigma_v^{-2}\mathbf{G}\mathbf{P}^2\mathbf{G}^H\ , \tag{2.12}$$

為前置編碼器 $p(n)$ 的方程式。藉由利用通道矩陣 $\mathbf{G}$ 的循環特性，可使容量最大化的 $p(n)$ 如以下所示（見［31］）

$$p(n) = 1 \text{ for } 0 \le n \le N-1. \tag{2.13}$$

因此，如同（2.11）式對角化前置編碼所引入的傳送功率調變將無可避免地造成容量損耗。為了進一步指出前置編碼器（2.11）的容量效能，我們注意到在高訊雜比的區域裡，［31］完善地估計了（2.12）式

$$I \approx \log\left\{\sigma_v^{-2N}\prod_{n=0}^{N-1} p(n)^2\right\} + E\log\det\tilde{\mathbf{D}}, \tag{2.14}$$

其中 $\tilde{\mathbf{D}} = \mathbf{D}^H\mathbf{D}$ ，且 $\mathbf{D}$ 為一對角矩陣，而其對角元素為與子載波相對的通道頻率響應值。從（3.3）式可知，在高訊雜比時，前置編碼對容量造成的影響主要由（2.14）式右手邊的第一個項造成。當這

個項越小時，容量損耗就越大。然而，在以下定理建立之後，原本最佳的抗雜訊前置編碼器（2.11）將變為最糟的選擇（詳細證明在［31］）。

定理 2.1：在（2.10）式的限制之下，前置編碼器（2.11）變為

$$\min \prod_{n=0}^{N-1} p(n)^2 = \delta^{N-1}\Big[N-(N-1)\delta\Big].$$

我們注意到在上節中，藉由盲蔽式機制以獲得精確通道資訊的方法，在估計接收共變數矩陣 $\mathbf{R}_{\mathbf{y}}$ 時需要無限長的同調間隔，例如：藉由時間平均（time average）。在同調間隔為有限的情況下，我們僅能利用有限的資料方塊以獲得取樣後的共變數矩陣，也因此，通道估計將變得不精確。在同調間隔中，若信號源符號方塊的大部分成分是藉由（2.11）式作前置編碼，則估計 $\mathbf{R}_{\mathbf{y}}$ 時造成的取樣誤差將相對地減少，且通道估計將更為精確。然而，若要達到以上的好處，則可能會造成容量損耗，因為在考慮（理想）容量效能時（比照定理 3.1），（2.11）式為最糟情況下的選擇。另一方面，若同調間隔花費一小部分作前置編碼，則通道估計的品質將變得很差，就算利用前置編碼來降低容量損耗，改善也相當有限。接下來將討論通道估計準確性以及藉由選擇前置編碼區間可達到的系統容量之間的取捨。

有限同調間隔的容量量測

A. 問題描述與容量量度

接下來我們將專注在塊衰落（block fading）環境，其通道在同一個符元的時間間隔 T 內維持不變，但不同時間間隔的通道則會變動。我們假設在每一個同調間隔中，初始時間 $1 < T_p \le T$ 內的信號源訊號會先經（2.11）式做前置編碼，以實現通道估測。在時間區間 T 範圍內的信號模型，可以用兩個不同的階段描述之

$$\begin{cases} \mathbf{y}_k = \mathbf{GPs}_k + \mathbf{v}_k,\ 1 \le k \le T_p, & \text{(前置編碼階段)} \\ \mathbf{y}_k = \mathbf{Gs}_k + \mathbf{v}_k,\ \ T_p + 1 \le k \le T, & \text{(直接資料傳輸階段).} \end{cases} \tag{2.15}$$

因此對基於盲蔽式技術的通道估測而言，在前置編碼階段範圍為 T_p 的接收方塊便可用來表示取樣後的共變數矩陣如下

$$\mathbf{R}_{\mathbf{y}} = \frac{1}{T_p}\sum_{k=1}^{T_p} \mathbf{y}_k \mathbf{y}_k^H . \tag{2.16}$$

為了尋找最佳的 T_p 以最佳地取捨”盲蔽式通道估計的準確性”與”可達到的容量”，我們需要一個可明確地將通道不匹配效應(或者估計 $\mathbf{R}_{\mathbf{y}}$ 的不完善之處)納入考量的容量指標。出於［32]，［33]，

[34]，在給定通道估計 $\hat{\mathbf{h}}$ （因此$\mathbf{G}$亦給定)的情況下，我們藉由將估計後的通道矩陣 $\mathbf{G}$ 視為已知以改寫（2.1）式，且將通道不匹配的部分歸類到雜訊成分，使得

$$\mathbf{y}_k = \mathbf{GPs}_k + \mathbf{v}_k = \mathbf{GPs}_k + \underbrace{\mathbf{GPs}_k + \mathbf{v}_k}_{:=\tilde{\mathbf{v}}_k},\ \ \mathbf{G} = \mathbf{G} - \mathbf{G}. \tag{2.17}$$

我們注意到，當（2.1）式中的雜訊 $\mathbf{v}_k$ 是白色高斯時，則（2.17）式中依據通道估計錯誤 $\mathbf{G}$ 而定的有效雜訊 $\tilde{\mathbf{v}}_k$ 既不是白雜訊也不是高斯雜訊。因此，一般而言在（2.17）式中精確的通道容量難以描述。取而代之，我們可以藉由漸近方式得到一個容易處理的通道容量下界（如［31］）。

B. **容量下界**

前置編碼階段期間的各態歷經的容量下界(每一傳送區塊）如下

$$\underline{I}_p(T_p) = E\log\det\left[\mathbf{I} + \left[\mathbf{R}_e / T_p + \sigma_v^2\mathbf{I}\right]^{-1}\mathbf{GP}^2\mathbf{G}^H\right]; \tag{2.18}$$

相似地，從（2.18）式，藉由設定 $\mathbf{P}=\mathbf{I}$ ，便可在直接資料傳輸階段獲得一個界限

$$\underline{I}_d(T_p) = E\log\det\left[\mathbf{I} + \left[\mathbf{R}_e / T_p + \sigma_v^2\mathbf{I}\right]^{-1}\mathbf{GG}^H\right]. \tag{2.19}$$

基於（2.18）及（2.19）式，橫越 T 個符元範圍的同調間隔之平均各態歷經的容量下界如下

$$\begin{aligned}\underline{I}(T_p) &= \frac{T_p}{T}\underline{I}_p(T_p) + \frac{(T-T_p)}{T}\underline{I}_d(T_p)\\ &= \frac{T_p}{T}E\log\det\left[\mathbf{I} + \left[\mathbf{R}_e / T_p + \sigma_v^2\mathbf{I}\right]^{-1}\mathbf{GP}^2\mathbf{G}^H\right]\\ &\quad + \frac{(T-T_p)}{T}E\log\det\left[\mathbf{I} + \left[\mathbf{R}_e / T_p + \sigma_v^2\mathbf{I}\right]^{-1}\mathbf{GG}^H\right].\end{aligned} \tag{2.20}$$

關於如何藉由最大化 $\underline{I}(T_p)$ 以選擇 T_p 這個問題，將在下一節中提到。

前置編碼間隔之選取

為了便利之後的分析與討論，我們定義前置編碼階段與 T 相關的標準化時間分數如下

$$\tau_p = T_p / T,\ 0 < \tau_p \le 1, \tag{2.21}$$

因此我們可將容量下界（2.20）式表示成 τ_p 的方程式如下：

$$\underline{I}(\tau_p) = \tau_p E\log\det\left\{\mathbf{I} + \left[\mathbf{R}_e / (\tau_p T) + \sigma_v^2\mathbf{I}\right]^{-1}\mathbf{G}\mathbf{P}^2\mathbf{G}^H\right\} + (1-\tau_p) E\log\det\left\{\mathbf{I} + \left[\mathbf{R}_e / (\tau_p T) + \sigma_v^2\mathbf{I}\right]^{-1}\mathbf{G}\mathbf{G}^H\right\}$$

(2.22)

給定 T 後，取捨之最佳化問題可被表示成：對所有的 $0<\tau_p\le 1$ ，最大化(2.22) 式中的 $\underline{I}(\tau_p)$ 。我們應該注意，因為 T_p 和 T 皆為正整數，因此$0<\tau_p\le 1$ 是一個有理數。為了簡化分析， τ_p 放寬限制為一個正實數；一旦發現 τ_p 之最佳解，則相對應的 T_p（雖然次優）可以定義成小於 $\tau_p T$ 的最大整數。然而，因為目標函式（2.22）是高度非線性，所以很難推導出此最佳化問題之解的明確表示式。不過，我們可以採取擾動分析來找出一個 $\underline{I}(\tau_p)$ 的近似表示式，使得分析最佳化τ_p的特性時更為便利。上述方法將在下一引理中介紹（見［31］）。

引理 2.1：令 $\underline{I}(\tau_p)$ 之定義如同（2.22）式。假設 σ_v^2 很小且 $\mathbf{I}/T \ll \sigma_v^2\tau_p\mathbf{R}_e^{-1}$ ，我們得到 $\underline{I}(\tau_p)\approx I_0 - f(\tau_p)$ ，其中 I_0 是與 τ_p 無關的常數，並且

$$f(\tau_p) \coloneqq \alpha\tau_p + \beta\tau_p^{-1}, \tag{2.23}$$

其中

$$\alpha \coloneqq E\log\det\left[\mathbf{I} + \sigma_v^{-2}\mathbf{G}\mathbf{G}^H\right] - E\log\det\left[\mathbf{I} + \sigma_v^{-2}\mathbf{G}\mathbf{P}^2\mathbf{G}^H\right] \tag{2.24}$$

$$\beta \coloneqq (T\sigma_v^4)^{-1} ETr\left[(\mathbf{I} + \sigma_v^{-2}\mathbf{G}\mathbf{G}^H)^{-1}\mathbf{R}_e\mathbf{G}\mathbf{G}^H\right]. \tag{2.25}$$

A. 最佳效能之取捨：分析上的特性

基於引理（2.1）， $\underline{I}(\tau_p)$ 對 τ_p 的一階導數近似於

$$\underline{I}'(\tau_p) \approx -f'(\tau_p) = (\beta - \alpha\tau_p^2)\tau_p^{-2} \tag{2.26}$$

依據(2.26)式，不難看出 $\underline{I}(\tau_p)$ 的最大值發生在 $\overline{\tau}_p \coloneqq \sqrt{\beta/\alpha}$ 附近。當$\tau_p < \sqrt{\beta/\alpha}$ ，從(2.26)式我們預期 $\underline{I}'(\tau_p) > 0$ ，且容量下界隨著 τ_p 遞增。當τ_p 超越 $\sqrt{\beta/\alpha}$ ，我們得出

$\underline{I}'(\tau_p) < 0$ ，且此時 $\underline{I}(\tau_p)$ 將變為隨著 τ_p 遞減。因為我們只考慮了 $0 < \tau_p \leq 1$ ，τ_p 的選取是否朝向最大化的容量下界前進將依照 $\sqrt{\beta / \alpha}$ 是否超過 1 而定。

<u>案例 1</u>：假如 $1 \leq \sqrt{\beta / \alpha}$ ，且使得 $\alpha \leq \beta$（也就是說，因前置編碼所引起的平均容量損失在最差的情況下還比因通道不匹配所產生的最小容量損失還小），則 $\underline{I}(\tau_p)$ 是一個在 $0 < \tau_p \leq 1$ 間的遞增函數。這表示我們應該直接設定成 $\tau_p = 1$ ，這是為了在整個同調間隔對符元作前置編碼，也是為了最大化 $\underline{I}(\tau_p)$ 。一個直觀上合理的看法是，只要通道不匹配之影響更鉅，便需要更長的前置編碼間隔來降低通道估測誤差，且依次擴增容量。

<u>案例 2</u>：假如 $1 > \sqrt{\beta / \alpha}$ ，且使得 $\alpha > \beta$ ，意味著前置編碼導致的容量損失更為嚴重，我們應該將 τ_p 設定成 $\sqrt{\beta / \alpha}$ 以獲得最大容量的最低邊界。這裡反應出一個事實，當前置編碼的影響更為不利，則應該要避免對符元作橫越整個同調間隔的前置編碼。取而代之，為了達到最大的容量增益，應該將前置編碼相位設定成 $\sqrt{\beta / \alpha}$ 這個分數。

基於以上討論，為了最大化前置編碼的容量，我們建議了以下的方程式以估測時間參數

$$\tilde{\tau}_p = \min\ 1,\ \sqrt{\beta / \alpha}\ , \tag{2.27}$$

其中 α 和 β 定義在 (2.24)式和 (2.25)式。因此，估測到的最佳前置編碼間隔為小於 $T\tilde{\tau}_p$ 的最大整數。我們注意到 α 和 β 皆包含了真實通道實現率的平均，並且一旦得知通道統計特性（例如高斯）便可以在離線狀態計算之。

結果與討論

這個部分提供了模擬結果來證實我們建議的 τ_p 選擇方法有巨大好處。在每一個同調間隔內，各個通道之通道值設置為平均值是 0，變異數為 1，同分布且相互獨立的複數高斯隨機變數。同 [1] 我們給定 $N = 32$ ，$L = 8$（循環字首的長度和通道的階數 L 相同），使用 QPSK 調變，且使用最佳的抗雜訊前置編碼器 (2.11) 做通道估測，臨界值為 $\delta = 0.9$ 。

我們考慮兩個訊雜比程度（25 dB 和 0 dB），且在每一個情況下，使用 (2.27)式來估測 4 個不同的同調間隔（T = 200, 2000, 8000, 20000）的最佳前置編碼時間分數。估測結果列於表一中（亦包含根據 (2.22)式之基於直接最大化的最佳解）。

Table I. Optimal precoding time fraction for different SNR and coherent time.

SNR=25 dB	T=200	T=2000	T=8000	T=20000
$\sqrt{\beta / \alpha}$	12.23	3.54	2.84	1.22
Est. via (5.7)	1	1	1	1
Optimal sol.	1	1	1	1
SNR= 0 dB	T=200	T=2000	T=8000	T=20000
$\sqrt{\beta / \alpha}$	1.22	0.55	0.32	0.21
Est. via (5.7)	1	0.55	0.32	0.21
Optimal sol.	1	0.60	0.35	0.25

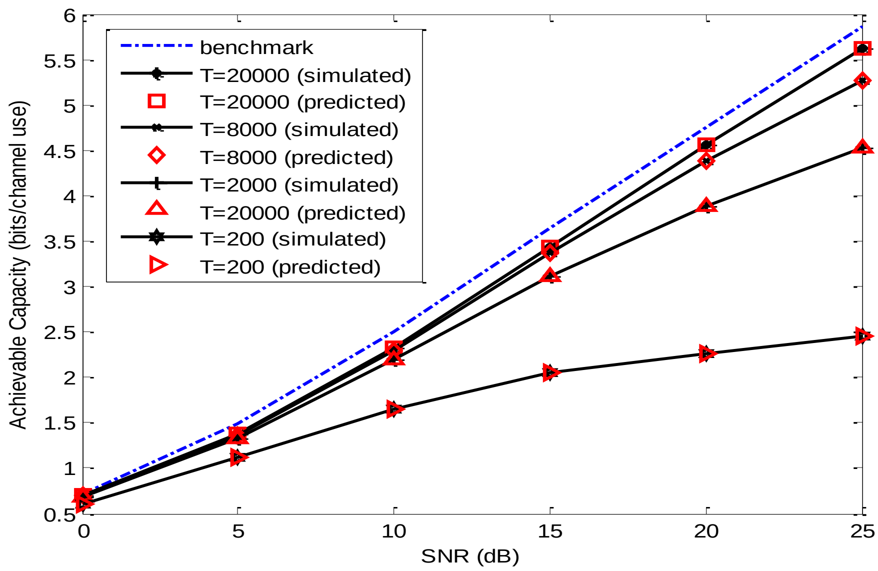

Figure 1. Achievable capacity performances for different coherent intervals.

(1) 當訊雜比很高時 (25 dB) ，最佳的策略是在整個同調間隔作前置編碼，且因此 $\tilde{\tau}_p = \tau_p^{(opt)} = 1$ 。一個粗略的解釋是，高訊雜比時，在系統 (2.17)中有效背景雜訊主要受通道估計的誤差支配，且經由一段長時間的前置編碼以降低通道的不確定性後，可實現最高通道容量。

(2) 當訊雜比較低 (0 dB) 且同調間隔 T 很小時，通道估測的品質有可能會相當的差，且將會成為通道容量損耗的主要原因。因此我們應該將整個同調間隔作前置編碼以改善通道估測的準確性，再加上 $\tilde{\tau}_p = \tau_p^{(opt)} = 1$ 便可最大化通道容量的上界。然而，當 T 愈來越大，使用太多同調間隔作前置編碼，沒有辦法太大地減少通道估測誤差 (因為誤差共變數的衰減率只有 $1/T_p = 1/(\tau_p T)$) ，相反地，更加擴大前置編碼的不利之處。因此， τ_p 應該保持在 1 以下以最大化通道容量的界限。

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主題三：

於感測雜訊參數誤差下的強健節能分散式參數估計技術

摘要

由於系統參數不匹配在實際的感測環境中時常發生，因此在考量感測雜訊變異度的不確定性之下，本研究提出了一個針對最佳線性非偏估計法的功率分配法則。我們採用貝氏定理，也就是感測雜訊變異度會遵循一種在文獻上被廣泛使用的統計分布，且各感測器與資料融合中心(FC)之間的通道皆預設為獨立且相同的瑞利衰減分佈。為利於分析，我們度量失真的方式是以平均均方誤差倒數(Average Riciprocal Mean Square Error)作為標準，其中，平均均方誤差倒數(ARMSE)是藉由平均化感測雜訊變異度和衰減通道的統計分佈而得。接著，對於 ARMSE 和平均均方誤差(Average Mean Square Error)之間的關係，可由一基本的不等式來表示。因為 ARMSE 的確切公式難以推導，我們因此改由推導一個相應的封閉形式下界，但此下界含有複雜且不完整的伽瑪函數。為了更進一步的簡化分析，我們推導了一個關鍵的不等式，確切說明 ARMSE 的下界範圍，更具體而言，此不等式的邊界點完全由高斯錯誤函數（$Q(\cdot)$）決定，因此相當益於分析。藉由最大化此函數，我們推導出各感測器的亞最佳功率分配系數。最後，電腦模擬的結果將證明我們提出的強健功率分配法的有效性。

關鍵字：感測器網路；分散式估計；功率分配

Abstract

Motivated by the fact that system parameter mismatch occurs in real-world sensing environments, this paper addresses power allocation for robust distributed Best-Linear-Unbiased-Estimation (BLUE) that takes account of the uncertainty in the local sensing noise variance. We adopt the Bayesian philosophy, wherein the sensing noise variance follows a statistical distribution widely used in the literature, and the communication channels between sensor nodes and the fusion center (FC) are assumed to be i.i.d. Rayleigh fading. To facilitate analysis, we propose to use the average reciprocal mean square error (ARMSE), averaged with respect to the distributions of sensing noise variance and fading channels, as the distortion metric. A fundamental inequality characterizing the relationship between ARMSE and the average mean square error (AMSE) is established. While the exact formula for ARMSE is difficult to find, we derive an associated closed-form lower bound which involves the complicated incomplete gamma function. To further ease analysis, we further derive a key inequality that specifies the range of the ARMSE lower bound. Particularly, it is shown that the boundary points of this inequality are characterized by a common quantity, which involves the Gaussian-tail function and is thus more analytically appealing. By conducting maximization of such a function, suboptimal sensor allocation factors are analytically derived. Computer simulation is used to evidence the effectiveness of the proposed robust power allocation scheme.

Key words: Sensor Networks; Distributed Estimation; Power Allocation.

研究目的與文獻探討

在情境感知的實作領域上，使用無線感測網路來作分散式估測是非常適合的，像是環境監測、定位與追蹤、溫控以及軍事用途上的監控等等[1]。而在現存眾多分散式估計法中，最佳線性非偏估計法(BLUE)[2-5]因為易於實作而受到矚目及廣為應用。為了符合無線感測網路對功率或能量效益的要求，

幾乎所有的分散式最佳線性非偏估計法都會為了達到最好的估計精準度，而採用功率有效分配或是最小化的相應機制[2-5]。在這些能量分配技術的開發中，基本上都會假設資料融合中心(FC)已知感測雜訊變異度以及瞬時通道增益(CSI)。

在現實的感測環境中，系統參數值的不確定性是無法避免的，例如隨著環境條件改變所造成的感測雜訊強度的波動，或是感測器不正常的運作。因此，除了考量能量效能之外，具有抵抗系統參數值誤差的能力也是在設計分散式感測演算法時的重要需求。在現有文獻中，雖然已有很多針對在感測網路下的分散式估計所作的研究[6]，然而，以最佳線性非偏估計法為法則所作的相關研究卻相當缺乏。因此，在本研究中，我們針對使用放大轉發演算法(Amplify-and-Forward Protocol)的無線感測網路 [5]，[7] 提出一個強健分散式最佳線性非偏估計法，此方法具備了抵抗感測雜訊功率不確定性的能力。首先，我們採用貝氏公式，並假設：(1)感測雜訊變異度的分佈遵循[2-4]的方式；(2)衰減通道為瑞利分佈，其在感知通道分散式訊號處理設計中，為一常用的假設[1]。根據感測雜訊變異度和衰減通道的分佈特性，我們可以計算 AMSE，而我們提出的方法的目標即為減少此 AMSE。接下來，本研究主要的技術貢獻總結如下：

（一）由於 AMSE 在分析上較複雜，所以我們採用藉由平均已知的分佈所得到的 ARMSE 作為評量成果的依據。值得注意的是，AMSE 和 ARMSE 之間基本的關係是可以從分析上去特徵化的。更明確地說，當給定目標 AMSE 的失真不超過ε，AMSE 的下界即為 ARMSE 的倒數；更重要地，AMSE 的上界即為 ARMSE 的倒數與ε的和。如此一來，這提供了一個改善估計精準度的設計方式：最小化 ARMSE 的倒數，或者最大化 ARMSE。這即為我們設計強健分散式最佳線性非偏估計法的基本設計準則。

（二）因為 ARMSE 的公式難以推導，這促使我們設法推導一個相關的且可分析的 ARMSE 下界，其為一複雜且不完整的伽瑪函數[7]。更進一步簡化分析，我們建立了一個重要的不等式，它代表 ARMSE 的下界值所可能座落的範圍。在這個不等式中，有一個很重要的發現是兩個邊界值完全由簡單的高斯錯誤函數決定。因此從分析的角度而言，這比起對 ARMSE 下界作分析更佳。因此，相對於直接最大化 ARMSE 或是 ARMSE 的下界，我們選擇根據這個函數來作最大化，進而推導出一個具封閉形式但亞最佳的感測功率分配法則。此方法在整體效能上所呈現的優點將在電腦模擬的章節作更進一步的展示。

研究方法

在無線感測器網路的架構下，我們考慮 N 個感測器與資料融合中心合作來估計一個未知的定型參數 $\theta \in \mathbb{R}$。在第 i 個感測器所觀測到的信號為

$$x_i = \theta + n_i,\ 1 \le i \le N \tag{2.1}$$

$n_i \in \mathbb{R}$ 為零均值量測雜訊，其變異度為 $\sigma_{n_i}^2$。如同[5]、[7]中的設置，我們假設每一個量測值 x_i 在傳送至資料融合中心的過程中，是透過放大轉發演算法分別經由 N 個平行的平緩衰減通道。於是，接收端收到從第 i 個感測器傳送的訊號，$1 \le i \le N$，可表示為

$$y_i = h_i p_i x_i + v_i = h_i p_i(\theta + n_i) + v_i = h_i p_i \theta + h_i p_i n_i + v_i, \tag{2.2}$$

$h_i \in \mathbb{R}$、p_i 分別為第 i 個感測器到接收端的通道增益與功率放大係數，$v_i \in \mathbb{R}$ 為零均值白雜訊，變異度為 $\sigma_{v_i}^2$；在此篇論文中，我們讓 $\sigma_{v_i}^2 = \sigma_v^2$。假設所有感測雜訊 n_i 是獨立同分布且與通道雜訊彼此間獨立，基於(2.2)式中的接收信號 y_i，參數 θ 可藉由在資料融合中心作最佳線性非偏估計法[1]而得到，形式如下：

$$\hat{\theta} = \left(\sum_{i=1}^{N} \frac{p_i h_i y_i}{p_i^2 h_i^2 \sigma_{n_i}^2 + \sigma_v^2} \right) \left(\sum_{i=1}^{N} \frac{1}{\sigma_{n_i}^2 + \sigma_v^2 / \ p_i^2 h_i^2} \right)^{-1} \qquad (2.3)$$

其相對應的均方誤差(Mean Square Error)為：

$$MSE = \left(\sum_{i=1}^{N} \frac{1}{\sigma_{n_i}^2 + \sigma_v^2 / \ p_i^2 h_i^2} \right)^{-1}. \qquad (2.4)$$

即便我們有區域性感測雜訊功率 $\sigma_{n_i}^2$ 一個名義上的值，但實際上的雜訊情況可能會更差，例如由於逐步流失的電池功率或者是感測器運作失誤所造成。對每一個感測器而言，一旦我們有了一名義上的雜訊功率臨界值 δ_i，下一步就是從 δ_i 出發，去找到一個合適的統計特性用來描述此雜訊功率的不確定性。參考[2-4]，我們可用一簡單且直觀的模型來模擬此種不確定性，即 $\sigma_{n_i}^2 = \delta_i + z_i$ ，其中 $z_i \sim \chi_1^2$ 為一中心卡方分佈，其自由度為 *1*，$1 \le i \le N$。更進一步的考慮，雜訊的不確定性可能會隨著感應器的不同而有程度上的差異，因此，在此篇論文中我們假設區域性感測雜訊變異度會循著以下模型：

$$\sigma_{n_i}^2 = \delta_i + \alpha_i z_i, 1 \le i \le N \qquad (2.5)$$

δ_i 是在第 i 個感測點名義上的雜訊變異度，$z_i \sim \chi_1^2$ 是自由度為 *1* 的中心卡方(Chi-Square)隨機變數(假設對不同的 i，皆為獨立同分佈)，且 α_i 反映出第 i 個感測點其相對應雜訊不確定性的程度。接著，關於衰減通道的分佈特性，我們採用一般文獻上所使用的假定（例如[1]），即通道增益 h_i 為獨立同分佈的瑞利分佈。

總而言之，本研究的目標是在考慮感測雜訊變異度分佈和衰減通道特性之下，設法針對每一個感測器去設計其功率分配係數 p_i，以改善整體傳送機制的 AMSE。

接下來，在效能分析上，我們作了以下的探討。

(1)ARMSE 法之估測效能

均方誤差(MSE)是一個被廣泛使用在效能評估上的方法，但在採用最佳線性非偏估計法的情況下，複雜的反運算(如(2.4)所示)會造成推導一可分析的 AMSE 公式的困難。面對這樣的問題，使得我們企圖去尋找更有選擇性的效能分析方法，一方面可以正確表示 AMSE 的趨勢，另一方面則可以簡化分析。

基於此目的，在開始前我們先決定感測雜訊變異數 $\sigma_{n_i}^2$ 和通道響應 h_i，並用均方誤差(2.4)來考慮估測效能的限制，如下：

$$\left(\sum_{i=1}^{N}\frac{1}{\sigma_{n_i}^2+\sigma_v^2/\ p_i^2h_i^2}\right)^{-1}\le\varepsilon \tag{3.1}$$

此處 ε 為目標失真等級。接著，極為重要的是，(3.1)可被改寫為由均方誤差倒數(Reciprocal Mean Square Error)為觀點的數學式：

$$RMSE=\sum_{i=1}^{N}\frac{1}{\sigma_{n_i}^2+\sigma_v^2/\ p_i^2h_i^2}\ge\varepsilon^{-1} \tag{3.2}$$

因此，當給定瞬時 $\sigma_{n_i}^2$ 和 h_i，我們也能以均方誤差倒數(RMSE)作為效能評估的指標；當 RMSE 愈大，估計的準確度愈高。而從分析的觀點來看，由於 RMSE 沒有涉及”反運算”，所以 RMSE 相較於 MSE 更易處理。在接下來我們會介紹，基於這樣的特性，在考慮功率分配問題時，使我們能夠找到一個相關的平均效能分析公式以提升分析效率。總之，基於上述所提之理由，對於強健分散性最佳線性非偏估計法的效能分析，我們將採用 ARMSE 做為評量標準，式子如下：

$$\begin{aligned}D&\triangleq\int_{\mathbf{h}}\int_{\mathbf{z}}\left[RMSE\right]d\mathbf{z}\,d\mathbf{h}\\&=\int_{\mathbf{h}}\int_{\mathbf{z}}\sum_{i=1}^{N}\frac{1}{\delta_i+\alpha_i z_i+\sigma_v^2/\ p_i^2h_i^2}f_{\mathbf{Z}}(\mathbf{z})f_{\mathbf{H}}(\mathbf{h})d\mathbf{z}\,d\mathbf{h},\end{aligned} \tag{3.3}$$

其中 $\mathbf{z}\triangleq[z_1\cdots z_N]^T$ 和 $\mathbf{h}\triangleq[h_1^2\cdots h_N^2]^T$，且 $f_{\mathbf{Z}}(\mathbf{z})$ 和 $f_{\mathbf{H}}(\mathbf{h})$ 分別為相關的機率分布。當 D 愈大時，會有愈好的估測準確度，因此在設計感測器功率分配系數時，目標是期望 D 要越大越好。

儘管上述提及的方法是非常直觀合理的設計方式，但 AMSE 一般來說並不等於 D^{-1}（可經由傑森不等式(Jensen’s Inequality)來證明）。因此，一旦 D 增大，AMSE 能否保持在一個小的值（小至何種程度）仍是一個尚未被解答的基本問題。以下定理證明了 D^{-1} 和實際的 AMSE 的基本關係(證明過程參考附錄):

定理 3.1: 令 D 為(3.3)的 ARMSE，則我們可以得到

$$D^{-1}\le E\left\{\left(\sum_{i=1}^{N}\frac{1}{\sigma_{n_i}^2+\sigma_v^2/\ p_i^2h_i^2}\right)^{-1}\right\}\le D^{-1}+\varepsilon, \tag{3.4}$$

其中 ε 是(3.1)中所設定的目標失真等級。 □

定理 3.1 明確肯定了 D^{-1} 為 AMSE 的下界，且上界無法超過 D^{-1} 和目標失真等級 ε 的和。尤其當

ε 被限制為一個很小的值時，會產生非常好的估計品質，此時 D^{-1} 可以近似為 AMSE。因此，使 D^{-1} 盡可能小，或相當於使 D 盡量大，是簡化 AMSE 的一個合理方法。

(2)ARMSE 下界

為了最大化 ARMSE，第一個可行的方式是找出(3.3)中 D 的分析式。然而，由於(3.3)式的雙重積分較難處理，無法直接導出一個公式解。為了克服這個問題，一個簡單的處理方式是去尋找 ARMSE 較容易處理的下界，然後最大化此下界。經過一些繁複的處理(因為篇幅關係有些細節被刪減)，D 的下界可以被寫為

$$D \geq \underline{D} \triangleq \frac{1}{2}\sum_{i=1}^{N}\int_0^{\infty}\frac{x_i e^{-x_i/2}}{\left[(\sigma_v^2 / p_i^2)+(\alpha_i+\delta_i)x_i\right]}dx_i . \tag{3.5}$$

以下定理提供了一個關於 $\underline{D}$ 下界的公式解，此定理的證明可於[9]中尋得(由於篇幅關係證明在此不提)

定理 3.2:令 $\underline{D}$ 被定義在(3.5)中，則我們可以得到

$$\underline{D} = \frac{1}{2}\sum_{i=1}^{N}\left(\frac{\sigma_v^2}{p_i^2(\alpha_i+\delta_i)^2}\right)e^{\sigma_v^2/[2p_i^2(\alpha_i+\delta_i)]}\mathbf{\Gamma}(2)\mathbf{\Gamma}\left(-1,\frac{\sigma_v^2}{p_i^2(\alpha_i+\delta_i)}\right), \tag{3.6}$$

其中

$$\mathbf{\Gamma}(v) \triangleq \int_0^{\infty} e^{-t}t^{v-1}dt \tag{3.7}$$

是一 Gamma 函數且

$$\mathbf{\Gamma}\ \beta,x\ \triangleq \int_x^{\infty} e^{-t}t^{\beta-1}dt \tag{3.8}$$

是一不完整的伽瑪函數[8]。 □

(3)ARMSE 下界的信賴區間

雖然(3.6)式是封閉形式，但它包含了不完整的伽瑪函數，造成分析上的困難。為了克服此缺點，接下來將會推導關於 $\underline{D}$ 的信賴區間不等式。在這不等式中，有一個重要特性是其兩個邊界點都牽涉到高斯錯誤函數，因此較 $\underline{D}$ 易處理。以下，我們用一定理來精準描述結果(證明的概述如附錄)：

定理 3.3: $\underline{D}$ 為(3.6)中的 ARMSE 的下界，則 $\underline{D}$ 遵守下列不等式

$$\sqrt{\frac{(2-3e^{-1/2})}{4(1-e^{-1/2})}}D' \leq \underline{D} \leq \frac{3e^{-1/2}}{\sqrt{8}\mathbf{\Gamma}(3/2,1/2)}D', \tag{3.9}$$

其中，

$$D' \triangleq \sum_{i=1}^{N}\left\{\frac{\sqrt{2\pi}}{\alpha_i+\delta_i}-\frac{2\pi e^{(\sigma_v^2/p_i^2)/[2(\alpha_i+\delta_i)]}\sqrt{(\sigma_v^2\,/\,p_i^2)}}{(\alpha_i+\delta_i)\sqrt{(\alpha_i+\delta_i)}}Q\left(\sqrt{\frac{(\sigma_v^2\,/\,p_i^2)}{\alpha_i+\delta_i}}\right)\right\} \tag{3.10}$$

□

從(3.9)式中可以看出 $\underline{D}$ 的上界和下界皆為 D' 函數的倍數關係(經由計算，(3.9)式可進一步改寫成 $0.3386D' \le \underline{D} \le 2.7479D'$)。由此可見，當對 $\underline{D}$ 作最大化的動作時，本來我們必須對不完整伽瑪函數作複雜困難的處理，現在轉為處理 D' 就行，這其中最主要的好處是 D' 只牽涉到高斯錯誤函數。在下一個章節，我們將會說明，利用高斯錯誤函數的某些特性，感測器功率分配問題可以被公式化為一凹最佳化問題，也因此能夠產生封閉形式的公式解。

結果與討論

(1) ***感測器能量分配問題的描述與最佳解***

本段主旨在於如何在有限能量的前提下，使感應器的能量分配能夠令估計的表現結果達到最佳性能表現。根據(3.10)式中所提供的成本函數 D'，欲使其最大化，則最佳化問題可以由下所表示：

$$\begin{aligned}&Maximize\\&\frac{1}{\sqrt{2\pi}}\sum_{i=1}^{N}\left\{\frac{\sqrt{2\pi}}{\alpha_i+\delta_i}-\frac{2\pi e^{(\sigma_v^2/p_i^2)/[2(\alpha_i+\delta_i)]}\sqrt{(\sigma_v^2\,/\,p_i^2)}}{(\alpha_i+\delta_i)\sqrt{(\alpha_i+\delta_i)}}Q\left(\sqrt{\frac{(\sigma_v^2\,/\,p_i^2)}{\alpha_i+\delta_i}}\right)\right\},\\&subject\ to\ \sum_{i=1}^{N}p_i^2 \le P,\ p_i \ge 0,\ 1 \le i \le N,\end{aligned} \tag{4.1}$$

其中 P 決定了所有可用的能量預算。由於在(4.1)式中的目標函式對於 p_i 仍具有高度的非線性關係，因此這個最佳化問題不容易解出。幸運的是，$Q(\cdot)$ 函數有以下幾個關鍵性的不等式可用來幫助分析：

$$\begin{aligned}&\frac{1}{\sqrt{2\pi}}\sum_{i=1}^{N}\left\{\frac{\sqrt{2\pi}}{\alpha_i+\delta_i}-\frac{2\pi e^{(\sigma_v^2/p_i^2)/[2(\alpha_i+\delta_i)]}\sqrt{(\sigma_v^2\,/\,p_i^2)}}{(\alpha_i+\delta_i)\sqrt{(\alpha_i+\delta_i)}}Q\left(\sqrt{\frac{(\sigma_v^2\,/\,p_i^2)}{\alpha_i+\delta_i}}\right)\right\}\\&\overset{(a)}{\ge}\frac{1}{\sqrt{2\pi}}\sum_{i=1}^{N}\left\{\frac{\sqrt{2\pi}}{\alpha_i+\delta_i}-\frac{\pi\sqrt{(\sigma_v^2\,/\,p_i^2)}}{(\alpha_i+\delta_i)\sqrt{(\alpha_i+\delta_i)}}\right\}\\&=\sum_{i=1}^{N}\left\{\frac{1}{\alpha_i+\delta_i}-\frac{\sigma_v\sqrt{\pi}}{p_i(\alpha_i+\delta_i)\sqrt{2(\alpha_i+\delta_i)}}\right\},\end{aligned} \tag{4.2}$$

其中(a)為知名的切爾諾夫(Chernoff)邊界：$Q(x) \le e^{-x^2/2}\,/\,2$。不等式(4.2)提供了(4.1)式中目的函數的一個下界，而對於能量分配係數 p_i 來說，此問題已成為一凹(convex)最佳化問題。因此，我們提議將此下界(4.2)最大化，用來取代直接將(4.1)式中的成本函數最大化的作法；稍後可以發現此做法能得到封閉形式之亞最佳解。現在此最佳化問題變成了：

$$Maximize \sum_{i=1}^{N}\left\{\frac{1}{\alpha_i+\delta_i}-\frac{\sigma_v\sqrt{\pi}}{p_i(\alpha_i+\delta_i)\sqrt{2(\alpha_i+\delta_i)}}\right\}$$
$$subject\ to \sum_{i=1}^{N} p_i^2 \le P,\ p_i \ge 0,\ 1 \le i \le N \qquad (4.3)$$

藉由標準的拉格朗日乘數技術(Lagrange Multiplier Technique)，(4.3)式的最佳解可由卡羅需－庫恩－塔克條件(KKT conditions)解出，形式如下(細節部分由於篇幅限制不再贅述)

$$\tilde{p}_i = \sqrt{\frac{P}{(\alpha_i+\delta_i)\left(\sum_{i=1}^{N}\frac{1}{\alpha_i+\delta_i}\right)}},\ 1 \le i \le N. \qquad (4.4)$$

(2)***數值效能分析***

本段落以數種在數值上的模擬結果來驗證先前的推導分析。我們考慮在一個擁有感應器數量為 $N=250$、通道雜訊變異數為 $\sigma_v^2=0.05$ 的網路下，區域性感測雜訊變異度的不確定性參數 α_i 均勻分布於區間 $[0\ \alpha]$，其中 $\alpha>0$，稱為整體不確定性參數；同樣地雜訊變異度臨界值 δ_i 也是均勻分布在區間 $[0\ \delta]$，其中 $\delta>0$ 代表最大額定值。當 $\alpha=5$ 且 $\delta=1$，在不同的傳送能量 P 之下，圖 1 針對(4.4)式所對應的強健解與在(4.4)中設定 $\alpha_i=0$ 之非強健解在 AMSE 上所作的比較。從圖上可看出強健解的 AMSE 的確有所降低。同時，AMSE 也隨著傳送能量 P 升高而降低。這部分是相當直觀合理的，因為較大的傳送能量可以增進在資料融合中心的整體訊號品質，進而改善整體估計的準確度；同樣的現象可以在許多先前的研究中發現，如[5]。當 $P=40$ 且 $\delta=1$，圖 2 描述了對於不同的整體不確定性參數 α 其 AMSE 的變化。圖中顯示出當系統功率固定時，AMSE 會隨著整體不確定性參數 α 而增加。這部分並沒有超出預期，因為當整體不確定性參數 α 增加時，真實的雜訊變異度與名義值之間的偏差也會增大，因此降低了整體估計的品質。

(3)***結論***

本篇論文是考慮在感測雜訊變異度的不確定性存在的情況下，對強健分散式最佳線性非偏估計法的能量分配法則提供了基本的貢獻。關於所提議的 ARMSE 設計準則有許多獨特的優點。第一，當目標的 AMSE 很小時，ARMSE 的倒數對 AMSE 的近似將會是一非常接近的估計。根據這具吸引力的基本結果，最大化 ARMSE 對於改善估計品質而言是一個正當的方法。第二，在使用 ARMSE 的方式來設計功率分配系數時，原本艱難的分析可由易分析處理的目標函數所取代。此法所得為一封閉形式解，且從電腦模擬結果來看，整體成果比非強健設計更佳。

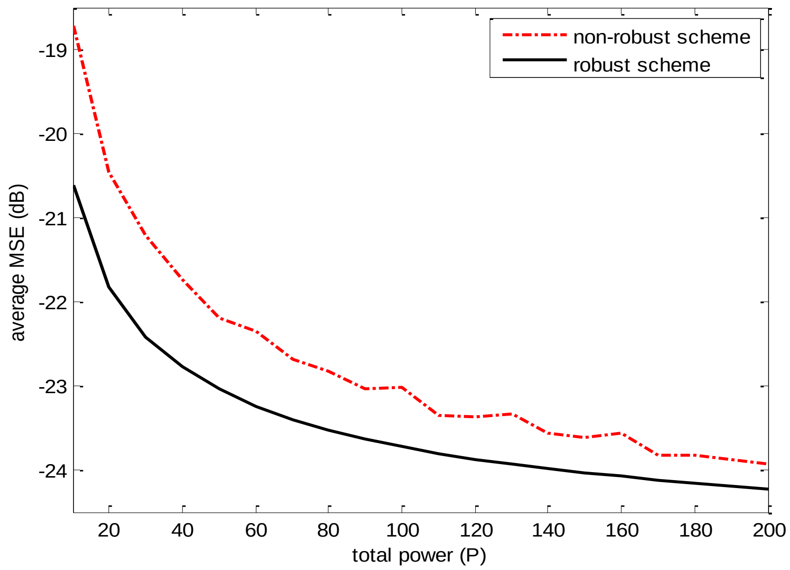

圖 1：在不同的總功率值之下，強健設計與非強健設計的 AMSE 比較

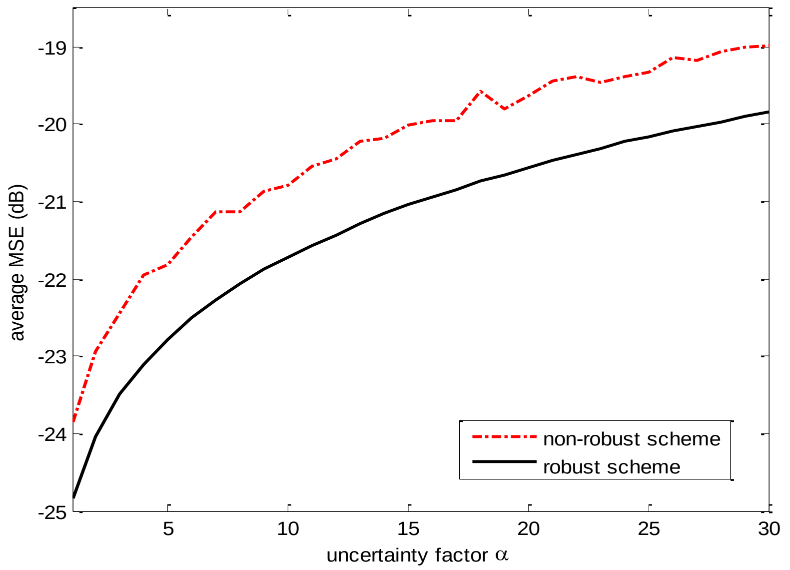

圖 2：在不同的不確定性參數 α 之下，強健設計與非強健設計的 AMSE 比較

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主題四：

基於能量偵測器之頻譜偵測機制於主要用戶信號時間延遲下之效能分析

摘要

頻譜偵測的研究在下一代的感知無線電系統中，一個典型的設計挑戰在主要傳送者跟次要接收者間的時間不同步，而毫微微覆蓋式的家用基地台網路就是個例子。在本年度的研究中，我們假設主要使用者訊號的到達時間為觀測範圍內均勻分布的隨機變數，並依此研究能量偵測的效能。而後經由數值模擬可以驗證我們的結果。為了更進一步改善偵測的效能，我們另外提出以貝式法則為基礎的方式以得到能有效對抗雜訊的能量感知技術，且經由電腦模擬證實此法結果較一般的能量偵測來的好。

關鍵字：感知無線電; 頻譜偵測; 能量偵測

Abstract

Spectrum sensing in next-generation wireless cognitive systems, such as overlay femtocell networks, is typically subject to timing misalignment between the primary transmitter and the secondary receiver. In this paper, we investigate the performance of the energy detector (ED) when the arrival time of the primary signal is modeled as a uniform random variable over the observation interval. The exact formula for the detection probability is derived and corroborated via numerical simulation. To further improve the detection performance, we propose a robust ED based on the Bayesian principle. Computer simulation confirms the effectiveness of the Bayesian based solution when compared with the conventional ED.

Keywords: Cognitive radio; Spectrum sensing; Energy detection.

研究目的與文獻探討

感知無線電是一個廣為人知的頻譜感測技術，此技術是藉由偵測並利用閒置的頻譜以提高頻譜的使用效率。所以頻譜偵測對感知無線電來說，是不可或缺的一部分。在文獻中，傳統上閒置頻譜的偵測，都是考慮在二元假說的試驗，信號模型如下 [1-2]

$$\begin{aligned} \mathcal{H}_0 &: x[n] = w[n], && n = 0,1,\cdots,N-1 \\ \mathcal{H}_1 &: x[n] = s[n] + w[n], && n = 0,1,\cdots,N-1 \end{aligned} \tag{1.1}$$

其中 N 為數據的長度，$s[n]$，$x[n]$和 $w[n]$分別是主要使用者的訊號，感知無線用戶接收訊號和通道雜訊。在 (1.1) 中，其假設為主要用戶傳送端和感知無線用戶接收端之間為完美同步。然而這個假設在實際情況下是不合理的。舉例來說，在一個毫微微家用基地台覆蓋式網路中，巨細胞的行動通訊使用者和巨細胞行動通訊的基地台是同步的，但是和毫微微家用基地台卻不同步。此外，在無線隨意網路的環境下，主要使用者可能會隨時進入網路，因此時間延遲的發生是無法避免的。故就前面提到的情況下，更適合的模型設計應如下

$$\begin{aligned} \mathcal{H}_0 &: x[n] = w[n], \qquad n = 0,1,\cdots,N-1 \\ \mathcal{H}_1 &: x[n] = \begin{cases} w[n], & n = 0,1,\cdots,n_0-1 \\ s[n]+w[n], & n = n_0,\cdots,N-1 \end{cases} \end{aligned} \tag{1.2}$$

其中，n_0 表示為主要使用者的到達時間。所以，和現有於同步假設下的頻譜感測法則相比，本研究記畫考慮的目標是在 (1.2) 式的訊號模型下，針對訊號到達時間未知的情況下做頻譜偵測的研究。

在目前存在的頻譜感測中，能量偵測 [6] 是主流，因為其只需要主要訊號的部分資訊 (二階統計量) ，而且其複雜度較低 [1-2]。此外，雖然對於能量偵測的效能變化特性目前已有研究 [7-9]，但是這些研究的討論，都是根據 (1.1) 的模型為準。我們研究在 (1.2) 模型下能量偵測的效能。在繁忙的隨機接取網路中，主要使用者的使用時機對於次要使用者來說是未知的，所以我們假設主要使用者訊號的到達時間n_0為在$0 \leq n \leq N-1$範圍內的均勻分布。本研究的技術貢獻如下:其一，根據(1.2)式的假設，我們可以推導出平均偵測機率的解析公式，本研究修改以往的假設使之較符合現實的頻譜感測狀況，並據此做出完整的效能分析。其二，為了能夠增進偵測效能，我們利用預先所知的n_0分佈，也提出了從貝式法則出發所得到的能量感知技術以有效對抗雜訊。數值模擬結果顯示，以貝式法則為基礎得到的結果可以有效提高偵測機率。此外，經由所設定的偵測機率臨界值，此方式得以降低假警報的機率進而增加感知無線電的頻譜使用效率。未來，我們將致力於研究如何把這些成果運用在合作式偵測領域上。

研究方法

(1) 一般的能量偵測的檢驗統計方式定義如下

$$T = \sum_{n=0}^{N-1} \left| x[n] \right|^2 \tag{2.1}$$

在 (1.2) 式中，且有一個固定 n_0 的 $\mathcal{H}_1$ 前提下，讓我們將檢驗統計量 T 分解成

$$T = \underbrace{\sum_{n=0}^{n_0-1} \left| x[n] \right|^2}_{:=T_1} + \underbrace{\sum_{n=n_0}^{N-1} \left| x[n] \right|^2}_{:=T_2} \tag{2.2}$$

藉由 (2.2) 式，我們將首先得到條件偵測機率；而平均機率可經由針對 n_0 取期望值而得到。機率密度函數 $f_{\overline{T}}(x)$ 可表示為

$$\begin{aligned}
f_{\overline{T}}(x) &= \frac{(1+SNR)^{[(N-n_0)/2]-1}}{\sqrt{2^N}} \times \left\{ \mathcal{L}^{-1} \left((s+1/2)^{-n_0/2} \right) * \mathcal{L}^{-1} \left(s+(1+SNR)/2 \right)^{-(N-n_0)/2} \right\} \\
&= \frac{(1+SNR)^{[(N-n_0)/2]-1}}{\sqrt{2^N}} \times \left\{ \left[\frac{x^{(n_0/2)-1} e^{-x/2} u(x)}{\Gamma(n_0/2)} \right] * \left[\frac{x^{[(N-n_0)/2)]-1} e^{-(1+SNR)x/2} u(x)}{\Gamma((N-n_0)/2)} \right] \right\} \\
&= \frac{(1+SNR)^{[(N-n_0)/2]-1}}{\sqrt{2^N}\,\Gamma(n_0/2)\Gamma((N-n_0)/2)} \int_0^x \tau^{[(N-n_0)/2)]-1} e^{-(1+SNR)\tau/2} (x-\tau)^{n_0/2-1} e^{-(x-\tau)/2} d\tau \\
&= \frac{(1+SNR)^{[(N-n_0)/2]-1}}{\sqrt{2^N}\,\Gamma(n_0/2)\Gamma((N-n_0)/2)} \times e^{-x/2} \int_0^x \tau^{[(N-n_0)/2)]-1} (x-\tau)^{n_0/2-1} e^{-SNR\tau/2} d\tau
\end{aligned} \tag{2.3}$$

因此，我們規定一個假警報機率而得到一個臨界值 γ，則條件偵測機率就可以藉由 (2.3) 式來計算

$$P_D(n_0)=\int_{\gamma}^{\infty} f_{\bar{T}}(x)dx=\frac{(1+SNR)^{[(N-n_0)/2]-1}}{\sqrt{2^N}\Gamma(n_0/2)\Gamma((N-n_0)/2)}\int_{\gamma}^{\infty}\underbrace{\left[e^{-x/2}\int_0^x \tau^{[(N-n_0)/2)]-1}(x-\tau)^{n_0/2-1}e^{-SNR\tau/2}d\tau\right]}_{:=p(x)}dx \quad (2.4)$$

吾人可以進一步證明 $P_D(n_0)$ 於(2.4)式中可表示成

$$\begin{aligned} P_D(n_0) &= \frac{(1+SNR)^{[(N-n_0)/2]-1}B\left(\frac{N-n_0}{2},\frac{n_0}{2}\right)}{\sqrt{2^N}\Gamma(n_0/2)\Gamma((N-n_0)/2)}\times\left[\sum_{i=0}^{\infty}a_i\int_{\gamma}^{\infty}e^{-x/2}x^{(N/2)+i-1}dx\right] \\ &= \frac{(1+SNR)^{[(N-n_0)/2]-1}B\left(\frac{N-n_0}{2},\frac{n_0}{2}\right)}{\sqrt{2^N}\Gamma(n_0/2)\Gamma((N-n_0)/2)}\sum_{i=0}^{\infty}a_i\left[\left(\frac{1}{2}\right)^{(N/2)+i}\Gamma\left(\frac{N}{2}+i,\frac{\gamma}{2}\right)\right] \end{aligned} \quad (2.5)$$

藉由 (2.5)式，再藉由對 n_0 作期望值的運算可以得到以下定理。

Theorem 2.3: 在 (1.2) 式中的前提試驗下，能量偵測的的平均偵測機率為

$$P_D=\frac{1}{N}\sum_{n_0=0}^{N-1}P_D(n_0)=\frac{1}{N}\sum_{n_0=1}^{N-1}\left\{\frac{(1+SNR)^{[(N-n_0)/2]-1}B\left(\frac{N-n_0}{2},\frac{n_0}{2}\right)}{\sqrt{2^N}\Gamma(n_0/2)\Gamma((N-n_0)/2)}\sum_{i=0}^{\infty}a_i\left[2^{(N/2)+i}\Gamma\left(\frac{N}{2}+i,\frac{\gamma}{2}\right)\right]\right\} \quad (2.6)$$

其中 γ 是經由規定假警報機率而得到的臨界值。

(2) 基於貝式法則之強健式能量偵測技術

利用事前 n_0 的統計資訊來提高偵測效能[6]。貝式法決定為 $\mathcal{H}_1$ 假如 (參考 [6, Chap. 6])

$$\begin{aligned} &\frac{\frac{1}{N}\sum_{n_0=0}^{N-1}p(\mathbf{x};n_0,\mathcal{H}_1)}{p(\mathbf{x};\mathcal{H}_0)} \\ &=\frac{\frac{1}{N}\sum_{n_0=0}^{N-1}\frac{1}{(2\pi\sigma_0^2)^{n_0/2}}\exp\left[\frac{-1}{2\sigma_0^2}\sum_{n=0}^{n_0-1}|x[n]|^2\right]\times\frac{1}{(2\pi(\sigma_0^2+\sigma_1^2))^{(N-n_0)/2}}\exp\left[\frac{-1}{2(\sigma_0^2+\sigma_1^2)}\sum_{n=n_0}^{N-1}|x[n]|^2\right]}{\frac{1}{(2\pi\sigma_0^2)^{N/2}}\exp\left[\frac{-1}{2\sigma_0^2}\sum_{n=0}^{N-1}|x[n]|^2\right]}>\gamma \end{aligned} \quad (3.1)$$

而經由數值模擬證實，使用貝式法的 (3.1) 式效能較使用一般分析方法的 (2.1) 式來的好。

結果與討論

所有的取樣數目為 $N=200$，訊號到達時間 n_0 為一個均勻分布範圍在 $0\le n_0\le 199$ 的隨機變數。圖 1 表示的是在 SNR 為 -5dB 時，（2.1）式的偵測機率和實驗的偵測機率比較。圖 2 是在假警報機率 $P_f=0.05$ 時偵測機率 P_D 在不同的 SNR 下的變化。由圖 1 和圖 2 可看出理論結果與模擬結果相

當一致。圖 3 是在 $P_f = 0.05$ 時，針對不同的 SNR 比較（3.1)式和（2.1）式的偵測機率（P_D）值。圖 4 則是在 $P_d = 0.95$ 時，針對不同的 SNR 比較（3.1)式和（2.1）式的次要使用者使用效率（$1 - P_f$）值。由圖 3 和圖 4 可看出基於貝式法則的偵測技術能更進一步改善信號偵測效能並提高次要用戶的頻譜使用效益。

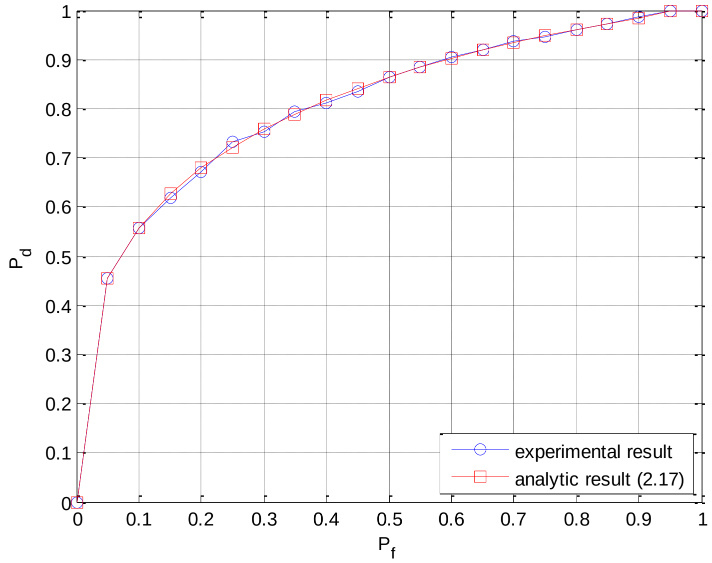

圖 1：在 SNR=-5dB 時，實驗和真實值偵測機率和假警報機率的關係比較。

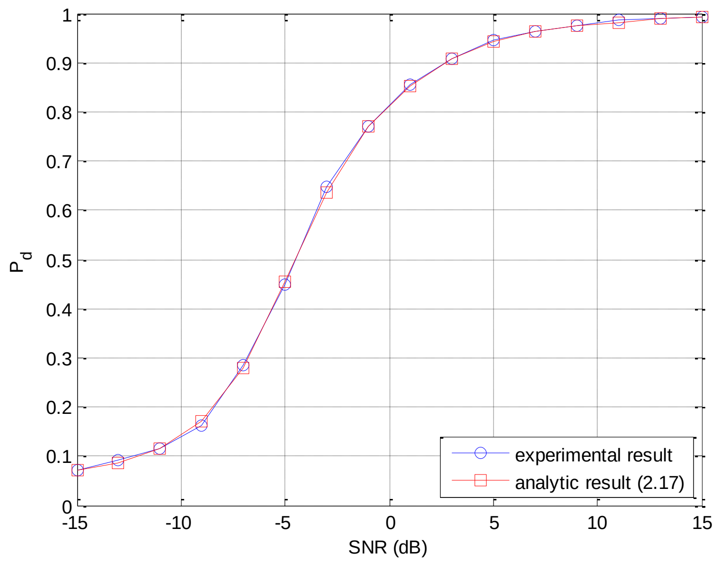

圖 2：在 $P_f = 0.05$ 時，實驗和真實值偵測機率和 SNR 的關係比較。

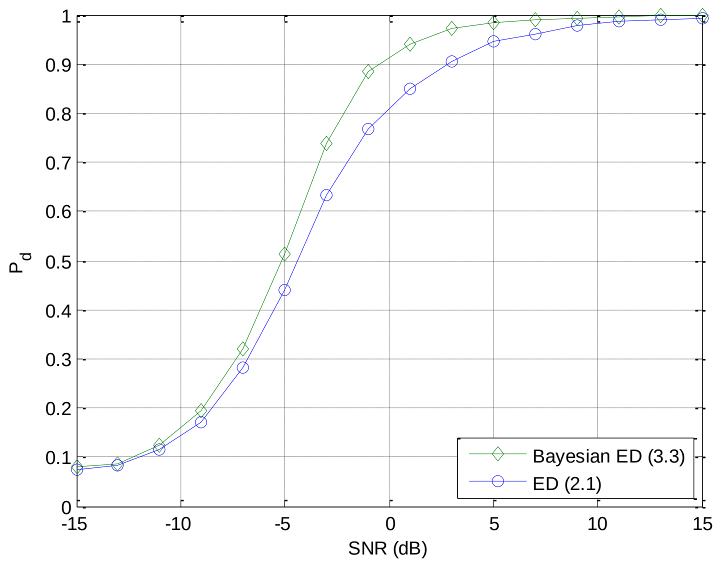

圖 3：在 $P_f = 0.05$ 時，(2.1) 式和 (3.1) 式偵測機率和 SNR 的關係比較。

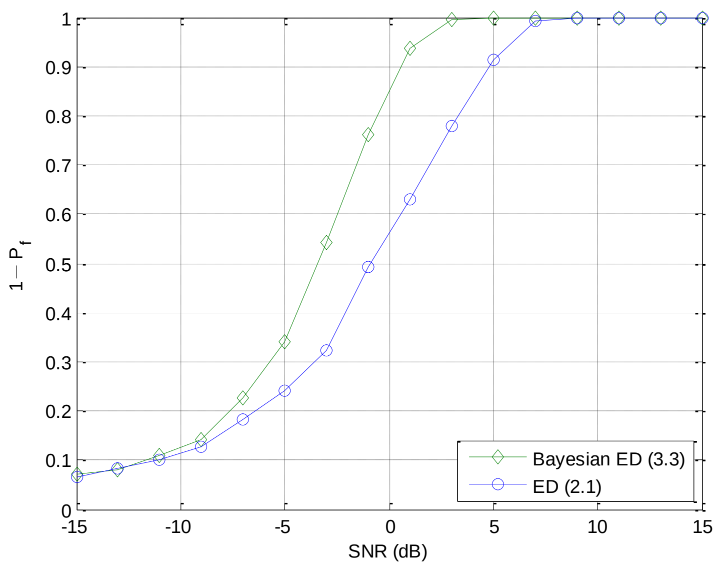

圖 4：在 $P_d = 0.95$ 時，$1 - P_f$ 和 SNR 的關係比

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成果自評

本計劃的研究成果頗為豐碩，藉由計劃的執行，於三年內總共發表了六篇頂尖IEEE國際期刊論文，以及十四篇指標型IEEE國際研討會論文(詳細內請見後面附錄)。而參與計劃的碩、博士班研究生，也獲得良好的專業訓練，畢業後都能到知名企業及相關研發單位服務，這也替國家通訊網路產業厚植研發人力。

Publication list

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附 錄

Performance Analysis of Energy Detection Based Spectrum Sensing with Unknown Primary Signal Arrival Time

Jwo-Yuh Wu, *Member, IEEE*, Chih-Hsiang Wang, and Tsang-Yi Wang, *Member, IEEE*

***Abstract*—Spectrum sensing in next-generation wireless cognitive systems, such as overlay femtocell networks, is typically subject to timing misalignment between the primary transmitter and the secondary receiver. In this paper, we investigate the performance of the energy detector (ED) when the arrival time of the primary signal is modeled as a uniform random variable over the observation interval. The exact formula for the detection probability is derived and corroborated via numerical simulation. To further improve the detection performance, we propose a robust ED based on the Bayesian principle. Computer simulation confirms the effectiveness of the Bayesian based solution when compared with the conventional ED.**

***Index Terms*—Cognitive radio, spectrum sensing, energy detection.**

I. Introduction

COGNITIVE radio (CR) is a widely known opportunistic spectrum access technique for enhancing the cell-wide spectrum utilization efficiency [1-2]. In order to detect the idle frequency band so as to gain the channel access, spectrum sensing performed at the CR users is indispensible. In the literature, the detection of idle spectrum is typically considered as a binary hypothesis test, and a commonly used signal model under both hypotheses is [1-2]

$$\begin{array}{lll}\mathcal{H}_0 : x[n] = v[n], & 0 \le n \le N-1 & \text{(idle)}\\ \mathcal{H}_1 : x[n] = s[n] + v[n], & 0 \le n \le N-1 & \text{(occupied)}\end{array} \tag{1.1}$$

where N is the length of the data record, $s[n]$, $x[n]$, $v[n]$ are, respectively, the signal of the primary user, the received signal at the CR terminal, and the measurement noise. The hypothesis model (1.1) implicitly assumes perfect synchronization between the primary transmitter and the CR receiver. Such an assumption, however, is not valid in many practical situations. For example, in an overlay femto cell network [3], the signal of the macro mobile subscriber, synchronized with the macro base station (BS), will arrive at a femto BS asynchronously. The spectrum detection at the femto BS is typically subject to timing misalignment of the primary signal [4], [5]. Also, in heavy-traffic networks in which primary users may dynamically enter the network, time delays observed in the sensing period is unavoidable, especially when a long sensing duration is adopted for obtaining good sensing performance. Thus, in the aforementioned cases, a more reasonable signal model for the binary hypothesis test is thus

$$\begin{array}{ll}\mathcal{H}_0 : x[n] = v[n], \quad 0 \le n \le n_0 - 1 & \text{(idle)}\\ \mathcal{H}_1 : \begin{cases} x[n] = v[n], & 0 \le n \le n_0 - 1 \\ x[n] = s[n] + v[n], & n_0 \le n \le N-1 \end{cases} & \text{(occupied)}\end{array} \tag{1.2}$$

where n_0 accounts for the primary signal arrival time. Therefore, in contrast to the spectrum sensing schemes in the literature focusing on the synchronized signal model (1.1) [1-2], this paper considers the spectrum detection aimed for tackling signal timing uncertainty under the hypothesis (1.2).

Among the existing spectrum sensing schemes, the energy detector (ED) [6] is quite popular mainly because it involves only the partial knowledge (the second moment) of the primary signal and is thus cost-effective to implement [1-2]. Even though various performance characteristics of the ED have recently been investigated, e.g., [7-9], the discussions in all these works were based on the idealized model (1.1). In this paper, we study the detection performance of ED under the hypothesis (1.2). As the detection of arrival is the main focus, as in [10], we consider the scenario that the primary user is present only after spectrum sensing is started. Motivated by the fact that, in high-traffic random access networks, the traffic patterns of primary users are typically unknown to the secondary users, the signal arrival time n_0 is assumed to be uniformly distributed over the observation window $0 \le n \le N-1$. Specific technical contributions of this paper can be summarized as follows. Firstly, conditioned on a fixed n_0, the exact formula for the conditional detection probability under the hypothesis model (1.2) is derived. The average detection probability can then be accordingly obtained by taking the expectation with respect to n_0. To the best of our knowledge, the performance study shown in this paper is the original contribution in the literature that is tailored for the ED scheme in the realistic sensing environment characterized by the model (1.2). Secondly, to further exploit the prior knowledge about n_0 for improving the detection performance, we also propose a robust ED based on the Bayesian formulation [6]. Simulation study shows that the Bayesian based solution improves the receiver operation characteristics (ROC). Moreover, under a prescribed detection probability threshold, the Bayesian scheme does lead to a smaller false-alarm

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How Much Coherent Interval Should be Dedicated to Non-Redundant Diagonal Precoding for Blind Channel Estimation in Single-Carrier Block Transmission?

Jwo-Yuh Wu, *Member, IEEE*

***Abstract*—Transmit precoding is a key technique for facilitating blind channel estimation at the receiver but the impact due to precoding on the channel capacity is scarcely addressed in the literature. In this paper we consider the single-carrier block transmission with cyclic prefix, in which a recently proposed diagonal-precoding assisted blind channel estimation scheme via covariance matching is adopted to acquire the channel information. It is shown that, when perfect channel knowledge is available at the receiver, the optimal noise resistant precoder proposed in the literature incurs the worst-case capacity penalty. When the coherent interval is finite, channel mismatch occurs due to finite-sample covariance matrix estimation. Thus, we aim to determine how much of the coherent interval should be dedicated to precoding in order to trade channel estimation accuracy for the maximal capacity. Toward this end, we leverage the matrix perturbation theory to derive a closed-form capacity measure which explicitly takes account of the channel uncertainty in the considered blind estimation setup. Such a capacity metric is seen to be a complicated function of the precoding interval. To facilitate analysis, an approximate formula for the derived capacity measure is further given. This allows us to find a closed-form estimate of the capacity-maximizing precoding time fraction, and can also provide insights into the optimal tradeoff between channel estimation accuracy and achievable capacity. Numerical simulations are used for evidencing the proposed analytic study.**

***Index Terms*—Blind channel estimation; channel capacity; precoding; single-carrier block transmission; cyclic prefix; matrix perturbation analysis; sample covariance matrix; circulant matrix.**

I. INTRODUCTION

A. Motivation and Paper Contributions

BLIND channel estimation is widely known as a bandwidth-efficient alternative as opposed to the training technique for acquiring the channel information at the receiver [11]. Among the existing blind estimation methods, the transmit-precoding assisted solutions attracted considerable attention in recent years [11]. Various channel estimation algorithms associated with different precoding schemes have been proposed, either in the serial transmission case [7], [17], [25], [30], or in the block transmission counterpart, e.g., [4], [18], [23], [26], [31], [33]. Unlike the multi-channel receive-diversity estimation algorithms, e.g., [20], [28], the transmit-precoding assisted approach is quite robust against channel order mismatch and the channel zero locations [17], [25], [30]. Nevertheless, most of the precoding based methods are developed under the assumption that certain second-order statistics of the received signal can be perfectly obtained. The resultant channel estimation performance, therefore, is dominated by the finite-sample estimation errors in the computed data statistics. Moreover, symbol precoding at the transmitter may have significant impact on the channel capacity [6]. Under the perfect channel knowledge assumption the capacity performances attained by various redundant and non-redundant precoding schemes were analyzed in [6]. More in-depth study of the achievable system capacity that explicitly takes into account the channel mismatch effect in the context of precoding-based blind estimation has not been seen in the literature yet.

In this paper we consider the single-carrier block transmission with cyclic prefix (CP)[1] [10], in which the transmitter implements a non-redundant diagonal precoder and, at the receiver the channel information is acquired through the precoding-assisted blind estimation scheme [31]. The main purpose of this paper is to investigate the optimal noise-resistant precoder [31] from a capacity perspective, and to further characterize an inherent tradeoff between channel estimation quality and the achievable system capacity. Specifically, it is shown that when the received signal covariance matrix is perfectly obtained, thus the channel estimate is exact[2], the optimal noise-resistant precoder results in the minimal capacity in the high SNR regime. Hence, if we adopt the considered precoder to improve the channel estimation accuracy, there is a potential loss in the achievable information

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[1]CP-based single carrier systems have been considered as one next-generation wireless standard, e.g., SC-OFDMA in LTE uplink [19].

[2]It is well-known that all blind estimation schemes can identify the channel only up to a scalar ambiguity, which has to be removed by further inserting some pilot symbols [11]. As in many previous works regarding performance analysis of blind algorithms [7], [32], we assume for analytical simplicity that the ambiguity is removed. In this sense, the channel estimate is considered to be exact if the received signal covariance matrix can be obtained without errors.

Channel-Aware Decision Fusion With Unknown Local Sensor Detection Probability

Jwo-Yuh Wu, Chan-Wei Wu, Tsang-Yi Wang, and Ta-Sung Lee

***Abstract*—Existing channel-aware decision fusion schemes assume that the local detection probability is known at the fusion center (FC). However, this paradigm ignores the possibility of unknown sensor alarm responses to the occurrence of events. Accordingly, this correspondence examines the binary decision fusion problem under the assumption that the local detection probability is unknown. Treating the communication links between the nodes and the FC as binary symmetric channels and assuming that the sensor nodes transmit simple one-bit reports to the FC, the global fusion rule is formulated initially in terms of the generalized likelihood ratio test (GLRT). Adopting the assumption of a high SNR regime, an approximate maximum likelihood (ML) estimate is derived for the unknown parameter required to implement the GLRT that is affine in the received data. The GLRT-based formulation is intuitively straightforward, but does not permit a tractable performance analysis. Therefore, motivated by the affine nature of the approximate ML solution, a simple alternative fusion rule is proposed in which the test statistic remains affine in the received data. It is shown that the proposed fusion rule facilitates the analytic characterization of the channel effect on the global detection performance. In addition, given a reasonable range of the local detection probability, it is shown that the global detection probability can be improved by reducing the total link error. Thus, a sensor power allocation scheme is proposed for enhancing the detection performance by improving the link quality. Simulation results show that: 1) the alternative fusion rule outperforms the GLRT; and 2) the detection performance of the fusion rule is further improved when the proposed power loading method is applied.**

***Index Terms*—Communication channels, distributed detection, power allocation, sensor networks.**

I. Introduction

The problem of distributed signal/event detection and decision fusion in wireless sensor networks has attracted significant attention in the literature [1], [12], [13]. However, most previous studies are based on the idealized assumption that the sensor reports are received at the fusion center (FC) without error [13], [16]. Recently, there have been several proposals that further take into account the communication channel impairments [2], [3], [6], [7], [11]; see [4] for a tutorial introduction to distributed detection in the presence of nonideal channel links. In general, these channel-aware schemes assume that the local sensor detection performance, characterized by the detection probability and the false-alarm probability, is known to the FC. However, this paradigm ignores the possibility of unknown sensor alarm responses to the occurrence of events within the sensing field. For example, consider a sensor network designed to monitor the rise in temperature within a room in order to detect the potential outbreak of a fire. In practice, the characteristics of a fire are uncertain, e.g., the mean temperature may vary from 100° to 1000° depending on the severity of the fire or the type of fire. Moreover, the characteristics of the fire may vary over time. As a result, the local detection probability (under a fixed threshold) could be unknown due to the response to the uncertain temperature of fire events. To accommodate such variations in the sensing field conditions, one conceivable approach is to simply model the local detection probability as an unknown parameter and to design suitable global decision rules for tackling such uncertainty.

This correspondence proposes a channel-aware decision fusion scheme tailored for the above-mentioned scenario. The communication links between the sensor nodes and the FC are modeled as binary symmetric channels. Each sensor, when triggered, sends a single bit to the FC to inform it of its local decision. Note that since the FC treats the local detection probability as an unknown parameter, the nodes do not need to send an additional message regarding the current local detection performance, and thus the communication overhead is reduced. Based solely on the received sensor reports, the global decision rule is formulated intuitively as a generalized likelihood ratio test (GLRT) [9]. The implementation of this test calls for the maximum likelihood (ML) estimate of the unknown parameter, which, in the current case, does not allow for a closed-form solution. Thus, under a high signal-to-noise ratio (SNR) assumption, an approximate ML estimate is derived that is *affine* in the received data. However, even when adopting this approximation, the detection performance of the GLRT decision rule remains difficult to characterize. Therefore, based on the approximated ML scheme, a simple alternative fusion rule is proposed in which the test statistic remains affine in the received data. The proposed fusion rule enables the derivation of a closed-form expression for the detection performance and, therefore, facilitates the analytic characterization of the channel effect. In addition, it is shown that, for reasonable ranges of the local detection and false alarm probabilities, the global detection performance can be improved by enhancing the communication-link quality, specifically, reducing the total link bit-error rate (BER). Hence, an optimal power allocation scheme is proposed to minimize the total BER subject to a total power budget. Simulations show that the proposed fusion rule outperforms the GLRT; in addition, the detection performances of both the proposed fusion rule and the GLRT decision rule are seen to be further improved via the application of the optimal sensor power loading scheme. The remainder of this correspondence is organized as follows. Section II formulates the problem, while Section III presents the GLRT based detection scheme and derives the approximate ML solution. Section IV introduces the proposed fusion rule and derives the associated analytic performance results. Section V formulates an algorithm for improving the channel link quality in order to improve the detection performance. Section VI presents the simulation results. Finally, Section VII provides some brief concluding remarks.

II. Problem Statement

Consider a sensor network with N identical binary nodes designed to monitor the occurrence of a certain event. Each sensor exists in one of two different states, namely active (e.g., when the measurement is above a certain threshold) or silent (e.g., the measurement is below the threshold, and the sensor simply remains quiet to conserve energy). Assume that each node is subject to a *known* false-alarm probability

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A Cooperative Multi-Group Priority MAC Protocol for Multi-Packet Reception Channels

Wen-Fang Yang, *Student Member, IEEE,* Jwo-Yuh Wu, *Member, IEEE,* Li-Chun Wang, *Senior Member, IEEE,* and Ta-Sung Lee, *Senior Member, IEEE*

***Abstract*—Medium access control (MAC) protocol design for cooperative networks over multi-packet reception (MPR) channels is a challenging topic, but has not been addressed in the literature yet. In this paper, we propose a cooperative multi-group priority (CMGP) based MAC protocol to exploit the cooperation diversity for throughput enhancement over MPR channels. The proposed approach can bypass the computationally-intensive active user identification process. Moreover, our method can efficiently utilize the idle periods for packet relaying, and can thus effectively limit the throughput loss resulting from the relay phase. By means of a Markov chain model, the worst-case throughput analysis is conducted. The results allow us to investigate the throughput performance of the proposed CMGP protocol directly in terms of the MPR channel coefficients. Simulation results confirm the system-wide throughput advantage achieved by the proposed scheme, and also validate the analytic results.**

***Index Terms*—Medium access control, multi-packet reception, cooperative communications.**

I. Introduction

COOPERATIVE medium access control (MAC) protocol design can exploit multi-user diversity for network-wide performance enhancement, and has attracted considerable attention in the recent years [1]-[5]. Most of the existing works, however, are devised exclusively for the collision channel model and do not exploit the multi-packet reception (MPR) capability at the physical (PHY) layer [6]-[11]. Toward more efficient solutions, one promising approach is thus to further take the MPR advantage into consideration so as to gain full benefits from the PHY-layer processing[1]. A cooperative MAC protocol design aimed for MPR channels is typically subject to the following challenges. Firstly, the central controller (CC) may require the knowledge of the MPR channels of all links, as well as the traffic conditions of all users, to determine the access set. However, this will call for extra communication overheads, and will degrade the system-wide throughput, especially in a large-scale mobile network. Secondly, when packet reception failure occurs due to collisions, a certain portion of the users may have to serve as the relay for data retransmission. Without properly designed MAC protocols for cooperative user scheduling, there would be a large throughput penalty incurred by the increase of transmission time in the packet relaying phase. To the farthest of our knowledge, cooperative MAC protocol designs for MPR channels have not been found in the literature yet.

Recently, relying on a simple flag-assisted mechanism and an associated multi-group priority (MGP) scheduling strategy, a new MPR MAC protocol was proposed in [16]. The MGP scheme has several distinctive features that make it a potential candidate for cooperative MPR MAC protocol designs. Firstly, in the MGP scheme the users are allowed to access the channel according to some prescribed service priority. There is no need for active user selection through exhaustive search over the channel knowledge and local traffic conditions. This will thus considerably reduce the communication overheads in dense cooperative networks. Secondly, the flag-bit can provide the CC with the knowledge of each user's buffer status. Combined with the multi-group service priority, the channel access can then be reserved for both direct data transmission and packet relaying in a more balanced fashion. Hence, in a high collision environment, the throughput penalty incurred by the relay phase can be largely reduced. To realize the aforesaid advantages, in this paper we extend the MGP scheme and propose a cooperative MAC protocol for MPR channels. Specific contributions of this paper can be summarized as follows.

1) The proposed protocol is, to our best knowledge, the first cooperative MPR MAC scheme. It is free from any assumptions on the channel characteristics and is applicable to the general heterogeneous environment [5].
2) The number of users permitted for channel access is deterministically set to attain the MPR channel capacity. This prevents the channel from being over-loaded, thereby avoiding irrecoverable packet failure due to collisions.
3) Based on the Markov chain model, the throughput performance in the worst-case scenario is analytically characterized. Specifically, we derive (i) a closed-form upper bound for the throughput penalty of the direct-link user that is incurred by the interference of relay packet transmission; (ii) a closed-form lower bound for throughput gain that a user with packet trnsmission failure can benefit thanks to cooperative packet relaying.

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[1]MAC protocol designs for MPR channels in a non-cooperative environment have been considered in [12]-[16].

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Joint Source/Relay Precoder Design in Nonregenerative Cooperative Systems Using an MMSE Criterion

Fan-Shuo Tseng, *Student Member, IEEE,* Wen-Rong Wu, *Member, IEEE,* and Jwo-Yuh Wu, *Member, IEEE*

***Abstract*—This paper considers transmitter precoding in an amplify-and-forward cooperative system where multiple antennas are equipped at the source, the relay, and the destination. Existing methods for the problem only consider the design of the relay precoder. To further improve the performance, we include the source precoder into the design. Using a minimum-mean-square-error (MMSE) criterion, we propose a joint source/relay precoder design method, taking both the direct and relay links into account. It is shown that the MMSE is a highly nonlinear function of the precoding matrices, and a direct minimization is not feasible. To facilitate analysis, we propose to design the precoders toward first diagonalizing the MSE matrix of the relay link. This imposes certain structural constraints on both precoders that allow us to derive an analytically tractable MSE upper bound. By conducting minimization with respect to this bound, the solution can be obtained by an iterative water-filling technique.**

***Index Terms*—Precoder, amplify-and-forward (AF), cooperative transmission schemes, channel state information (CSI), multiple-input multiple-output (MIMO), mean-square-error (MSE).**

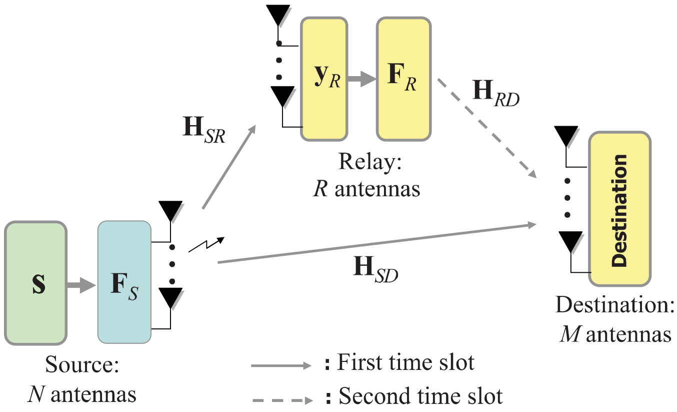

Fig. 1. Three-node AF MIMO relay system.

I. Introduction

Cooperative communications can realize spatial diversity in a distributed manner and has attracted considerable attention in the past few years [2]-[11]. Most of the existing works focused on devising, and analyzing, different cooperative transmission protocols such as amplify-and-forward (AF) and decode-and-forward (DF) [2]. Also, there have been many proposals which leverage the traditional MIMO processing techniques, e.g., beamforming and space-time block coding, and develop the corresponding distributed realizations for enhancing the link quality [3]-[10]. In the study of conventional cooperative systems, each user terminal is commonly assumed to be equipped with a single antenna. To further increase the spatial degrees-of-freedom, one simple approach is to place multiple antennas at each node [11]-[14]. Current research on such MIMO cooperative networks mainly focuses on precoder designs under the AF protocol, either for boosting capacity [12],[13], or for improving link reliability [14]. All of these proposals, however, consider precoders only at the relays. Some of them even neglect the direct (source-to-destination) link in the problem formulation so as to ease the relay precoder design [12], [14]. Hence, the available link resources are not yet fully exploited in the existing schemes.

As far as we know, the joint source-relay precoder design for AF MIMO relay networks which take both the direct and relay links into account has not been studied before. This work aims to provide a solution to this problem in the typical three-node system scenario [12]-[14]. Using the minimum-mean-square-error (MMSE) criterion and individual power constraints at the source and the relay, we formulate the design as a joint optimization problem. However, it is found that the MMSE is a complicated function of precoding matrices. Direct minimization with the cost function is not feasible. To overcome the difficulty, we propose to design the precoders toward first diagonalizing the MSE matrix of the relay link. This imposes certain structural constraints on the precoding matrices that allow us to derive a tractable MSE upper bound. Minimization with this upper bound, instead of the original MMSE, then becomes feasible and a suboptimal closed-form solution is then obtained. The proposed precoders can be computed via an iterative water-filling technique. The rest of this paper is organized as follows. Section 2 introduces the system model and problem formulation. The main results are given in Section 3. Finally, Section 4 concludes this paper.

II. Proposed System Model and Problem Formulation

A. System Model

We consider a three-node precoded AF system over flat fading channels as depicted in Figure 1, in which the source, the relay, and the destination are equipped with N, R, M antennas. Using the typical two-phase transmission scheme

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Robust Receiver Design for MIMO Single-Carrier Block Transmission over Time-Varying Dispersive Channels Against Imperfect Channel Knowledge

Chih-Yuan Lin, *Member, IEEE,* Jwo-Yuh Wu, *Member, IEEE,* and Ta-Sung Lee, *Senior Member, IEEE*

***Abstract*—We consider MIMO single-carrier block transmission over time-varying multipath channels, under the assumption that the channel parameters are not exactly known but are estimated via the least-squares training technique. While the channel temporal variation is known to negate the tone-by-tone frequency-domain equalization facility, it is otherwise shown that in the time domain the signal signatures can be arranged into groups of orthogonal components, leading to a very natural yet efficient group-by-group symbol recovery scheme. To realize this figure of merit we propose a constrained-optimization based receiver which also takes into account the mitigation of channel mismatch effects caused by time variation and imperfect estimation. The optimization problem is formulated in an equivalent unconstrained generalized-sidelobe-canceller setup. This enables us to directly model the channel mismatch effect into the system equations through the perturbation technique and, in turn, to further exploit the statistical assumptions on channel temporal variation and estimation errors for deriving a closed-form solution. Within the considered framework the proposed robust equalizer can be combined with the successive interference cancellation mechanism for further performance enhancement. Flop count evaluation and numerical simulation are used to evidence the advantages of the proposed scheme.**

***Index Terms*—MIMO, single carrier block transmission, time-varying multipath channels, channel estimation, constrained optimization, generalized sidelobe canceller, perturbation analysis.**

I. INTRODUCTION

MULTI-INPUT multi-output (MIMO) single-carrier (SC) block transmission with cyclic prefix (CP) has been identified as one key technique for supporting high data rates over frequency selective fading channels [1]; such a system configuration can be found in the uplink mode of the next-generation wireless communication standards like 3GPP-LTE [2], [3]. One particularly attractive feature unique to MIMO-SC systems is the low-complexity per-tone frequency-domain equalization (FDE) scheme, which facilitates the development of several efficient (batch or adaptive) receiver implementations [1], [4]. Such a figure of merit, however, hinges crucially on the time-invariant channel assumption. When the channel is otherwise subject to fast temporal variation, orthogonality among the signal components in the frequency domain will no longer be preserved, and tone-by-tone signal recovery is then rendered impossible. Moreover, in a time-varying environment channel parameter mismatch due to the mere availability of the out-dated channel estimate will become another detrimental factor dominating the system performance. For MIMO-SC block transmission over time-varying dispersive channels, robust receiver designs which can efficiently tackle the joint impacts due to channel time variation and estimation errors, to the best of our knowledge, are hardly found in the literature.

This paper proposes a robust receiver design scheme for MIMO-SC systems when the multipath channels undergo time selectivity, and are not exactly known but instead estimated via the least-squares (LS) training technique [5], [6]. In lieu of performing signal recovery in the frequency domain, the proposed approach relies on received data processing in the time domain. Specifically, by exploiting the cyclic shifting property of the time-domain channel matrix it is shown that the signal signatures can be arranged into groups of orthogonal columns. In case that the inter-group interference can be effectively mitigated, the orthogonality structure in conjunction with space-time matched filtering will lead to a low-complexity intra-group symbol recovery scheme. Toward realizing such a time-domain processing facility, a linear weighting matrix is designed for each group based on the constrained optimization formulation [7], [8]. To further mitigate channel mismatch due to time variation and estimation errors, we leverage the generalized side-lobe canceller (GSC) principle [9], [10], [11] to transform the constrained optimization problem into an equivalent unconstrained setup. The unconstrained GSC formulation enables us to leverage the perturbation analysis technique [12], [13] to explicitly model the channel mismatch effect into the system equations, in turn providing a unique two-fold advantage. First, this allows a very natural cost function for weighting matrix design against channel mismatch. Second, we can then exploit the underlying statistical assumptions on the channel errors, due to both temporal variation and imperfect estimation, to derive an *analytic* solution.

We note that constrained optimization based designs resistant to signal/channel parameter uncertainty has been ad-

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Research Article

A Multigroup Priority Queueing MAC Protocol for Wireless Networks with Multipacket Reception

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Relying on a simple flag-assisted mechanism, a multigroup priority queueing (MGPQ) medium access control (MAC) protocol is proposed for the wireless networks with multipacket reception (MPR). The proposed MGPQ scheme is capable of overcoming two major performance bottlenecks inherent in the existing MPR MAC protocols. First, the proposed solution can automatically produce the list of active users by observing the network traffic conditions, remove the need of active user estimation algorithm, and thus can largely reduce the algorithm complexity. Second, the packet blocking constraint imposed on the active users for keeping compliant with prediction is relaxed. As a result, the proposed MGPQ is not only applicable to both homogeneous and heterogeneous cases, but also outperforms the existing MPR MAC protocols. Simulation results show that the network throughput can be improved by 40% maximum and 14% average as compared with the well-known dynamic queue (DQ) MAC protocol.

1. INTRODUCTION

1.1. *Overview*

An efficient medium access control (MAC) mechanism is characterized by high throughput and low delay. Traditionally, the design of MAC protocols is based on the so-called collision channel model, that is, a transmitted packet is successfully received only when no concurrent transmission occurs. Such a paradigm, however, ignores the multipacket reception (MPR) capability at the physical layer, for example, multiuser detection [1]. Recently MAC protocols with the MPR capability draw increasing attention. Several proposals have been reported in the literatures [2–11], almost all of which are devised for the homogeneous environment, that is, all users are associated with the same packet generating probability. An initial attempt to reflect the MPR facility is the channel model with capture effect characterized via the probability of successful reception [2]. The impact of capture effects on various existing MAC protocols such as slotted ALOHA, and FCFS has been addressed in [3–5]. However, the capture model overall remains a simplified representation of the actual channel characteristics and does not explicitly account for the MPR capability. This thus motivates the development of more realistic MPR channel model [6], based on which several MAC protocols have been proposed for realizing various system-wide performance requirements [7–11]. The multiqueue service room (MQSR) protocol [7] is, to the best of our knowledge, the first proposal which relies on the MPR model [6] for user scheduling. It calls for active user prediction via an exhaustive search over all the available network-traffic and physical layer channel capacity information up to the current slot. However, as the total number of users increases, the number of search states grows exponentially thereby incurring high-computational complexity. Moreover, the transmission of the newly generated packets of selected users is not allowed in order to maintain the active user prediction determined via the previous network traffic, inevitably resulting in throughput degradation. The dynamic queue (DQ) protocol introduced in [8] delivers a large portion of performance gain attained by MQSR solution but at reduced complexity. By viewing the traffic as a flow of transmission periods (TP), the DQ protocol otherwise aims for minimization of the expected TP duration by exploiting the MPR property. To further reduce the idle period of users with empty buffer, a modification of DQ scheme that includes active user identification at the receiver is subsequently introduced in [9]. In [10],

BER Improved Transmit Power Allocation for D-STTD Systems with QR-Based Successive Symbol Detection

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***Abstract*-We propose a BER improved power allocation scheme for D-STTD systems over i.i.d. Rayleigh fading channels under the QR-based successive detection framework. Instead of relying on BER under a fixed channel realization, the adopted design criterion is the mean BER (assuming there is no inter-layer error propagation) averaged with respect to the channel distribution. Such a design metric has two-fold advantages: (i) It is analytically tractable and is closely related to a block error probability upper bound when inter-layer error propagation occurs, and (ii) There is no need for repeated feedback of the instantaneous channel information. By exploiting a distinctive channel matrix structure unique to D-STTD systems we derive a closed-form approximate upper bound of the considered BER metric; through minimization of this bound an optimal power allocation scheme is obtained. Numerical simulation is used to illustrate the performance of the proposed method.**

Index Terms: **Space-time block codes; successive detection; power allocation; bit error rate; QR decomposition.**

I. Introduction

Spatially multiplexing multiple groups of orthogonal space-time block coded (STBC) signals is one key approach to realizing high-rate yet high-reliability wireless communications [2], [9], [12]. The double space-time transmit diversity (D-STTD) scheme [6], in which two Alamouti signal groups [1] are simultaneously transmitted, is the building block for such a system configuration. There have been many related research works reported for D-STTD systems, including antenna shuffling to combat channel spatial correlation [6], [8], adaptive modulation [3], and efficient low-complexity receiver designs [4], [5], [9].

QR-based successive symbol detector can strike a bit-error-rate (BER) performance balance between linear equalization and joint maximum-likelihood (ML) decoding. Such a scheme has been widely considered for signal detection in D-STTD and general multi-group STBC systems [2], [4]. This paper addresses the QR based successive signal detection problem for D-STTD systems, focusing on further symbol power loading for improving the BER performance. There have been many plausible performance measures for QR-based successive signal recovery [11], [13]-[15], depending on whether or not inter-layer error propagation is taken into account. The average BER with errorless front-layer decision feedback, although being merely a lower bound of the true mean error rate, remains simple to characterize and, moreover, is closely related to an upper bound of the block error probability when error-propagation occurs [11]: it thus serves as an efficient and meaningful performance metric accounting for the actual error rate outcome. Motivated by this fact and to also guarantee a performance improvement regardless of the instantaneous channel conditions, we propose to design the power loading weights for D-STTD transmission toward minimizing such a mean BER, averaged with respect to the channel distribution. Specifically, by exploiting a distinctive channel matrix structure of the D-STTD transmission we first derive an explicit formula of the associated QR-decomposition. Based on this result, we then derive an approximate closed-from upper bound of the considered BER metric. Through minimizing this bound the power allocation factors are obtained via numerical search. The proposed scheme depends only on the link SNR but not on the instantaneous channel gains: repeated channel state update via feedback is no longer needed. Simulation results show that the QR receiver combined with the proposed power allocation compares favorably with the zero-forcing (ZF) V-BLAST detector [10], in terms of both simulated BER and algorithm complexity.

II. Problem Statement

A. System Model and Basic Assumptions

We consider a D-STTD system with symbol power loading over a flat-fading channel. Following [6] the input-output relation, in terms of block signals, can be described as[a]

$$\mathbf{y} = \underbrace{\begin{bmatrix} h_{11} & h_{12} & h_{13} & h_{14} \\ h_{12}^* & -h_{11}^* & h_{14}^* & -h_{13}^* \\ h_{21} & h_{22} & h_{23} & h_{24} \\ h_{22}^* & -h_{21}^* & h_{24}^* & -h_{23}^* \end{bmatrix}}_{:=\mathbf{H}} diag\{p_1,\cdots,p_4\}\begin{bmatrix} s_1 & s_2 & s_3 & s_4 \end{bmatrix}^T + \mathbf{n}, \quad (2.1)$$

where $\mathbf{y}$ is the received signal vector, $\mathbf{n}$ is a zero-mean complex white Gaussian noise with covariance $N_0\mathbf{I}_4$, $\mathbf{H}$ is the effective channel matrix with h_{ij} being the channel gain between the (j,i)th transmit-receive antenna pair, s_j is the symbol sent through the jth transmit antenna, and p_j is the

a. The symbols $(\cdot)^*$, $(\cdot)^T$, $(\cdot)^H$, $\mathbf{I}_n$, $\det(\cdot)$, and $diag\{\mathbf{x}\}$ denote, respectively, the complex conjugate, transpose, Hermitian, the $n\times n$ identity matrix, determinant, and the diagonal matrix with elements of the vector $\mathbf{x}$ on the main diagonal.

power loading factor for s_j satisfying the power normalization constraint $\sum_{i=1}^{4} p_i^2 = 4$. We assume that the channel gains h_{ij}'s are i.i.d. zero-mean complex white Gaussian with unit-variance.

B. BER of QR-Based Successive Detection

By factorizing $\mathbf{H} = \mathbf{QR}$, where $\mathbf{Q}$ is unitary and $\mathbf{R}$ is upper triangular, and multiplying (2.1) from the left by $\mathbf{Q}^H$, we have

$$\tilde{\mathbf{y}} := \mathbf{Q}^H \mathbf{y} = \mathbf{R} diag\left\{p_1, \cdots, p_4\right\}\left[s_1\ s_2\ s_3\ s_4\right]^T + \mathbf{Q}^H \mathbf{n}\,. \quad (2.2)$$

Since $\mathbf{R}$ is upper triangular, successive symbol detection through canceling the contributions of the previously detected components can be performed. We assume QPSK modulation is used with average symbol power equal to E_s; the generalization of our results to high-order constellations are straightforward by using related BER expressions in terms of Q function, as in [11]. As long as the symbol in each stage is correctly detected and, thus, there is no layer-wise error propagation, the space-time model (2.2) decouples into four independent links. The resultant average BER, given a channel realization $\mathbf{h}$, is

$$P_{b|\mathbf{h}} := \frac{1}{4}\sum_{i=1}^{4} Q\left(\sqrt{\rho} p_i \left|R_{ii}\right|\right), \quad (2.3)$$

where R_{ii} denotes the ith diagonal entry of $\mathbf{R}$, $\rho := E_s / N_0$ is the signal-to-noise ratio, and $Q(\cdot)$ is the Gaussian tail function. We emphasize that, when inter-layer error propagation occurs, $4P_{b|\mathbf{h}}$ is an upper bound for the block error probability [11]. This implies that, if $P_{b|\mathbf{h}}$ is small, the decision performance can be potentially improved even in the presence of inter-layer error propagation. Motivated by this fact and also to devise a solution irrespective of different channel realizations, we propose to design p_i's by minimizing $P_{b|\mathbf{h}}$ averaged with respect to the channel distribution, i.e.,

$$P_b := \frac{1}{4}\sum_{i=1}^{4}\int_0^{\infty} Q(\sqrt{\rho} p_i \left|R_{ii}\right|) p(\left|R_{ii}\right|) d\left|R_{ii}\right|\,. \quad (2.4)$$

This is addressed in the next section.

III. Main Results

Based on the well-known Chernoff bound for Q function, we have from (2.4)

$$P_b \le \frac{1}{4}\sum_{i=1}^{4}\int_0^{\infty} \frac{1}{2}\exp\left(-\frac{(\sqrt{\rho} p_i \left|R_{ii}\right|)^2}{2}\right) p(\left|R_{ii}\right|) d\left|R_{ii}\right|\,. \quad (3.1)$$

The proposed power allocation scheme is based on an explicit (but approximate) formula of the upper bound (3.1). For this we shall first specify the diagonal entries R_{ii}'s in terms of the channel gains h_{ij}'s, $1 \le i \le 4$; this will be done in Section III-A. Based on the established results, in Section III-B we then derive a closed-form expression of the upper bound (3.1).

A. Formulae of R_{ii}'s

Recall from (2.1) that the effective channel matrix $\mathbf{H}$ consists of four Alamouti's blocks [1]. By exploiting this property the formulae of R_{ii}'s can be obtained as follows.

Proposition 3.1: Let us partition the channel matrix $\mathbf{H}$ in (2.1) into four 2×2 submatrices as $\mathbf{H} = \begin{bmatrix}\mathbf{H}_1 & \mathbf{H}_2 \\ \mathbf{H}_3 & \mathbf{H}_4\end{bmatrix}$, and let $\mathbf{H} = \mathbf{QR}$ be an associated QR-decomposition. Then the diagonal entries R_{ii}, $1 \le i \le 4$, in $\mathbf{R}$ are given by

$$R_{11} = R_{22} = \sqrt{\det(\mathbf{H}_1) + \det(\mathbf{H}_3)}\,, \quad (3.2)$$

and

$$R_{33} = R_{44} = \sqrt{\frac{\det(\mathbf{H})}{\det(\mathbf{H}_1) + \det(\mathbf{H}_3)}}\,. \quad (3.3)$$

[*Proof*]: The proof is based on an explicit expression for $\mathbf{Q}$ and $\mathbf{R}$ constructed according to [7], and the detailed derivation is relegated to the Appendix. □

B. Upper Bound of P_b in Closed-Form

As $R_{11} = R_{22}$ and $R_{33} = R_{44}$ (cf. (3.2) and (3.3)), we can rewrite P_b in (3.1) into

$$P_b \le \frac{1}{8}\left\{\underbrace{\sum_{i=1}^{2}\int_0^{\infty}\exp\left(-\frac{(\sqrt{\rho} p_i \left|R_{11}\right|)^2}{2}\right) p(\left|R_{11}\right|) d\left|R_{11}\right|}_{:=\varepsilon_1} + \underbrace{\sum_{i=3}^{4}\int_0^{\infty}\exp\left(-\frac{(\sqrt{\rho} p_i \left|R_{33}\right|)^2}{2}\right) p(\left|R_{33}\right|) d\left|R_{33}\right|}_{:=\varepsilon_2}\right\}. \quad (3.4)$$

In what follows we will derive analytic expressions for ε_1 and ε_2; this in turn yields a closed-form upper bound of P_b.

i) Analytic Form of ε_1: By definitions of $\mathbf{H}_1$ and $\mathbf{H}_3$, we have $\det(\mathbf{H}_1) = \left|h_{11}\right|^2 + \left|h_{21}\right|^2$ and $\det(\mathbf{H}_3) = \left|h_{12}\right|^2 + \left|h_{22}\right|^2$, which together with (3.2) imply

$$2\left|R_{11}\right|^2 = 2\left|h_{11}\right|^2 + 2\left|h_{21}\right|^2 + 2\left|h_{12}\right|^2 + 2\left|h_{22}\right|^2\,. \quad (3.5)$$

Since $2\left|h_{ij}\right|^2$ is a central chi-square random variable with degrees-of-freedom equal to two, $2\left|R_{11}\right|^2$ is thus central chi-square distributed with degrees-of-freedom equal to eight, with the probability density function (PDF) given by

$$f(2\left|R_{11}\right|^2) = \frac{(2\left|R_{11}\right|^2)^{4-1}}{2^4\Gamma(4)}\exp(-\left|R_{11}\right|^2)\,, \quad (3.6)$$

where $\Gamma(\bullet)$ is the Gamma function. By performing a change of variable the PDF of $\left|R_{11}\right|$ is obtained as

$$f(\left|R_{11}\right|) = \frac{2\left|R_{11}\right|^{2(4-1)+1}}{(4-1)!}\exp(-\left|R_{11}\right|^2)\,. \quad (3.7)$$

With (3.7), the summand in ε_1 becomes

$$\int_0^\infty \exp\left(-\frac{(\sqrt{\rho}p_i|R_{11}|)^2}{2}\right)\frac{2|R_{11}|^{2(4-1)+1}}{(4-1)!}\exp(-|R_{11}|^2)d|R_{11}|$$
$$=\frac{2}{(4-1)!}\int_0^\infty |R_{11}|^{2(4-1)+1}\exp\left[-|R_{11}|^2(1+\frac{\rho p_i^2}{2})\right]d|R_{11}| \quad (3.8)$$
$$\underset{(a)}{=}\frac{2}{(4-1)!}\cdot\frac{(4-1)!}{2(1+\frac{\rho p_i^2}{2})^4}=(1+\frac{\rho p_i^2}{2})^{-4},$$

where (a) is obtained by performing integration with respect to $|R_{11}|$. Based on (3.8), a closed-form expression for ε_1 is

$$\varepsilon_1=\sum_{i=1}^{2}(1+\frac{\rho p_i^2}{2})^{-4}. \quad (3.9)$$

ii) Analytic Approximation of ε_2: We shall note that the closed-form expression of ε_1 in (3.9) hinges entirely chi-square nature of $2|R_{11}|^2$. Such a property, however, no longer holds for $2|R_{33}|^2$, since according to (3.3) straightforward manipulations show

$$2|R_{33}|^2=2\cdot\frac{\det(\mathbf{H})}{\det(\mathbf{H}_1)+\det(\mathbf{H}_3)}$$
$$=2\cdot\frac{\det(\mathbf{H}_1)\det(\mathbf{H}_4-\mathbf{H}_3\mathbf{H}_1^{-1}\mathbf{H}_2)}{\det(\mathbf{H}_1)+\det(\mathbf{H}_3)}$$
$$=2\cdot\frac{\det(\mathbf{H}_1)\left[\det(\mathbf{H}_4)+\frac{\det(\mathbf{H}_3)\det(\mathbf{H}_2)-2C}{\det(\mathbf{H}_1)}\right]}{\det(\mathbf{H}_1)+\det(\mathbf{H}_3)}$$
$$=2\cdot\frac{\det(\mathbf{H}_1)\det(\mathbf{H}_4)+\det(\mathbf{H}_3)\det(\mathbf{H}_2)-2C}{\det(\mathbf{H}_1)+\det(\mathbf{H}_3)} \quad (3.10)$$

where

$$C=\mathrm{Re}\{h_{23}[h_{21}^*(h_{11}h_{13}^*+h_{14}h_{12}^*)+h_{22}^*(h_{12}h_{13}^*-h_{14}h_{11}^*)] + h_{24}[h_{21}^*(h_{11}h_{14}^*-h_{13}h_{12}^*)+h_{22}^*(h_{12}h_{14}^*+h_{13}h_{11}^*)]\}. \quad (3.11)$$

It seems quite formidable to analytically characterize the exact PDF of $2|R_{33}|^2$ based on (3.10). To sidestep this difficulty, we will instead seek for an approximate PDF via curve-fitting to the simulated density of $2|R_{33}|^2$. Through intensive numerical test and curve fitting procedures (details omitted due to space limitation) it is found that the true density of $2|R_{33}|^2$ is well approximated by the following Gamma PDF:

$$f_{gamma}(x\mid k,\theta)=\left[\frac{x^{k-1}}{\theta^k\Gamma(k)}\right]\exp\left(-\frac{x}{\theta}\right), \text{ with } k=2 \text{ and } \theta=2. \quad (3.12)$$

Figure 1 shows the computed histogram of $2|R_{33}|^2$ and the proposed approximate Gamma PDF (3.12); the proposed analytic approximation (3.12) is seen to well predict the simulated results. With the aid of (3.12), an approximate PDF of $|R_{33}|$ is in turn found as

$$f(|R_{33}|)\approx\frac{2|R_{33}|^{2(2-1)+1}}{(2-1)!}\exp(-|R_{33}|^2). \quad (3.13)$$

Based on (3.13), the summand in ε_2 can be approximated by

$$\int_0^\infty \exp\left(-\frac{(\sqrt{\rho}p_i|R_{33}|)^2}{2}\right)\frac{2|R_{33}|^{2(2-1)+1}}{(2-1)!}\exp(-|R_{33}|^2)d|R_{33}|$$
$$=\frac{2}{(2-1)!}\int_0^\infty |R_{33}|^{2(2-1)+1}\exp\left[-|R_{33}|^2(1+\frac{\rho p_i^2}{2})\right]d|R_{33}| \quad (3.14)$$
$$=\frac{2}{(2-1)!}\cdot\frac{(2-1)!}{2(1+\frac{\rho p_i^2}{2})^2}=(1+\frac{\rho p_i^2}{2})^{-2},$$

and hence

$$\varepsilon_2\approx\sum_{i=3}^{4}(1+\frac{\rho p_i^2}{2})^{-2}. \quad (3.15)$$

Combining (3.4), (3.9), and (3.15), P_b in (3.4) can thus be (approximately) upper bounded by

$$P_b\le\frac{1}{8}\left\{\sum_{i=1}^{2}(1+\frac{\rho p_i^2}{2})^{-4}+\sum_{i=3}^{4}(1+\frac{\rho p_i^2}{2})^{-2}\right\}. \quad (3.16)$$

We thus propose to design the power loading factors (p_1,p_2,p_3,p_4) toward minimizing the average BER upper bound in (3.16), subject to the power normalization constraint $\sum_{i=1}^{4}p_i^2=4$. As the cost function is highly nonlinear in p_i's, there do not seem to exist closed-form optimal solutions. Instead, the problem is solved via numerical search (e.g., by using **fmincom** in MATLAB Optimization Toolbox).

VI. PERFORMANCE

We compare the proposed approach with four other schemes, namely, linear ZF receiver, Stamoulis's decoupled signal recovery scheme [9], QR receiver without power loading, and the ZF V-BLAST detector [10], in terms of simulated BER. The proposed power loading factors via minimizing the closed-form bound in (3.16) are obtained by fmincom in MATLAB Optimization Toolbox. The results are shown in Figure 2. As we can see, the proposed method does outperform the QR receiver without power loading: there is about a 2 dB gain in the moderate-to-high SNR regime. Also, our method compares favorably with the ZF V-BLAST detector when SNR is above 20 dB. In terms of algorithm complexity, the ZF V-BLAST receiver involves signal ordering and pseudo-inverse computations; the total flop cost is 576 multiplications and 484 additions. The QR receiver involves mainly a QR decomposition which calls for 262 multiplications and 112 additions: it is thus more computationally efficient compared with the V-BLAST based solution.

APPENDIX: PROOF OF PROPOSITION 3.1

Since $\mathbf{H}_i^H\mathbf{H}_i=\mathbf{H}_i\mathbf{H}_i^H=\det(\mathbf{H}_i)\mathbf{I}_2$, through manipulations it can be shown that

$$\underbrace{\begin{bmatrix}\mathbf{H}_1 & \mathbf{H}_2\\ \mathbf{H}_3 & \mathbf{H}_4\end{bmatrix}^H}_{=\mathbf{H}^H} \cdot \underbrace{\frac{1}{\sqrt{\det(\mathbf{H}_1)+\det(\mathbf{H}_3)}}\begin{bmatrix}\mathbf{H}_1 & -\mathbf{H}_3^H\\ \mathbf{H}_3 & \mathbf{H}_3^{-H}\mathbf{H}_1^H\mathbf{H}_3^H\end{bmatrix}}_{:=\mathbf{Q}_1}$$

$$= \underbrace{\begin{bmatrix}\sqrt{\det(\mathbf{H}_1)+\det(\mathbf{H}_3)}\mathbf{I}_2 & \mathbf{0}\\ \dfrac{\mathbf{H}_2^H\mathbf{H}_1+\mathbf{H}_4^H\mathbf{H}_3}{\sqrt{\det(\mathbf{H}_1)+\det(\mathbf{H}_2)}} & \dfrac{-\mathbf{H}_2^H\mathbf{H}_3^H+\mathbf{H}_4^H\mathbf{H}_3^{-H}\mathbf{H}_1^H\mathbf{H}_3^H}{\sqrt{\det(\mathbf{H}_1)+\det(\mathbf{H}_3)}}\end{bmatrix}}_{:=\mathbf{G}}, \quad \text{(A.1)}$$

and

$$\mathbf{G}\cdot\underbrace{\begin{bmatrix}\mathbf{I}_2 & \mathbf{0}\\ \mathbf{0} & \dfrac{\left(-\mathbf{H}_2^H\mathbf{H}_3^H+\mathbf{H}_4^H\mathbf{H}_3^{-H}\mathbf{H}_1^H\mathbf{H}_3^H\right)^H}{\sqrt{\det(-\mathbf{H}_2^H\mathbf{H}_3^H+\mathbf{H}_4^H\mathbf{H}_3^{-H}\mathbf{H}_1^H\mathbf{H}_3^H)}}\end{bmatrix}}_{:=\mathbf{Q}_2}$$

$$= \underbrace{\begin{bmatrix}\sqrt{\det(\mathbf{H}_1)+\det(\mathbf{H}_3)} & \mathbf{0}\\ \dfrac{\mathbf{H}_2^H\mathbf{H}_1+\mathbf{H}_4^H\mathbf{H}_3}{\sqrt{\det(\mathbf{H}_1)+\det(\mathbf{H}_3)}} & \dfrac{\sqrt{\det(-\mathbf{H}_2^H\mathbf{H}_3^H+\mathbf{H}_4^H\mathbf{H}_3^{-H}\mathbf{H}_1^H\mathbf{H}_3^H)}}{\sqrt{\det(\mathbf{H}_1)+\det(\mathbf{H}_3)}}\end{bmatrix}}_{:=\mathbf{R}^H} \quad \text{(A.2)}$$

It is straightforward to verify that $\mathbf{Q}_1$ in (A.1) is unitary; since $-\mathbf{H}_2^H\mathbf{H}_3^H+\mathbf{H}_4^H\mathbf{H}_3^{-H}\mathbf{H}_1^H\mathbf{H}_3^H$ remains an Alamouti block [7], $\mathbf{Q}_2$ in (A.2) is also unitary. Combining (A.1) and (A.2) we have $\mathbf{H}^H\mathbf{Q}_1\mathbf{Q}_2=\mathbf{R}^H$, and hence $\mathbf{H}=\mathbf{QR}$ with $\mathbf{Q}=\mathbf{Q}_1\mathbf{Q}_2$ is an associated QR decomposition. We finally note that

$$\begin{aligned}\det(\mathbf{H}) &= \det\left(\mathbf{QR}\right)=\det\left(\mathbf{R}\right)\\ &= \sqrt{\det(-\mathbf{H}_2^H\mathbf{H}_3^H+\mathbf{H}_4^H\mathbf{H}_3^{-H}\mathbf{H}_1^H\mathbf{H}_3^H)}\end{aligned}, \quad \text{(A.3)}$$

where the second equality holds since $\mathbf{Q}$ is unitary and the last equality follows by definition of $\mathbf{R}$ in (A.2). The assertion thus follows from (A.2) and (A.3). □

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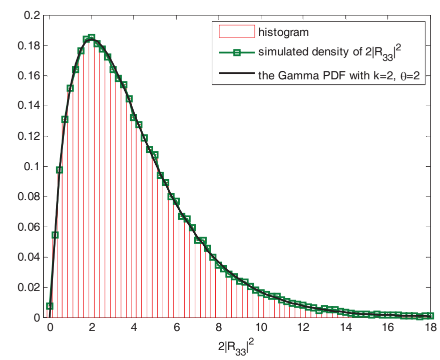

Figure 1. Simulated density of $2\left|R_{33}\right|^2$ and the associated approximation via Gamma PDF with $k=2$ and $\theta=2$.

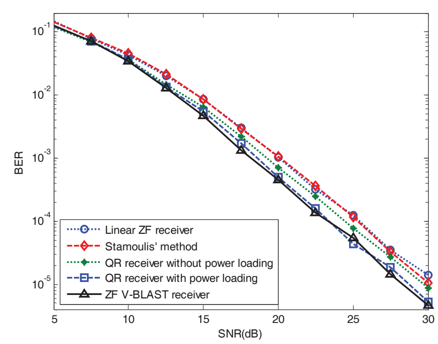

Figure 2. BER performances of D-STTD systems with different receivers (QPSK modulation).

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FURTHER RESULTS ON DECISION FUSION IN CENSORING SENSOR NETWORKS: AN UNKNOWN NETWORK SIZE

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ABSTRACT

Energy consumption is a vital concern when implementing distributed decision fusion in most wireless sensor networks. This paper studies the impact of sensor censoring on the decision fusion performance when the number of sensors is unknown at the fusion center. The global decision rule adopted at the fusion center is the Chair-Varshney fusion rule modified to take account of the unknown network size. It is shown that under the assumption of equally likely hypotheses, allowing more transmitting sensors does not necessarily yield better decision fusion; rather, there exists a censoring probability threshold below which the increase in the number of active sensors just incurs more intra-network communication overhead but will not improve the global decision performance. Our findings establish that the design of energy-efficient local detection rules should commence with the censoring rate threshold.

Index Terms— Sensor networks, decision fusion, distributed detection, energy efficiency, sensor censoring

1. INTRODUCTION

Energy consumption is a vital concern when implementing distributed decision fusion in most wireless sensor networks (WSNs). It has been shown that significant savings in the communication overhead can be achieved by utilizing a sensor censoring policy in which the local nodes transmit their decisions to the fusion center (FC) if they are judged to be informative, but remain silent if they are not [1–5]. In the scheme presented in [1], the entire log-likelihood ratio (LLR) value is transmitted, whereas in [2], only a binary decision is sent to the fusion center (FC) if the LLR falls within the "send" region. The present study adopts a similar "yes/no" sensor censoring scheme. However, to increase the amount of information made available to the FC when performing the global decision making process, the LLR is divided not into two regions as in [2], but into three, namely "send 1", "send -1" and "no send", as shown in Fig. 1. A similar censoring scheme with two "send" regions and one "no send" region is also considered in [4].

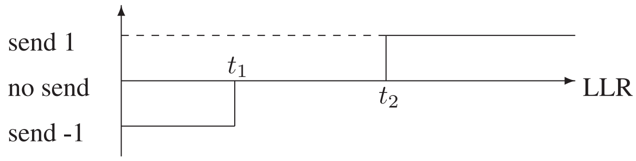

Fig. 1. Proposed censoring scheme at local nodes.

In fact, the censoring scheme depicted in Fig. 1 can be regarded as a three-level quantizer, in which the censored region represents an additional quantization level (see also [4, eq. (2)]). It has been shown in [4] that by using an additional quantization level in the case in which the number of nodes is known to the FC can improve the performance by overcoming the negative effects of erroneous local decisions. This finding implies that in WSNs with a known number of sensor nodes, three-level quantization schemes offer the potential for achieving the same quality of detection performance as two-level quantizers, but with a lower energy consumption. A major objective of the present study is to investigate whether this finding still holds when the number of nodes is unknown to the FC.

The problem of distributed detection with an unknown number of sensors in the region of interest (ROI) is essential in WSNs [6, 7]. The issue of whether or not the number of nodes is known has a fundamental effect upon the fusion process performed in the networks utilizing sensor censoring schemes. Specifically, when the number of nodes is known, the fusion center can obtain information from the no-transmission nodes based on the knowledge of their corresponding "no-send" regions and the number of no-transmission nodes (see [1, eq. (4)] and [4, eq. (7)]). However, information contributed by no-transmission nodes is difficult to infer when the number of sensors is unknown to the FC.

This study considers the decentralized detection with decision fusion performed in accordance with the modified Chair-Varshney (MCV) fusion rule, a modification of the Chair-Varshney rule (see [8]) for the case in which the number of local sensors is unknown to the FC. We derive for the consid-

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ered MCV rule a closed-form error probability function formula, which is expressed as a function of the censoring probability. With the aid of this result, it is shown that under the assumption of equally likely hypotheses, the minimum of the error probability is attained at a nonzero censoring probability, called the "starting point" for sensor censoring, for most reasonable censoring detectors. Hence, the fundamental contribution of this paper is the findings that, when the number of sensors is unknown, decreasing the censoring probability, i.e., allowing more sensors to report their decisions, does not necessarily improve the global decision performance; rather, the design of a suitable censoring scheme should commence by considering the censoring probability corresponding to the starting point.

2. PRELIMINARY

2.1. System model

Consider N sensors observing sensor measurements $\{z_j\}_{j=1}^N$ generated from a common phenomenon according to two hypotheses, namely H_0 or H_1, respectively. In addition, let the prior probabilities of H_0 and H_1 be known and denoted by π_0 and π_1, respectively. Furthermore, assume that the number of sensors, N, is unknown to the FC. The sensor measurements $\{z_j\}_{j=1}^N$ are assumed to be conditionally independent and identically distributed given each hypothesis. Each node makes a preliminary decision u_j, where $j = 1, \ldots, N$, based on its own observation. In this study, we denote $\mathcal{U}$ as the set of the decisions made by all nodes, i.e., $\mathcal{U} \triangleq \{u_j\}_{j=1}^N$. In the event that the jth sensor node determines the existence of H_1, a decision of $u_j = 1$ is sent to the FC. Conversely, if the node detects H_0, it transmits a decision of $u_j = -1$. If neither condition is determined, the node remains silent, i.e. $u_j = 0$. In this study, $\mathcal{U}_s$ denote the set of the decisions which do not mute, i.e., $\mathcal{U}_s \triangleq \{u_j : u_j \neq 0\}$, and $\mathcal{U}_c$ denote the set of the decisions of being silent, i.e., $\mathcal{U}_c \triangleq \{u_j : u_j = 0\}$. Hence, $\mathcal{U}_s$ and $\mathcal{U}_c$ are with the properties that $\mathcal{U}_s \cap \mathcal{U}_c = \emptyset$ and $\mathcal{U}_s \cup \mathcal{U}_c = \mathcal{U}$.

It is assumed that the decisions made by $K = |\mathcal{U}_s|$ sensors are transmitted to the FC over independent flat fading channels, where $|\mathcal{A}|$ denotes the cardinality of a set $\mathcal{A}$. As a result, the data received at the FC can be expressed as[1]

$$y_k = h_k u_k + n_k, u_k \in \mathcal{U}_s, \tag{1}$$

where h_k is a real-valued attenuation factor with $h_k > 0$ and n_k is a Gaussian random variable with zero mean and a variance σ^2. Having received the signals, $\{y_k\}_{k=1}^K$, the FC makes a global decision regarding the existence of H_1 in accordance with a predesigned fusion rule.

[1]This paper assumes the FC does not receive any signal y_j if $u_j \in \mathcal{U}_c$.

2.2. Some definitions

The detection performance of the local sensors is characterized by the false alarm and the detection probabilities, denoted by $p_{f_j} = \Pr(u_j = 1|H_0)$ and $p_{d_j} = \Pr(u_j = 1|H_1)$, respectively. Note that we also define the missing probability $p_{m_j} = \Pr(u_j = -1|H_1)$, and the local censoring probabilities under the two hypotheses as $q_{0_j} = \Pr(u_j = 0|H_0)$ and $q_{1_j} = \Pr(u_j = 0|H_1)$ in this study. To facilitate subsequent analysis an identical local decision rule is assumed to be employed at all nodes, i.e. $u_1, \ldots, u_N$ are independent and identically distributed, and, therefore, we denote $p_{f_j} = p_f$, $p_{d_j} = p_d$, $p_{m_j} = p_m$, $q_{0_j} = q_0$, and $q_{1_j} = q_1$ for all j.

Definition 1 *Let the censoring probability p_c be defined as* $\Pr(u_j = 0) = \pi_0 q_0 + \pi_1 q_1$.

If p_c is large, more sensors will be put in the silent mode. In this way, the network-wide energy consumption is reduced but less local decision information is available at the FC. On the contrary, if p_c is small, more sensors will report their decisions. The FC can aggregate more local decisions to make a global inference at the expense of a large energy cost. A fundamental question when the total number of sensors is unknown is whether decreasing the censoring probability p_c without bound, i.e., allowing more and more transmitting sensors, can actually yield better decision fusion. To answer this question, some mathematical definitions are needed.

Let $P_e(p_c)$ be the probability of the fusion error associated with the censoring probability p_c. Define $\mathcal{S} \triangleq \{p_c | p_c = \arg \min_{p_c \in [0,1]} P_e(p_c)\}$, which is the set containing the p_c's that attain the minimal error probability.

Definition 2 *We say that the starting point for sensor censoring, or starting point for short, exists if S contains at least one nonzero element. In this case, the starting point is defined to be $p_c^* = \max_{p_c \in \mathcal{S}} p_c$.*

Among all $p_c \in \mathcal{S}$ that can achieve the best decision fusion, the starting point p_c^*, if it exists, results in the least energy consumption. Hence, the starting point should serve as a design target for any plausible censoring schemes.

3. MAIN RESULTS

3.1. Proposed modified Chair-Varshney fusion rule

The fusion rule which makes use of the quantized decisions being the observations instead of the received y_k is adopted in this paper. Since the alphabet of $u_k \in \mathcal{U}_s$ is $\{+1, -1\}$, the maximum likelihood (ML) estimate for u_k given (1) is

$$\hat{u}_k = \text{sign}(y_k), \text{ for } k : u_k \in \mathcal{U}_s. \tag{2}$$

Therefore, the considered fusion rule is to make use of $\hat{u}_k = \text{sign}(y_k)$ to determine which hypothesis is true. Viewing the estimated local decisions $\hat{u}_k$ as the observations, it is well known that the Chair-Varshney fusion rule [8] is optimal in the sense of minimizing the Bayesian cost.

Define $p_{1_j} := \Pr(y_j > 0, u_j \neq 0|H_1)$ and $p_{0_j} := \Pr(y_j > 0, u_j \neq 0|H_0)$. When the number of operating nodes is known to the FC, the Chair-Varshney fusion rule for the considered censoring local decisions can be derived as [8] (see also [9, 10])[2]

$$\Lambda_{CV} = \sum_{j:u_j \in \mathcal{U}_c} \log \frac{q_{1_j}}{q_{0_j}} + \sum_{j:u_j \in \mathcal{U}_s, \mathrm{sign}(y_j)=1} \log \frac{p_{1_j}}{p_{0_j}} + \sum_{j:u_j \in \mathcal{U}_s, \mathrm{sign}(y_j)=-1} \log \frac{1-p_{1_j}-q_{1_j}}{1-p_{0_j}-q_{0_j}}. \quad (3)$$

However, for the case in which the number of local sensors is unknown to the FC, the set $\mathcal{U}_c$ is unknown and hence the Chair-Varshney rule given in (3) cannot be applied. A heuristic way to modify the Chair-Varshney rule is then simply ignoring the information contained in the term $\sum_{j:u_j \in \mathcal{U}_c} \log \frac{q_{1_j}}{q_{0_j}}$ in (3), which results in the proposed MCV fusion rule given by

$$\Lambda_{MCV} = \sum_{j:u_j \in \mathcal{U}_s, \mathrm{sign}(y_j)=1} \log \frac{p_{1_j}}{p_{0_j}} + \sum_{j:u_j \in \mathcal{U}_s, \mathrm{sign}(y_j)=-1} \log \frac{1-p_{1_j}-q_{1_j}}{1-p_{0_j}-q_{0_j}}. \quad (4)$$

In the following, we first provide an analysis of the error probability using the MCV fusion rule. Since all of the sensors employ an identical local decision rule, the signals received at the FC, i.e. $\{y_k\}_{k=1}^K$, are independent and identically distributed, thus $p_1 = p_{1_k}$, $p_0 = p_{0_k}$, $q_1 = q_{1_k}$, and $q_0 = q_{0_k}, \forall k$. The fusion error probability of the MCV fusion rule can be derived as (5) (see the top of next page), where τ_i is a function of the number of the transmitting sensors, i.e., $N-i$. When the identical local decision rule is utilized, it can be shown that the MCV rule reduces to the τ_i out of $N-i$ fusion rule, and the value of τ_i can be obtained as $\tau_i = \lceil \tau_i^* \rceil$, where

$$\tau_i^* \triangleq \frac{\log\left\{\frac{\pi_0}{\pi_1}\left(\frac{1-p_0-q_0}{1-p_1-q_1}\right)^{N-i}\right\}}{\log\left\{p_1(1-p_0-q_0)/p_0(1-p_1-q_1)\right\}}, \quad (6)$$

and $\lceil \cdot \rceil$ denotes the standard ceiling function. The probability of the fusion error given in (5) provides the exact error probability. For computational feasibility in large scale sensor networks, the proposition below provides an upper bound of the fusion error probability. Note that the proof of the proposition is omitted due to the page limit imposed for the publication.

[2]The Chair-Varshney fusion rule considered in this paper uses p_{1_j} and p_{0_j} as the local detection performance instead of p_{f_j} and p_{d_j} considered in [9, 10]. That is, the effect of channel error is incorporated into the local detection performance in our considered Chair-Varshney fusion rule.

Proposition 1 *Let P_e be the average probability of detection error defined in* (5). *Assume that all of the local sensors apply an identical decision rule. Then, P_e is given by* (7) *(see the top of next page), where $\eta_i = 2\tau_i - N + i$, and $E_{i|H_0}$ and $E_{i|H_1}$ denote the conditional expectations with respect to the random number of silent nodes i under H_0 and H_1, respectively, where i follows the binomial distribution with parameters N and q_0 if H_0 is true and follows the binomial distribution with parameters N and q_1 if H_1 is true. In addition, if the MCV rule reduces to the majority voting rule, i.e., $\eta_i = 0$ for all i, we obtain*

$$P_e \leq \pi_0 \left(2\sqrt{p_0(1-p_0-q_0)} + q_0\right)^N + \pi_1 \left(2\sqrt{p_1(1-p_1-q_1)} + q_1\right)^N. \quad (8)$$

3.2. The proof of the existence of a starting point when utilizing MCV fusion rule

Based on the true error probability function given in (5), this subsection aims to prove the existence of a starting point for the MCV rule.

To prove the existence of a starting point, the following lemma is needed.

Lemma 1 $\lim_{p_c \to 1} P_e(p_c) = 1$ *and* $\lim_{p_c \to 0} P_e(p_c) \leq 1$.

Proof: The proof is omitted here due to the page limit. □

Based on Lemma 1, we have the following key result.

Theorem 1 *Consider the case in which the hypotheses are equally likely. Assume that*

$$-1 < p_0' \triangleq \frac{\partial p_0(q_0)}{\partial q_0} < 0, 0 > p_1' \triangleq \frac{\partial p_1(q_1)}{\partial q_1} > -1, \quad p_0 < \frac{\tau_0}{N}, p_1 > \frac{\tau_0 - 1}{N}, \quad (9)$$

and

$$p_0'(0) - \frac{(N-\tau_0)p_0}{(1-p_0)\tau_0} p_0'(0) + \mathbf{1}(\tau_1 = \tau_0 - 1) - (1 + p_1'(0)) + \frac{(\tau_0 - 1)(1-p_1)}{p_1(N-\tau_0+1)}(1 + p_1'(0)) + \mathbf{1}(\tau_1 = \tau_0) < 0. \quad (10)$$

Then $\mathcal{S}$ contains at least one nonzero element, and, hence, a starting point exists.

Proof: Due to the page limit, we only sketch the proof. By Lemma 1, we have $\lim_{p_c \to 0} P_e(p_c) \leq \lim_{p_c \to 1} P_e(p_c)$. Given conditions (9) and (10), it can be shown that $P_e(p_c)$ decreases when p_c increases from zero. This then guarantees the existence of a local minimum attained at a nonzero p_c. □

It is noted that condition (10) given in Theorem 1 can easily hold in most censoring detectors based on our investigation. Specifically, for the case in which the local detection

$$P_e = \pi_0 \sum_{i=0}^{N} \binom{N}{i} q_0^i \sum_{k=\tau_i}^{N-i} \binom{N-i}{k} p_0^k \left(1-q_0-p_0\right)^{N-i-k} + \pi_1 \sum_{i=0}^{N} \binom{N}{i} q_1^i \sum_{k=N-i-\tau_i+1}^{N-i} \binom{N-i}{k} (1-q_1-p_1)^k p_1^{N-i-k} \tag{5}$$

$$P_e \le \pi_0 E_{i|H_0} \left[\left(\sqrt{\frac{(N-i-\eta_i)p_0}{(N-i+\eta_i)(1-p_0-q_0)}} \right)^{\eta_i} \left(\sqrt{\frac{(N-i+\eta_i)p_0(1-p_0-q_0)}{(N-i-\eta_i)(1-q_0)^2}} + \sqrt{\frac{(N-i-\eta_i)p_0(1-p_0-q_0)}{(N-i+\eta_i)(1-q_0)^2}} \right)^{N-i} \right]$$
$$+ \pi_1 E_{i|H_1} \left[\left(\sqrt{\frac{(N-i-\eta_i)p_1}{(N-i+\eta_i)(1-p_1-q_1)}} \right)^{\eta_i} \left(\sqrt{\frac{(N-i+\eta_i)p_1(1-p_1-q_1)}{(N-i-\eta_i)(1-q_1)^2}} + \sqrt{\frac{(N-i-\eta_i)p_1(1-p_1-q_1)}{(N-i+\eta_i)(1-q_1)^2}} \right)^{N-i} \right] \tag{7}$$

performance and channel status are very good, i.e., $p_0 \to 0$ and $p_1 \to 1$, a sufficient condition for (10) is given by

$$-1 \le p_0'(0) \le \varepsilon \text{ and } 0 \ge p_1'(0) \ge -\varepsilon \quad \text{for some } 0 < \varepsilon < 1, \tag{11}$$

which is a much simpler condition than condition (10).

4. NUMERICAL AND SIMULATION RESULTS

In evaluating the performance, we consider two different scenarios. In all examples, it is assumed that the hypotheses are equally likely and all of the sensor observations have the same distribution when conditioned on each hypothesis. The number of operating sensors N is assumed to be 30. In addition, the number of operating sensors inside the ROI is unknown to the FC whenever the MCV rule is applied. For performance comparison, the result of the CV rule is also plotted. Of course, when the CV rule is applied, it has been assumed that the number of operating sensors is known to the FC. In the performance evaluation, the channel signal-to-noise ratio (CSNR) is defined as $\gamma = E[h_k^2]/\sigma^2$, and all performances are evaluated when CSNR= 5 dB. Finally, in both examples, the censoring region of the local quantizer is assumed to be a single interval and is set by the thresholds $b+t$ and $b-t$, where b is a fixed point and t varies in accordance with the value of p_c.

In the first example, the sensor observations are randomly drawn from unit-variance Gaussian distributions with means of m_0 and m_1 corresponding to H_0 and H_1, respectively. When making their decisions, the local sensors apply the thresholds $\frac{m_0+m_1}{2}+t$ and $\frac{m_0+m_1}{2}-t$, where t is determined by the specified value of the censoring probability p_c. Specifically, $p_c = Q(\frac{m_0-m_1}{2}-t) - Q(\frac{m_0-m_1}{2}+t)$ in the example. The observation signal-to-noise ratio (OSNR) is defined as $20\log_{10}|m_1-m_0|$, and it is set to be 0 dB in the example. Figure 2 plots the simulated error probability, the theoretical error probability using (5), and the bound of error probability using (8). As illustrated in the figure, the error probability varies as a convex function of the censoring probability, and the behavior of the error bound is consistent with the true error probability. From an inspection of the numerical result, the optimum point of the theoretical error probability is determined to be 0.4042. This value represents the suitable starting point for the local sensors when designing a distributed decision fusion network based upon the MCV fusion rule. As can be observed form Fig. 2, the performances of the MCV rule and the CV rule are the same. This is because q_0 and q_1 have the same value in this example, and the CV rule in (3) reduces to the MCV rule in (4).

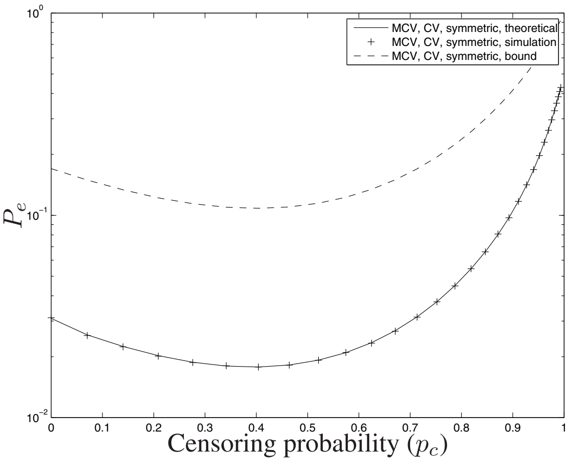

Fig. 2. Simulation and theoretical results for probability of fusion error as function of censoring probability p_c for the case in which the observations under both hypotheses are drawn from symmetrical Gaussian distributions.

Unlike the first example, the distributions under H_0 and H_1 are asymmetric in the second example. Specifically, under

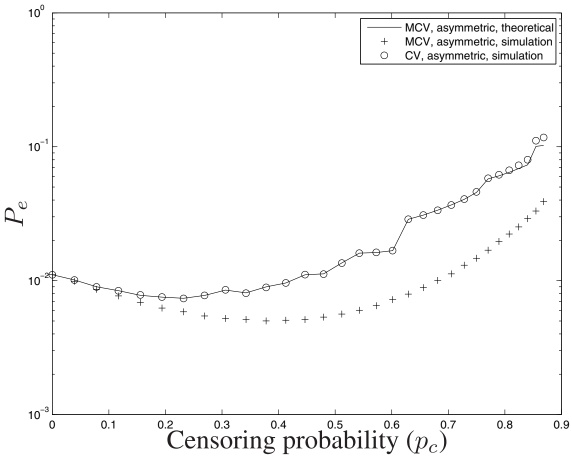

Fig. 3. Simulation and theoretical results for probability of fusion error as function of censoring probability p_c for the case in which the observations under both hypotheses are drawn from asymmetrical Gaussian distributions.

H_0, the sensor observations are distributed as Gaussian random variable with mean $m_0 = -1$ and variance $\sigma_0^2 = 2$, and, under H_1, the observations are distributed as Gaussian random variable with mean $m_0 = 1$ and variance $\sigma_1^2 = 4$. When making their decisions, the local sensors apply the thresholds $b + t$ and $b - t$, where b is the point at which the densities of both hypotheses have the same value, and t is determined by the censoring probability p_c. Specifically, $p_c = \frac{1}{2}(Q(\frac{b-t-m_1}{\sigma_1}) - Q(\frac{b+t-m_1}{\sigma_1}) + Q(\frac{b-t-m_0}{\sigma_0}) - Q(\frac{b+t-m_0}{\sigma_0}))$ in the example. Figure 3 plots the simulated error probability and the theoretical error probability using (5) for the MCV rule. The simulated error probability of the CV rule is also plotted. It is evident from the figure that the starting point also exists when the distributions under both hypotheses are asymmetric. It can be also observed from the figure that the performances of the MCV rule and the CV rule are generally not the same because q_0 and q_1 are distinct in general. As expected, the CV fusion rule has the better performance due to using the additional information of the number of silent nodes.

5. CONCLUSIONS

Based on a modified Chair-Varshney fusion rule, this study has addressed the impact of sensor censoring on the global decision performance when the number of sensors is unknown to the FC. Under quite mild conditions on local detection performances as well as under the assumption of equally likely hypotheses, this study has proved the existence of an error probability threshold, below which more transmitting sensors are allowed but the proportional increase in the energy expenditure does not improve the global decision performance. Therefore, the design of energy-efficient censoring decision fusion should commence from the starting point, since a censoring probability lower than this point not only yields a poorer fusion result, but also consumes a greater amount of energy.

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On the Performance of Receive ZF MIMO Broadcast Systems with Channel Estimation Errors

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***Abstract*— While the zero-forcing (ZF) transmit beamforming is a widely used technique for realizing multiple-input multiple-output (MIMO) broadcast transmissions, the ZF receiver combined with multiuser scheduling is an effective alternative that yields improved robustness against channel state information (CSI) mismatch caused by feedback link errors. In this paper we consider the practical scenario that channels are imperfectly estimated at the receiver. Our goal is to characterize the sum rate performance of the receive ZF MIMO broadcast systems under channel estimation errors. We derive analytic sum-rate expressions for both the uniform transmit power and transmit water-filling cases. Our analytic results characterize the sum-rate floor incurred by channel estimation errors. Numerical simulations are used to confirmed the analytic study.**

***Index Terms*— MIMO, MIMO broadcast systems, zero-forcing receiver, estimation errors, sum-rate analysis.**

I. Introduction

Multiple-input multiple-output (MIMO) antenna techniques have become the key to support high-speed data rates in current and future wireless communication systems. In the point-to-multipoint broadcast environment, the huge capacity gain offered by MIMO antenna techniques can be further exploited to support personalized data services for multiple users concurrently. This point-to-multipoint broadcast system is the so called MIMO broadcast channels [1].

The MIMO broadcast transmissions with transmit beamforming including zero-forcing (ZF) based beamforming [1] and block diagonalization (BD) [2] can approach the optimal sum rate obtained by dirty-paper coding (DPC) with feasible implementation complexity as the number of users is large. However, the available resource for channel state information (CSI) feedback will dominate the system performance. For example, the feedback load per user of the MIMO broadcast systems with transmit ZF beamforming must be scaled together with both the number of transmit antennas as well as the system signal-to-noise ratio (SNR) to achieve the full multiplexing gain with the near-perfect CSI [3].

By taking advantage of multiuser scheduling, the MIMO systems with the ZF receiver become another choice to realize point-to-multipoint broadcast transmissions [4]–[6] contrary to traditional MIMO broadcast systems with transmit beamforming/precoding [1]. One important advantage of the receive ZF MIMO broadcast systems is that it can achieve similar sum rate compared to the transmit ZF MIMO broadcast systems with less feedback requirement (i.e., SNR quality feedback) and provides robust resistance to feedback link errors [7]. Specifically, the benefits of the receive ZF MIMO broadcast systems come from utilizing feedback CSI for user selection instead of utilizing feedback CSI for calculating antenna beamforming weights in transmit MIMO broadcast systems. As a result, feedback uncertainty only causes slight sum-rate degradation for the receive ZF MIMO broadcast systems, while maintaining the same sum-rate slope.

In this paper, we consider the practical scenario that the ZF receiver may present imperfect channel estimation and provide corresponding sum-rate capacity analysis for the receive ZF MIMO broadcast systems. In the presence of imperfect CSI at receiver (CSI-R) caused by mismatched channel estimations, [8] provided approximated bit-error rate (BER) analysis for point-to-point single-user MIMO system with ZF receiver. The achievable sum rates of the point-to-multipoint MIMO broadcast systems with receive ZF beamforming combined with multiuser scheduling were analyzed in [6] and [7] with equal and water-filling power allocations, respectively. However, the provided closed-form expressions are constrained to the case of $M_R = M_T$, i.e., the number of receive antennas at user end equals to the number of transmit antennas at the base station. In this paper, we relax our analysis to the case of $M_R \geq M_T$ and further consider the effect of channel estimation errors on the sum-rate capacity. Our analytical results characterize the sum-rate floor caused by channel estimation errors.[1]

The paper is organized as follows. Section II illustrates the system model and the concept of MIMO broadcast systems with ZF receivers and scheduling. In Section III, we provide the analytically closed-form expressions for sum-rate capacity of the receive ZF MIMO broadcast systems. We show numerical results in Section IV and give conclusion in Section V.

II. Background

A. System Model

Consider a downlink MIMO system with one base station and K user terminals. The numbers of transmit antennas at the base station and receive antennas at each user terminal are M_T and $M_R \geq M_T$, respectively. Denote $\mathbf{x} \in \mathbb{C}^{M_T \times 1}$ as the transmitted signal vector with power $E[\mathbf{x}\mathbf{x}^H] = \frac{P_T}{M_T}\mathbf{I}_{M_T}$

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[1]Similar results can be found in [9] which provides an analytical sum-rate approximation

and $\mathbf{y} \in \mathbb{C}^{M_R \times 1}$ the received signal vector, where $E[\cdot]$ is the expectation operation, $(\cdot)^H$ denotes conjugate transpose, and $\mathbf{I}_M$ is an $M \times M$ identity matrix. Let $\mathbf{n} \in \mathbb{C}^{M_R \times 1}$ be the complex Gaussian noise vector with $E[\mathbf{n}\mathbf{n}^H] = \sigma^2 \mathbf{I}_{M_R}$. Then, the input-output system model between the base station and a certain user terminal in flat-faded MIMO channel is

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n} \ , \tag{1}$$

where $\mathbf{H}$ is the $M_R \times M_T$ channel matrix with independent identically distributed (i.i.d.) Rayleigh faded entries. Assume that imperfect CSI is obtained at the receiver with the following model [8]

$$\hat{\mathbf{H}} = \mathbf{H} + \mathbf{E} \ , \tag{2}$$

where $\hat{\mathbf{H}} \in \mathbb{C}^{M_R \times M_T}$ is the available CSI at the receiver with an uncorrelated error matrix $\mathbf{E} \in \mathbb{C}^{M_R \times M_T}$. Each entry of the channel uncertainty $\mathbf{E}$ is distributed by $\mathcal{CN}(0, \epsilon_e^2)$ that accounts for estimation errors at the receiver with $E[\mathbf{E}\mathbf{E}^H] = M_T \epsilon_e^2 \mathbf{I}_{M_R}$ [10]. The normalized mean square error (NMSE) between the actual channel state and the estimated value is [8]

$$\text{NMSE} = \frac{E[|h_{i,j} - \hat{h}_{i,j}|^2]}{E[|h_{i,j}|^2]} = \epsilon_e^2 \ , \tag{3}$$

where $h_{i,j}$ and $\hat{h}_{i,j}$ represent the (i,j)-th element of $\mathbf{H}$ and $\hat{\mathbf{H}}$, respectively.

B. MIMO Systems with ZF Receiver under Imperfect CSI-R

The ZF receiver is realized by multiplying the received signal $\mathbf{y}$ from the left by the pseudo-inverse of estimated channel matrix $\hat{\mathbf{H}}^\dagger = (\hat{\mathbf{H}}^H \hat{\mathbf{H}})^{-1} \hat{\mathbf{H}}^H$. The post-processed received signal $\hat{\mathbf{y}}$ becomes

$$\begin{aligned} \hat{\mathbf{y}} &= \hat{\mathbf{H}}^\dagger \mathbf{y} \\ &= (\hat{\mathbf{H}}^H \hat{\mathbf{H}})^{-1} \hat{\mathbf{H}}^H \left[(\hat{\mathbf{H}} - \mathbf{E})\mathbf{x} + \mathbf{n} \right] \\ &= \mathbf{x} + \underbrace{(\hat{\mathbf{H}}^H \hat{\mathbf{H}})^{-1} \hat{\mathbf{H}}^H \mathbf{n} - (\hat{\mathbf{H}}^H \hat{\mathbf{H}})^{-1} \hat{\mathbf{H}}^H \mathbf{E}\mathbf{x}}_{\triangleq \hat{\mathbf{n}}} \ . \end{aligned} \tag{4}$$

The noise covariance matrix $E[\hat{\mathbf{n}}\hat{\mathbf{n}}^H]$ of the ZF receiver is

$$\begin{aligned} E[\hat{\mathbf{n}}\hat{\mathbf{n}}^H] &= E\left\{ (\hat{\mathbf{H}}^\dagger \mathbf{n} - \hat{\mathbf{H}}^\dagger \mathbf{E}\mathbf{x})(\hat{\mathbf{H}}^\dagger \mathbf{n} - \hat{\mathbf{H}}^\dagger \mathbf{E}\mathbf{x})^H \right\} \\ &= \sigma^2 \hat{\mathbf{H}}^\dagger (\hat{\mathbf{H}}^\dagger)^H + \frac{P_T}{M_T} \hat{\mathbf{H}}^\dagger E[\mathbf{E}\mathbf{E}^H] (\hat{\mathbf{H}}^\dagger)^H \\ &\overset{(a)}{=} (\sigma^2 + P_T \epsilon_e^2)(\hat{\mathbf{H}}^H \hat{\mathbf{H}})^{-1} \ , \end{aligned} \tag{5}$$

where (a) comes from the fact $\hat{\mathbf{H}}^\dagger (\hat{\mathbf{H}}^\dagger)^H = (\hat{\mathbf{H}}^H \hat{\mathbf{H}})^{-1}$. From (5), $(\hat{\mathbf{H}}^H \hat{\mathbf{H}})^{-1}$ may have nonzero off-diagonal elements, resulting in correlated noise across different data streams. To lower complexity, the noise correlation is usually ignored and each stream is decoded independently [4] [11]. With equal power across transmit antennas, the output post processing SNR at the n-th stream is

$$\begin{aligned} \gamma_n &= \frac{P_T / M_T}{\left[E\left\{ \hat{\mathbf{n}}\hat{\mathbf{n}}^H \right\} \right]_{n,n}} \\ &= \frac{\rho}{M_T (1 + \rho \epsilon_e^2) \left[(\hat{\mathbf{H}}^H \hat{\mathbf{H}})^{-1} \right]_{n,n}} \ , \quad n = 1, \cdots, M_T \ , \end{aligned} \tag{6}$$

where $\rho = P_T / \sigma^2$ is the mean received SNR and $[\mathbf{A}]_{i,i}$ represents the i-th diagonal element of a squared matrix $\mathbf{A}$. The term $z = 1 / \left[(\hat{\mathbf{H}}^H \hat{\mathbf{H}})^{-1} \right]_{n,n}$ is Chi-square distributed with $l = 2(M_R - M_T + 1)$ degrees of freedom [4] [11] and the probability density function (PDF) is [12]

$$f_Z(z) = \frac{z^{\frac{l}{2} - 1} \, e^{-z / 2\Sigma^2}}{\Sigma^l \, 2^{l/2} \, \Gamma(l/2)} \ , \quad z \geq 0 \ , \tag{7}$$

where $\Sigma^2 = (1 + \epsilon_e^2)/2$ and $\Gamma(a) = \int_0^\infty t^{a-1} e^{-t} dt$ is the complete gamma function. As a result, the ZF receiver has identical post processing SNR γ_n with PDF (8) for all n

$$f_{\gamma_n}(\gamma) = \frac{M_T}{\hat{\rho}} \frac{e^{-M_T \gamma / \hat{\rho}}}{(M_R - M_T)!} \left(\frac{M_T}{\hat{\rho}} \gamma \right)^{M_R - M_T} \ , \quad \gamma \geq 0 \ , \tag{8}$$

where $\hat{\rho} \triangleq \rho (1 + \epsilon_e^2)/(1 + \rho \epsilon_e^2)$. The corresponding cumulative distribution function (CDF) of γ_n is expressed by

$$\begin{aligned} F_{\gamma_n}(\gamma) &= 1 - \frac{\Gamma\left(M_R - M_T + 1, \frac{M_T \gamma}{\hat{\rho}} \right)}{\Gamma\left(M_R - M_T + 1 \right)} \\ &= 1 - \Gamma_{\text{R}}\left(M_R - M_T + 1, \frac{M_T \gamma}{\hat{\rho}} \right) \ , \end{aligned} \tag{9}$$

where $\Gamma(a, x) = \int_x^\infty t^{a-1} e^{-t} dt$ is the upper incomplete gamma function and $\Gamma_{\text{R}}(a, x) = \frac{\Gamma(a,x)}{\Gamma(a)}$ is the regularized gamma function.

C. MIMO Broadcast Systems with Receive ZF Beamforming and Scheduling

With the aid of multiuser scheduling, the MIMO antenna techniques with simple ZF linear receiver can realize the point-to-multipoint concurrent transmissions instead of traditional point-to-point communication. For this receive ZF-based MIMO broadcast systems, each user feedbacks the channel SNR vector $\{\gamma_n^k\}_{n=1}^{M_T}$ to the transmitter for selecting the target group of users, where γ_n^k is the n-th output SNR of user k defined in (6). Since the ZF receiver can change an $M_R \times M_T$ channel matrix into M_T parallel subchannels, the scheduler at the transmitter can assign each transmit antenna to serve one of the selected target users. It is unnecessary to assign all the subchannels to a single user in a point-to-point way [4]–[6]. Under a homogeneous environment, i.e., all users having the same ρ value, the scheduler assigns data to the target user k^* via the n-th transmit antenna according to the criterion:

$$k^* = \arg\max_{k \in \mathcal{K}} \gamma_n^k \ , \tag{10}$$

where $\mathcal{K}$ is the user set with $|\mathcal{K}| = K$. Since there are K spatially-independent choices for an arbitrary transmit antenna, such a **broadcast** scheduling algorithm is called independent stream scheduler in [4], [5] and called spatially-independent scheduling in [6].

III. Sum-Rate Analysis

A. Sum-Rate Analysis under Equal Power Allocation

According to the order statistics analysis, the PDF of post processing SNR for the considered receive ZF MIMO broadcast system is

$$f_{\gamma_n^*}(\gamma) = K f_{\gamma_n}(\gamma)\left[F_{\gamma_n}(\gamma)\right]^{K-1} = \frac{KA}{L!}\, e^{-A\gamma}(A\gamma)^L\left[1-\Gamma_{\text{R}}\left(L+1, A\gamma\right)\right]^{K-1} \quad , \tag{11}$$

where

$$A \triangleq \frac{M_T}{\hat{\rho}} = \frac{M_T(1+\rho\epsilon_e^2)}{\rho(1+\epsilon_e^2)} \quad \text{and} \quad L \triangleq M_R - M_T \ . \tag{12}$$

With the aid of the following property of $\Gamma(n,x)$ [13, p.900]

$$\Gamma(a,x) = (a-1)!\, e^{-x}\sum_{m=0}^{a-1}\frac{x^m}{m!} \qquad a = 1, 2, \cdots \ , \tag{13}$$

we can have

$$\begin{aligned}
&\left[1-\Gamma_{\text{R}}\left(L+1, A\gamma\right)\right]^{K-1} \\
&= \left(1 - \frac{L!\, e^{-A\gamma}\sum_{m=0}^{L}\frac{(A\gamma)^m}{m!}}{\Gamma(L+1)}\right)^{K-1} \\
&\overset{(a)}{=} \left(1 - e^{-A\gamma}\sum_{m=0}^{L}\frac{(A\gamma)^m}{m!}\right)^{K-1} \\
&\overset{(b)}{=} \sum_{i=0}^{K-1}\binom{K-1}{i}(-1)^i e^{-iA\gamma}\left(\sum_{m=0}^{L}\frac{(A\gamma)^m}{m!}\right)^i \\
&= \sum_{i=0}^{K-1}\binom{K-1}{i}(-1)^i e^{-iA\gamma}\left(\sum_{m_1=0}^{L}\cdots\sum_{m_i=0}^{L}\frac{(A\gamma)^{m_1+\ldots+m_i}}{m_1!\cdots m_i!}\right),
\end{aligned} \tag{14}$$

where (a) follows $\Gamma(a) = (a-1)!$ when a is positive integer and (b) comes from the binomial expansion $(1-x)^n = \sum_{i=0}^{n}\binom{n}{i}(-1)^i x^i$. The average sum rate of the receive ZF MIMO broadcast systems thus yields the following closed-form expression

$$\begin{aligned}
C_{\text{ZFR}}^{\epsilon_e^2} &= \sum_{n=1}^{M_T} E\left\{\log(1+\gamma_n)\right\} = M_T\int_0^\infty \log(1+\gamma) f_{\gamma_n^*}(\gamma)d\gamma \\
&= \frac{M_T K A}{L!}\int_0^\infty \log(1+\gamma)\sum_{i=0}^{K-1}\binom{K-1}{i}(-1)^i e^{-(i+1)A\gamma} \\
&\qquad \times\left(\sum_{m_1=0}^{L}\cdots\sum_{m_i=0}^{L}\frac{(A\gamma)^{m_1+\ldots+m_i+L}}{m_1!\cdots m_i!}\right)d\gamma \\
&\overset{(a)}{=} \frac{M_T K A}{L!}\sum_{i=0}^{K-1}\binom{K-1}{i}(-1)^i\sum_{m_1=0}^{L}\cdots\sum_{m_i=0}^{L} \\
&\left(\frac{(m_1+\ldots+m_i+L)!A^{m_1+\ldots+m_i+L}}{m_1!\cdots m_i!}\, e^{(i+1)A}\, \times\right. \\
&\left.\sum_{j=1}^{m_1+\ldots+m_i+L+1}\frac{\Gamma\left(j-(m_1+\ldots+m_i+L+1), (i+1)A\right)}{(i+1)^j A^j}\right),
\end{aligned} \tag{15}$$

where the parameters A and L are defined in (12) and equality (a) is based on the following integral identity [14]

$$\int_0^\infty \log(1+t)\, e^{-\alpha t} t^{\beta-1}dt = (\beta-1)!\, e^{\alpha}\sum_{i=1}^{\beta}\frac{\Gamma(i-\beta,\alpha)}{\alpha^i}, \qquad \alpha > 0;\ \beta = 1, 2, \cdots \ . \tag{16}$$

The subscript "ZFR" represents the MIMO broadcast system with ZF receivers. Note that as SNR (i.e., ρ) approaches to the infinite, the sum rate of the receive ZF MIMO broadcast systems with channel estimation error $\epsilon_e^2 \neq 0$ will be bounded by a value $\overline{C_{\text{ZFR}}^{\epsilon_e^2}}$

$$\overline{C_{\text{ZFR}}^{\epsilon_e^2}} = \lim_{\rho\to\infty} C_{\text{ZFR}}^{\epsilon_e^2} = C_{\text{ZFR}}^{\epsilon_e^2}\Big|_{A=\frac{M_T\epsilon_e^2}{(1+\epsilon_e^2)}} \quad , \tag{17}$$

which represents a sum-rate floor incurred by mismatched channel estimations.

1) Special Case: $(M_R = M_T = M)$: In the special case $M_R = M_T$, $L = 0$, the corresponding average sum rate of the receive ZF MIMO broadcast systems becomes

$$\begin{aligned}
C_{\text{ZFR}|_M}^{\epsilon_e^2} &= MKA\sum_{i=0}^{K-1}\binom{K-1}{i}(-1)^i e^{(i+1)A}\frac{\Gamma\left(0,(i+1)A\right)}{(i+1)A} \\
&\overset{(a)}{=} MKA\sum_{i=0}^{K-1}\binom{K-1}{i}(-1)^i h\left((i+1)A\right) \quad ,
\end{aligned} \tag{18}$$

where (a) is obtained by the property $\Gamma(0,x) = E_1(x)$ and $E_r(x) = \int_1^\infty e^{-xt}t^{-r}dt$ is the exponential integer function of order r. Note that the function $h(\cdot)$ in (18) is defined in [6] as

$$h(x) \triangleq \int_0^\infty e^{-xt}\log(1+t)\, dt = \frac{e^x E_1(x)}{x} \quad . \tag{19}$$

Furthermore, if there is no channel estimation error in receiver sides, i.e., $\epsilon_e^2 = 0$, the term A in (12) becomes M_T/ρ and the ergodic capacity becomes

$$C_{\text{ZFR}|_M} = \frac{KM^2}{\rho}\sum_{i=0}^{K-1}\binom{K-1}{i}(-1)^i h\left(\frac{(i+1)M}{\rho}\right) \quad , \tag{20}$$

which is identical to the closed-form expression provided in [6].

B. Sum-Rate Analysis with Water-Filling Power Allocation

When receiver end has perfectly estimated channel knowledge to feedback the base station, the scheduler can further improve the sum rate using water-filling power allocation, instead of equally allocating power among the transmit antennas. With the aid of long-term power constraint for solving average water level [15], we have provided the sum-rate closed-form expression under water-filling power allocation in the case of $M_R = M_T$ [7]. In the section, we extend our analytical expressions to the general case $M_R \geq M_T$.

Based on (6), we define the term $d_n = 1/\left[(\mathbf{H}^H\mathbf{H})^{-1}\right]_{n,n}$ as the effective channel gain of the n-th substream due to

$\epsilon_e^2 = 0$ and $\hat{\mathbf{H}} = \mathbf{H}$. Similar to the approach in (11), we have the PDF of scheduled d_n^* from (8)

$$f_{d_n^*}(d) = \frac{K}{L!} e^{-d} d^L \left[1 - \Gamma_{\mathrm{R}}\left(L+1, d\right)\right]^{K-1} \quad . \tag{21}$$

With water-level solution ς_0 for the long-term power constraint (23), the average sum rate of the receive ZF MIMO broadcast systems with water-filling power allocation is given by

$$\begin{aligned}
C_{\text{ZFR}}^{\text{water}} &= \sum_{n=1}^{M_T} E\left[\log(\varsigma_0 d_n)\right]_+ \\
&= M_T \int_{1/\varsigma_0}^{\infty} \log(\varsigma_0 z) f_{d_n^*}(z) dz \\
&\overset{(a)}{=} \frac{M_T K}{\varsigma_0 L!} \int_1^{\infty} \log(z) \sum_{i=0}^{K-1} \binom{K-1}{i} (-1)^i e^{-\frac{i+1}{\varsigma_0} z} \\
&\qquad \times \left(\sum_{m_1=0}^{L} \cdots \sum_{m_i=0}^{L} \frac{\left(\frac{d}{\varsigma_0}\right)^{m_1+\ldots+m_i+L}}{m_1! \cdots m_i!} \right) dz \\
&\overset{(b)}{=} \frac{M_T K}{L!} \sum_{i=0}^{K-1} \binom{K-1}{i} (-1)^i \sum_{m_1=0}^{L} \cdots \sum_{m_i=0}^{L} \\
&\left(\frac{(m_1+\ldots+m_i+L)!}{m_1! \cdots m_i! \, (i+1)^{m_1+\ldots+m_i+L+1}} \sum_{j=0}^{m_1+\ldots+m_i+L} \frac{\Gamma\left(j, \frac{(i+1)}{\varsigma_0}\right)}{j!} \right)
\end{aligned} \tag{22}$$

subject to the long-term power constraint

$$\begin{aligned}
&\sum_{n=1}^{M_T} E\left[\varsigma - \frac{1}{d_n}\right]_+ \\
&= \frac{M_T K}{L!} \sum_{i=0}^{K-1} \binom{K-1}{i} (-1)^i \sum_{m_1=0}^{L} \cdots \sum_{m_i=0}^{L} \\
&\quad \left(\frac{1}{m_1! \cdots m_i!} \left[\varsigma^{-(m_1+\ldots+m_i+L)} E_{-(m_1+\ldots+m_i+L)}\left(\frac{i+1}{\varsigma}\right) \right.\right. \\
&\quad \left.\left. -(i+1)^{-(m_1+\ldots+m_i+L)} \Gamma\left(m_1+\ldots+m_i+L, \frac{i+1}{\varsigma}\right) \right] \right) \\
&= P_T \quad ,
\end{aligned} \tag{23}$$

where (a) is obtained by modifying (14) and changing integral variable, and (b) is derived from the integral identity provided in [14]

$$\int_1^{\infty} \log(t) \, e^{-\alpha t} t^{\beta-1} dt = \frac{(\beta-1)!}{\alpha^{\beta}} \sum_{i=0}^{\beta-1} \frac{\Gamma(i, \alpha)}{i!}, \quad \alpha > 0; \; \beta = 1, 2, \cdots \quad . \tag{24}$$

Note that the water-level solution ς_0 can be found by mathematical tools and the general forms (22) and (23) will be identical to the analytical formulas provided in [7] as $M_R = M_T$.

IV. Numerical Results

In this section, we show the sum rate performance of the receive ZF MIMO broadcast systems with imperfect CSI-R. Fig. 1 presents the simulative and analytical sum-rate performance

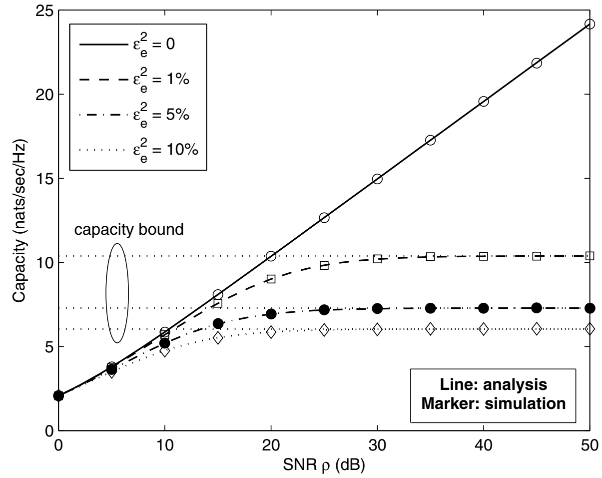

Fig. 1. Capacity of the $(M_T = 2, M_R = 3, K = 5)$ receive ZF MIMO broadcast systems with $\epsilon_e^2 = 0, 1\%, 5\%$, and 10%.

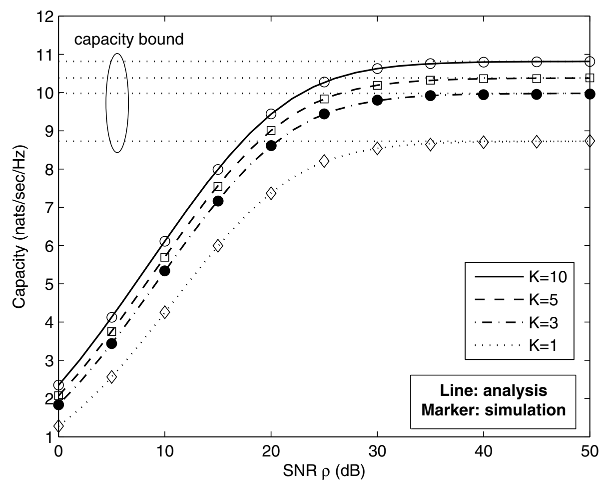

Fig. 2. Capacity of the $(M_T = 2, M_R = 3, K)$ receive ZF MIMO broadcast systems with different number of users K under $\epsilon_e^2 = 1\%$.

of the receive ZF MIMO broadcast systems $(M_T = 2, M_R = 3, K = 5)$ with $\epsilon_e^2 = 0, 1\%, 5\%$, and 10%, where the value of ϵ_e^2 represents NMSE (in percentage) between the actual channel state and the estimated value. Clearly, the sum rate will increase linearly as SNR ρ increases in dB under ideal channel estimation, i.e., $\epsilon_e^2 = 0$. Different from the effects of feedback link errors on the sum rate discussed in [7], the imperfect CSI-R will largely decrease the sum rate of the receive ZF MIMO broadcast systems. More serious estimation errors lead to more degradation of the sum rate performance. The resulting sum rate will no longer increase as SNR (denoted by ρ) increases and tend towards the value $\overline{C_{\text{ZFR}}^{\epsilon_e^2}}$ provided in (17). For example, the sum rate of the $(2, 3, 5)$ receive ZF MIMO broadcast systems with $\epsilon_e^2 = 0$ is 15 nats/s/Hz at $\rho = 30$ dB. However, the corresponding sum rates reduce to 10.38, 7.28, and 6.04 nats/s/Hz for $\epsilon_e^2 = 1\%, 5\%$, and 10%, respectively.

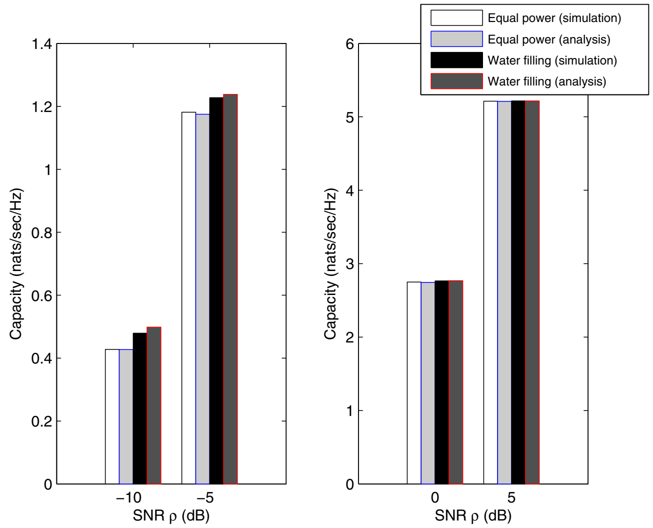

Fig. 3. Capacity comparison of the ($M_T = 3, M_R = 4, K = 10$) receive ZF MIMO broadcast systems under equal power and water-filling power allocations.

Next, we like to discuss what advantage can multiuser diversity reflect on the sum rate of a receive ZF MIMO broadcast system with imperfect CSI-R. Fig. 2 shows the sum rate of the receive ZF MIMO broadcast systems with $M_T = 2, M_R = 3, \epsilon_e^2 = 1\%$ and different numbers of users K. In this figure, the sum-rate performance can be improved as available user population K increases, but it can not be raised any more as ρ approaches to about 35 dB. In fact, multiuser diversity can not resolve the sum rate floor issue caused by imperfect CSI-R. The corresponding $\overline{C_{\text{ZFR}}^{\epsilon_e^2}}$ values are 8.73, 9.98, 10.38, and 10.82 nats/s/Hz for $K = 1, 3, 5,$ and 10, respectively.

Finally, we illustrate the benefits of utilizing water-filling power allocation on the sum-rate performance via Fig. 3 which evaluates a receive ZF MIMO broadcast system, where $M_T = 3, M_R = 4$, and $K = 10$. This figure confirms the well-known information that the advantage of the water-filling power allocation over the equal power allocation is significant only in the low SNR region. As shown, our provided closed-form expressions can evaluate the sum-rate performance of the receive ZF MIMO broadcast systems under both the equal and water-filling power allocations.

V. Conclusion

In this paper, we provided exact closed-form expressions for the sum rate achieved by the receive ZF MIMO broadcast systems subject to channel estimation errors. From the analytic and numerical results, we find that imperfect CSI-R will cause serious sum-rate performance degradation and cause the sum-rate floor. That is, the sum-rate capacity will no longer linearly increase with SNR in decibel and be bounded. This phenomenon is entirely different from the effect caused by feedback link errors which only leads to slight sum-rate degradation but maintains the same performance slope [7]. Although multiuser diversity can enhance capacity, it can not compensate the sum-rate performance degradations caused by imperfect CSI-R and resolve the problem of the bounded sum rate.

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Power Allocation for Robust Distributed Best-Linear-Unbiased Estimation Against Sensing Noise Variance Uncertainty

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Abstract-*Motivated by the fact that system parameter mismatch occurs in real-world sensing environments, this paper addresses power allocation for robust distributed Best-Linear-Unbiased-Estimation (BLUE) that takes account of the uncertainty in the local sensing noise variance. We adopt the Bayesian philosophy, wherein the sensing noise variance follows a statistical distribution widely used in the literature, and the communication channels between sensor nodes and the fusion center (FC) are assumed to be i.i.d. Rayleigh fading. To facilitate analysis, we propose to use the average reciprocal mean square error (ARMSE), averaged with respect to the distributions of sensing noise variance and fading channels, as the distortion metric. A fundamental inequality characterizing the relationship between ARMSE and the average mean square error (AMSE) is established. While the exact formula for ARMSE is difficult to find, we derive an associated closed-form lower bound which involves the complicated incomplete gamma function. To further ease analysis, we further derive a key inequality that specifies the range of the ARMSE lower bound. Particularly, it is shown that the boundary points of this inequality are characterized by a common quantity, which involves the Gaussian-tail function and is thus more analytically appealing. By conducting maximization of such a function, suboptimal sensor allocation factors are analytically derived. Computer simulation is used to evidence the effectiveness of the proposed robust power allocation scheme.*

Index Terms—Sensor networks; distributed estimation; power allocation.

I. INTRODUCTION

Distributed estimation using wireless sensor networks is well suited for many situation awareness applications, such as environmental monitoring, positioning and tracking, temperature control, and military surveillance, to name just a few [1]. Among existing distributed estimation rules, the best linear unbiased estimation (BLUE) scheme [2-5] received considerable attention due to the ease of implementation. To meet the critical demand of power/energy efficiency in wireless sensor networks, most of the existing distributed BLUE proposals dealt with power allocation or minimization in order to achieve the utmost estimation accuracy [2-5]. The development of power scheduling schemes therein typically assumed that the local sensing noise variance and the instantaneous channel state information (CSI) are exactly known at the fusion center (FC).

In real-world sensing environments, uncertainty in the system parameters, such as variation in the sensing noise level caused by the change of environmental conditions or malfunction of sensor nodes, is unavoidable. Hence, in addition to energy efficiency, robustness against the system parameter mismatch is also a crucial requirement in the design of distributed estimation algorithms. Even though there have been several works about robust distributed estimation via sensor networks, e.g., [6], related study in the context of the distributed BLUE, however, remains lacking. In this paper we consider a wireless sensor network employing the amplify-and-forward protocol (as in [5], [7]), and propose a robust distributed BLUE scheme that takes into account the uncertain nature of the local sensing noise power. We adopt the Bayesian formulation, and assume that (i) the sensing noise variance follows the distribution as considered in [2-4]; (ii) the fading channels are Rayleigh distributed, as commonly assumed in many studies of channel-aware distributed signal processing schemes [1]. The proposed design aims at reducing the mean square error (MSE) averaged with respect to the distributions of both the sensing noise variance and fading channels, hereafter referred to as average mean square error (AMSE). The main technical contributions of this paper can be summarized as follows.

(I) While the AMSE is not analytically tractable, we propose to adopt the *reciprocal* MSE averaged over the considered distributions, termed as the averaged reciprocal MSE (ARMSE) in the sequel, as the performance measure. A fundamental relation between the ARMSE and the exact AMSE is analytically characterized. Specifically, given that the target AMSE distortion does not exceed ε, it is shown that the true AMSE is lower bounded by the inverse of ARMSE, and more importantly, is upper bounded by the sum of the inverse of ARMSE and ε. This suggests a tractable design strategy for improving the estimation accuracy: minimization of the inverse of ARMSE, or equivalently, maximization of ARMSE. This forms the foundation for the design principle behind the proposed robust distributed BLUE.

(II) While the exact formula of ARMSE remains difficult to find, it allows us to derive an associated *analytic* lower bound that involves the complicated incomplete Gamma function [7]. To further ease analysis, a key inequality that characterizes a feasible range of the derived ARMSE lower bound is established. The crucial fact of our findings is that the two boundary points of the inequality are entirely characterized by a common quantity, which involves the Gaussian-tail $Q(\cdot)$ function and, thus, is more analytically appealing than the ARMSE lower bound. Hence, instead of directly maximizing the ARMSE or its lower bound, we propose to conduct maximization with respect to this function, and then derive a closed-form though suboptimal sensor power allocation scheme. The performance advantage of the proposed robust scheme is further demonstrated via computer simulation.

II. PROBLEM STATEMENT

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We consider a wireless sensor network, in which N sensors cooperate with a FC for estimating an unknown deterministic parameter $\theta \in \mathbb{R}$. The local observation at the ith sensor node is

$$x_i = \theta + n_i,\ 1 \le i \le N \quad , \quad (2.1)$$

where $n_i \in \mathbb{R}$ is the zero-mean measurement noise with variance $\sigma_{n_i}^2$. As in [5], [7], we assume that the local measurements x_i's are transmitted over N parallel flat-fading channels to the FC via the amplify-and-forward protocol. The received signal from the ith sensor, $1 \le i \le N$, can thus be described as

$$y_i = h_i p_i x_i + v_i = h_i p_i (\theta + n_i) + v_i = h_i p_i \theta + h_i p_i n_i + v_i, \quad (2.2)$$

where $h_i \in \mathbb{R}$ is channel gain, p_i is the power amplification factor for the ith sensor, and $v_i \in \mathbb{R}$ is the zero-mean white noise with variance $\sigma_{v_i}^2$; throughout the paper we shall set $\sigma_{v_i}^2 = \sigma_v^2$. Based on the received data y_i's in (2.2) and assuming that the sensing noise n_i's are i.i.d. and are independent of the channel noise, the parameter θ is estimated at the FC via the BLUE principle [1] as

$$\hat{\theta} = \left(\sum_{i=1}^{N} \frac{p_i h_i y_i}{p_i^2 h_i^2 \sigma_{n_i}^2 + \sigma_v^2} \right) \left(\sum_{i=1}^{N} \frac{1}{\sigma_{n_i}^2 + \sigma_v^2 / \left(p_i^2 h_i^2\right)} \right)^{-1}. \quad (2.3)$$

The incurred MSE of the estimate (2.3) is known to be

$$MSE = \left(\sum_{i=1}^{N} \frac{1}{\sigma_{n_i}^2 + \sigma_v^2 / \left(p_i^2 h_i^2\right)} \right)^{-1}. \quad (2.4)$$

Even though one may have a nominal measurement of the local sensing noise power $\sigma_{n_i}^2$, the true noise condition could be even more worse due to, e.g., gradual drainage of battery power or sensor failures. Once a nominal noise power threshold, say, δ_i, is determined for the ith sensor, we shall seek for a statistical characterization of the uncertain noise power degradation from δ_i. Motivated by [2-4], a simple yet intuitive model to pin down such uncertainty is $\sigma_{n_i}^2 = \delta_i + z_i$, where $z_i \sim \chi_1^2$ is the central Chi-Square random variable of degrees-of-freedom equal to one, for each $1 \le i \le N$. To further take into consideration that the severity of uncertainty could be different from sensor to sensor, in this paper we thus assume that the local sensing noise variance follows the model:

$$\sigma_{n_i}^2 = \delta_i + \alpha_i z_i,\ 1 \le i \le N, \quad (2.5)$$

where δ_i is the nominal noise variance at the ith node, $z_i \sim \chi_1^2$ is the central Chi-Square random variable with degrees-of-freedom equal to one (assumed to be i.i.d. over i), and α_i reflects the severity of uncertainty of the ith sensor node. Regarding the distribution of the fading channels, we adopt the common assumption made in the literature (e.g., [1]) that the channel gains h_i's are i.i.d. Rayleigh distributed.

The goal of this paper is to design the sensor power allocation factors p_i's so as to improve the average MSE performance, taking into account the distributions of the sensing noise variance and fading channels.

III. PROPOSED PERFORMANCE MEASURE

A. Estimation Performance in Terms of ARMSE

Even though the MSE is a widely used performance measure, the involved inverse operation (cf. (2.4)) in the considered BLUE scenario makes it rather difficult to derive an analytic expression for AMSE. This thus motivates us to seek for alternative performance measures that can, on the one hand, reflect the true AMSE tendency and is more analytically tractable on the other hand. For this purpose, let us start with fixed realizations of sensing noise variances $\sigma_{n_i}^2$'s and channel gains h_i's, and consider the estimation performance constraint via the MSE (2.4):

$$\left(\sum_{i=1}^{N} \frac{1}{\sigma_{n_i}^2 + \sigma_v^2 / \left(p_i^2 h_i^2\right)} \right)^{-1} \le \varepsilon, \quad (3.1)$$

where ε denotes the target distortion level. It is crucial to observe that (3.1) can be equivalently rewritten in terms of the reciprocal of MSE (RMSE) as

$$RMSE = \sum_{i=1}^{N} \frac{1}{\sigma_{n_i}^2 + \sigma_v^2 / \left(p_i^2 h_i^2\right)} \ge \varepsilon^{-1}. \quad (3.2)$$

Hence, given the instantaneous $\sigma_{n_i}^2$'s and h_i's, it is equivalent to consider RMSE as the performance measure; the larger RMSE is, the better the estimation accuracy will be. From an analytical perspective, the RMSE is more appealing than MSE since it no longer involves the "inverse operation"; as will be shown later, this attractive feature allows us to find an associated average performance metric that will facilitate analytic study of the power allocation problem. Motivated by these facts, we thus propose to consider the *average reciprocal MSE (ARMSE)* as the performance metric for the robust distributed BLUE:

$$D \triangleq \int_{\mathrm{h}} \int_{\mathrm{z}} [RMSE] d\mathrm{z} d\mathrm{h} = \int_{\mathrm{h}} \int_{\mathrm{z}} \sum_{i=1}^{N} \frac{1}{\delta_i + \alpha_i z_i + \sigma_v^2 / \left(p_i^2 h_i^2\right)} f_{\mathrm{Z}}(\mathrm{z}) f_{\mathrm{H}}(\mathrm{h}) d\mathrm{z} d\mathrm{h}, \quad (3.3)$$

where $\mathrm{z} \triangleq [z_1 \cdots z_N]^T$ and $\mathrm{h} \triangleq [h_1^2 \cdots h_N^2]^T$, with $f_{\mathrm{Z}}(\mathrm{z})$ and $f_{\mathrm{H}}(\mathrm{h})$ being the associated distributions. A large D is expected to yield good estimation accuracy, which in turn suggests that the sensor power allocation factors should be designed to keep D as large as possible.

Even thought the aforementioned approach is intuitively reasonable, the AMSE is in general not equal to D^{-1} (this can be directly verified by using the Jensen's inequality). Thus, a fundamental question that remains yet to be answered is whether the true AMSE can be kept small (and to what extent) once D is enlarged. The following theorem characterizes a fundamental relationship between D^{-1} and the true AMSE (the proof is given in the appendix).

Theorem 3.1: Let D be the ARMSE defined in (3.3). Then we have

$$D^{-1} \le E\left\{\left(\sum_{i=1}^{N}\frac{1}{\sigma_{n_i}^2 + \sigma_v^2/\left(p_i^2 h_i^2\right)}\right)^{-1}\right\} \le D^{-1} + \varepsilon\,, \quad (3.4)$$

where ε is the target distortion level specified in (3.1). □

Theorem 3.1 asserts that the AMSE, while lower bounded by D^{-1}, does not exceed the sum of D^{-1} and the target distortion level ε. In particular, if ε is constrained to be small so as to yield good estimation quality, D^{-1} will then be a tight approximation of the average MSE. Hence, keeping D^{-1} small, or equivalently, making D large, is indeed a justified approach for AMSE reduction.

B. Tractable ARMSE Lower Bound

To maximize the ARMSE, a conceivable approach would be to first find an analytic formula for D in (3.3). This, however, turns out to be intractable since the double integral involved in (3.3) does not directly lead to a closed-form expression. To overcome this difficulty, a commonly used design strategy (though suboptimal) is to seek for a tractable lower bound for the ARMSE, and then conduct maximization with respect to this lower bound. To proceed we first note that, after some tedious manipulations (the details are omitted due to space limitation), D in (3.3) can be lower bounded as

$$D \ge \underline{D} \triangleq \frac{1}{2}\sum_{i=1}^{N}\int_0^{\infty}\frac{x_i e^{-x_i/2}}{\left[(\sigma_v^2/p_i^2)+(\alpha_i+\delta_i)x_i\right]}dx_i\,. \quad (3.5)$$

The following theorem provides a closed-form lower bound $\underline{D}$; the proof of theorem can be found in [9], and due to space limitation is omitted here).

Theorem 3.2: Let $\underline{D}$ be defined in (3.5). Then we have

$$\underline{D} = \frac{1}{2}\sum_{i=1}^{N}\left(\frac{\sigma_v^2}{p_i^2(\alpha_i+\delta_i)^2}\right)e^{\sigma_v^2/[2p_i^2(\alpha_i+\delta_i)]}\Gamma(2)\Gamma\left(-1,\frac{\sigma_v^2}{p_i^2(\alpha_i+\delta_i)}\right), \quad (3.6)$$

where

$$\Gamma(v) \triangleq \int_0^{\infty} e^{-t}t^{v-1}dt \quad (3.7)$$

is the Gamma function and

$$\Gamma(\beta,x) \triangleq \int_x^{\infty} e^{-t}t^{\beta-1}dt \quad (3.8)$$

is the incomplete Gamma function [8]. □

C. Plausible Range of the ARMSE Lower Bound

Even though (3.6) admits a closed form, it nonetheless involves the incomplete Gamma function and is thus difficult to analyze. To overcome this drawback, in the sequel we will further derive an inequality which specifies the plausible range of $\underline{D}$. An important feature of this result is that both the two boundary points of the inequality are entirely characterized by a common function, which involves the $Q(\cdot)$ function and is thus more analytically appealing than $\underline{D}$. More precisely, we have the following theorem (a sketched proof is given in the appendix).

Theorem 3.3: Let $\underline{D}$ be the ARMSE lower bound defined in (3.6). Then it follows

$$\sqrt{\frac{(2-3e^{-1/2})}{4(1-e^{-1/2})}}D' \le \underline{D} \le \frac{3e^{-1/2}}{\sqrt{8}\Gamma(3/2,1/2)}D'\,, \quad (3.9)$$

where

$$D' \triangleq \sum_{i=1}^{N}\left\{\frac{\sqrt{2\pi}}{\alpha_i+\delta_i} - \frac{2\pi e^{\{(\sigma_v^2/p_i^2)/[2(\alpha_i+\delta_i)]\}}\sqrt{(\sigma_v^2/p_i^2)}}{(\alpha_i+\delta_i)\sqrt{(\alpha_i+\delta_i)}}Q\left(\sqrt{\frac{(\sigma_v^2/p_i^2)}{\alpha_i+\delta_i}}\right)\right\} \quad (3.10)$$

□

From (3.9), the ARMSE lower bound $\underline{D}$ is seen to be bounded from above, and below, by a scalar multiple of the common function D' (by computation, (3.9) reads $0.3386D' \le \underline{D} \le 2.7479D'$). Hence, while maximization of $\underline{D}$ has to deal with the incomplete Gamma function and is intractable, we propose to conduct maximization instead based on D'. The main advantage of this alternative approach is that D' in (3.10) now involves the $Q(\cdot)$ function. As we will see in the next section, by exploiting some attractive properties of the $Q(\cdot)$ function, the sensor power allocation problem can be formulated in the form of convex optimization that can yield closed-form solutions.

IV. SENSOR POWER ALLOCATION

A. Problem formulation and Optimal Solution

This section addresses the sensor power allocation problem for enhancing the estimation performance subject to a limited power budget. In terms of maximization of the proposed cost function D' in (3.10), the optimization problem can be stated as follows:

$$\begin{aligned}&Maximize\\ &\frac{1}{\sqrt{2\pi}}\sum_{i=1}^{N}\left\{\frac{\sqrt{2\pi}}{\alpha_i+\delta_i} - \frac{2\pi e^{\{(\sigma_v^2/p_i^2)/[2(\alpha_i+\delta_i)]\}}\sqrt{(\sigma_v^2/p_i^2)}}{(\alpha_i+\delta_i)\sqrt{(\alpha_i+\delta_i)}}Q\left(\sqrt{\frac{(\sigma_v^2/p_i^2)}{\alpha_i+\delta_i}}\right)\right\},\\ &subject\ to\ \sum_{i=1}^{N}p_i^2 \le P,\ p_i \ge 0,\ 1 \le i \le N,\end{aligned} \quad (4.1)$$

where P denotes the total available power budget. Since the objective function in (4.1) is still highly nonlinear in p_i, the problem is thus difficult to solve. Thanks to the $Q(\cdot)$ function, we can obtain the following crucial inequality to facilitate analysis:

$$\begin{aligned}&\frac{1}{\sqrt{2\pi}}\sum_{i=1}^{N}\left\{\frac{\sqrt{2\pi}}{\alpha_i+\delta_i} - \frac{2\pi e^{\{(\sigma_v^2/p_i^2)/[2(\alpha_i+\delta_i)]\}}\sqrt{(\sigma_v^2/p_i^2)}}{(\alpha_i+\delta_i)\sqrt{(\alpha_i+\delta_i)}}Q\left(\sqrt{\frac{(\sigma_v^2/p_i^2)}{\alpha_i+\delta_i}}\right)\right\}\\ &\overset{(a)}{\ge}\frac{1}{\sqrt{2\pi}}\sum_{i=1}^{N}\left\{\frac{\sqrt{2\pi}}{\alpha_i+\delta_i} - \frac{\pi\sqrt{(\sigma_v^2/p_i^2)}}{(\alpha_i+\delta_i)\sqrt{(\alpha_i+\delta_i)}}\right\}\\ &=\sum_{i=1}^{N}\left\{\frac{1}{\alpha_i+\delta_i} - \frac{\sigma_v\sqrt{\pi}}{p_i(\alpha_i+\delta_i)\sqrt{2(\alpha_i+\delta_i)}}\right\},\end{aligned} \quad (4.2)$$

where (a) follows from the well-known Chernoff bound $Q(x) \le e^{-x^2/2}/2$. Inequality (4.2) provides a lower bound for the cost function in problem (4.1) which is now convex in terms of the power allocation factor p_i. Hence, instead of directly maximizing the cost function in (4.1), we propose to maximize the lower bound (4.2); this will allow us to derive closed-form suboptimal solution, as will be seen later. The optimization problem thus becomes

$$\begin{aligned}&Maximize \sum_{i=1}^{N}\left\{\frac{1}{\alpha_i+\delta_i}-\frac{\sigma_v\sqrt{\pi}}{p_i(\alpha_i+\delta_i)\sqrt{2(\alpha_i+\delta_i)}}\right\}\\ &subject\ to \sum_{i=1}^{N} p_i^2 \le P,\ p_i \ge 0,\ 1 \le i \le N.\end{aligned} \tag{4.3}$$

By means of the standard Lagrange multiplier technique, the optimal solution to (4.3) can be obtained by solving the KKT conditions, and is found to be (details are omitted due to space limitation)

$$\tilde{p}_i = \sqrt{\frac{P}{(\alpha_i+\delta_i)\left(\sum_{i=1}^{N}\frac{1}{\alpha_i+\delta_i}\right)}},\ 1 \le i \le N. \tag{4.4}$$

B. Numerical Performance

This section conducts several numerical simulations to evidence the presented analyses. We consider a network of $N = 250$ sensors, and the channel noise variance is set to be $\sigma_v^2 = 0.05$. The local sensing noise variance uncertainty parameters α_i's are generated uniformly in the interval $[0\ \alpha]$, where $\alpha > 0$ is the global uncertainty factor; the noise variance thresholds δ_i's are likewise drawn uniformly from $[0\ \delta]$, where $\delta > 0$ accounts for the maximal nominal value. With $\alpha = 5$ and $\delta = 1$, Figure 1 compares the AMSE performance of the robust scheme (4.4) and the nominal non-robust solution obtained via setting $\alpha_i = 0$ in (4.4) for different total transmit power P. It can be seen that the proposed robust design does reduce the AMSE. Also, the AMSE is seen to decrease with P. This is intuitively reasonable since a large transmit power can enhance the overall signal quality at the FC for improving the global estimation accuracy; a similar phenomenon has also been seen in many previous works, e.g., [5]. With $P = 40$ and $\delta = 1$, Figure 2 depicts the AMSE with respect to different global uncertainty factors α. The figure shows that, with a fixed system power, the AMSE increases with the uncertainty factor α. This is not unexpected since, as α increases, the deviation of the true noise variance from its nominal value also increases, thereby degrading the global estimation quality.

V. CONCLUSIONS

This paper has presented an original contribution to the study of power allocation for robust distributed BLUE in the presence of sensing noise variance uncertainty. The proposed design criterion in terms of ARMSE has several unique advantages. Firstly, it is established that with a small target AMSE the inverse of ARMSE is a close approximation to the true AMSE. Given this appealing fundamental result, maximization of the ARMSE is thus a justified approach for enhancing the estimation quality. Secondly, starting from the ARMSE design metric, rigorous analyses are carried out to derive an analytically tractable objective function for the design of power allocation factors. The obtained solution is in a closed form, and is seen to outperform the non-robust design via computer simulation.

APPENDIX

A. Proof of Theorem 3.1

To prove the second inequality, we need the following lemma.

Lemma A.1: Let $0 < a < b$. Then $\frac{1}{x} \le \frac{a+b}{ab}$ for any $x \in [a, b]$.

[Proof]: The result follows since

$$\frac{a+b}{ab} - \frac{1}{x} = \frac{(a+b)x - ab}{abx} \ge \frac{(a+b)a - ab}{abx} = \frac{a^2}{abx} \ge 0.\ \square$$

From (3.2), we have

$$\varepsilon^{-1} \le \sum_{i=1}^{N}\frac{1}{\sigma_{n_i}^2 + \sigma_v^2/\left(p_i^2h_i^2\right)} \le \sum_{i=1}^{N}\frac{1}{\sigma_{n_i}^2} = \sum_{i=1}^{N}\frac{1}{\delta_i + \alpha_i z_i} \le \sum_{i=1}^{N}\frac{1}{\delta_i}. \tag{A.1}$$

which then implies

$$\varepsilon^{-1} \le E\left(\sum_{i=1}^{N}\frac{1}{\sigma_{n_i}^2 + \sigma_v^2/\left(p_i^2h_i^2\right)}\right) \le \sum_{i=1}^{N}\frac{1}{\delta_i}. \tag{A.2}$$

Now take $a = \varepsilon^{-1}$, $x = \sum_{i=1}^{N}\frac{1}{\sigma_{n_i}^2 + \sigma_v^2/\left(p_i^2h_i^2\right)}$, $b = \sum_{i=1}^{N}\frac{1}{\delta_i}$, and using Lemma A.1, we have

$$\begin{aligned}&\left(\sum_{i=1}^{N}\frac{1}{\sigma_{n_i}^2 + \sigma_v^2/\left(p_i^2h_i^2\right)}\right)^{-1} \le \frac{a+b}{ab}\\ &= \frac{1}{a} + \frac{1}{b} = \varepsilon + \left(\sum_{i=1}^{N}\frac{1}{\delta_i}\right)^{-1} \le \varepsilon + \left[E\left(\sum_{i=1}^{N}\frac{1}{\sigma_{n_i}^2 + \sigma_v^2/\left(p_i^2h_i^2\right)}\right)\right]^{-1}\end{aligned} \tag{A.3}$$

where the last equality follows from (A.2). Based on (A.3), it follows

$$\begin{aligned}&E\left[\left(\sum_{i=1}^{N}\frac{1}{\sigma_{n_i}^2 + \sigma_v^2/\left(p_i^2h_i^2\right)}\right)^{-1}\right]\\ &\le \varepsilon + \left[E\left(\sum_{i=1}^{N}\frac{1}{\sigma_{n_i}^2 + \sigma_v^2/\left(p_i^2h_i^2\right)}\right)\right]^{-1} = \varepsilon + D^{-1}.\end{aligned} \tag{A.4}$$

The assertion follows from (A.4). $\square$

B. Sketched Proof of Theorem 3.3

The proof is based on $\underline{D}$ in (3.5). To proceed, let us first introduce the next lemma (the proof is based on the Cauchy-Schwartz inequality, and details are referred to [9]).

Lemma A.2: For $a > 0$ and $b > 0$, we have

$$\sqrt{\frac{(2-3e^{-1/2})}{(1-e^{-1/2})}}\int_0^\infty \frac{\sqrt{x}e^{-x/2}}{a+bx}\,dx \\ \le \int_0^\infty \frac{xe^{-x/2}}{a+bx}\,dx \le \frac{6e^{-1/2}}{\sqrt{8}\Gamma(3/2,1/2)}\int_0^\infty \frac{\sqrt{x}}{a+bx}\,e^{-x/2}dx. \quad \text{(A.5)}$$

where $\Gamma(\beta,x)$ is the incomplete gamma function defined in (3.8).

□

Based (A.5) and by definition of $\underline{D}$ in (3.5), it follows that

$$\sqrt{\frac{(2-3e^{-1/2})}{4(1-e^{-1/2})}}\sum_{i=1}^{N}\int_0^\infty \frac{\sqrt{x_i}e^{-x_i/2}}{\left[(\sigma_v^2/p_i^2)+(\alpha_i+\delta_i)x_i\right]}dx_i \\ \le \underline{D} \le \frac{3e^{-1/2}}{\sqrt{8}\Gamma(3/2,1/2)}\sum_{i=1}^{N}\int_0^\infty \frac{\sqrt{x_i}e^{-x_i/2}}{\left[(\sigma_v^2/p_i^2)+(\alpha_i+\delta_i)x_i\right]}dx_i. \quad \text{(A.6)}$$

We go on to rewrite inequality (A.6) by means of the following lemma (see [9] for a proof).

Lemma A.3: For $a>0$ and $b>0$, we have

$$\int_0^\infty \frac{\sqrt{x}}{a+bx}\,e^{-x/2}dx = \frac{\sqrt{2\pi}}{b} - \frac{2\pi\sqrt{a}e^{a/2b}}{b\sqrt{b}}Q\left(\sqrt{a/b}\right). \quad \text{(A.7)}$$

□

The result of Theorem 3.3 follows from (A.6), (A.7), and after some manipulations. □

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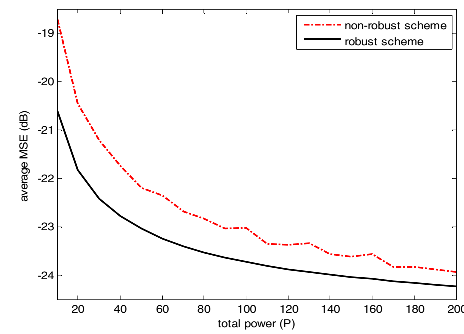

Figure 1. Average MSE versus total power ($\alpha=5$ and $\delta=1$).

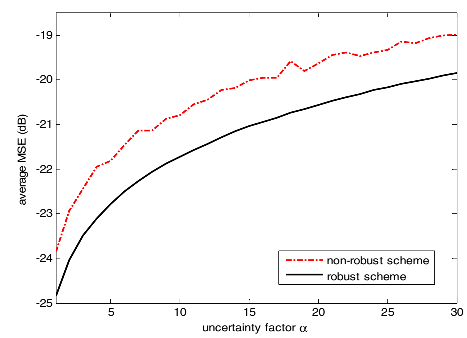

Figure 2. Average MSE versus global uncertainty factor α ($P=40$ and $\delta=1$).

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