Weighted Sum Secrecy Rate Maximization via Minorization–Maximization

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***Abstract*—This paper studies the weighted sum secrecy rate (WSSR) maximization problem in single-input single-output interference wiretap channels, which is a fundamental yet challenging problem in physical layer security. Given the inherent nonconvexity of the WSSR objective, we develop a novel fast iterative algorithm based on the minorization–maximization (MM) framework. By exploiting the flexibility of the MM principle in surrogate function design, the proposed algorithm admits closed-form updates at each iteration. From a unified perspective, we show that many existing algorithms can be interpreted as instances of MM methods. We further analyze the surrogate functions employed by several state-of-the-art approaches together with the proposed method, clarifying their intrinsic connections and highlighting the advantages of the proposed method. Numerical results demonstrate that the proposed algorithm achieves comparable convergence behavior to baseline methods while significantly reducing computational time across a wide range of network configurations and signal-to-noise ratio regimes.**

***Index Terms*—information theoretic security, physical layer security, secrecy rate maximization, minorization–maximization, wiretap channel.**

I. Introduction

Communication security is a fundamental topic in wireless communications, and a wide range of techniques have been proposed to ensure confidentiality against unauthorized receivers [1]. Among them, physical layer security has attracted considerable attention because it enables secure transmission by exploiting the inherent randomness of wireless channels without relying on traditional key-based encryption mechanisms. In this context, the secrecy rate has been widely adopted as a key performance metric for evaluating beamforming designs and power allocation strategies [2]. The study of physical layer secrecy dates back to the seminal work by Wyner in the 1970s [3], which established the notion of a positive secrecy rate for degraded wiretap channels. This result was subsequently extended to single-input single-output (SISO) Gaussian wiretap channels in [4].

Depending on the underlying system model, the existing literature on secrecy rate maximization can be broadly categorized into two classes. The first class considers wiretap channels without multiuser interference and/or artificial noise, e.g., [5]–[8]. The second class incorporates multiuser interference and/or artificial noise into the secrecy rate optimization problem, e.g., [9]–[14].

Specifically, [5] proposed an alternating optimization approach for multiple-input multiple-output (MIMO) wiretap channels that converges to stationary points. [6] considered scenarios with multiple eavesdroppers and employed difference-of-convex (DC) programming for problem resolution. Compared with [5], this offers more flexible forms of constraints to consider. [7] introduced the weighted minimum mean-square error (WMMSE) algorithm into secrecy rate optimization, proposing a method in which each convex subproblem admits a closed-form solution. [8] demonstrated that, under certain conditions, the secrecy rate optimization problem can be directly transformed into a convex problem and introduced an efficient algorithm to solve it.

The second class of approaches considers wiretap channels with multi-user interference or artificial noise. [9] considered both multi-user interference and artificial noise for MIMO wiretap channels, developing an MM algorithm that relies on convex solvers for subproblem solutions. [10] introduced a generalized quadratic matrix programming (GQMP) method capable of handling a broad class of mutual information optimization problems, which also include the optimization model established in [9]. [11] investigated cell-free massive MIMO networks and proposed a path-following algorithm, which requires a convex solver for subproblem optimization. This approach was subsequently extended to Rician fading channels in [12]. In [15], a successive convex approximation (SCA) method was used to solve the problem of maximizing WSSR for the MISO system. For each subproblem, the convex solver must be called to obtain a solution. [13] proposed two efficient methods based on fractional programming to maximize the WSSR in SISO interference channels, but both methods still require a convex solver to obtain the convex subproblem solutions. [14] introduced a technique that reformulates the secrecy rate in single-user scenarios to directly apply the WMMSE algorithm.

In this paper, we study WSSR maximization in SISO interference channels and propose a novel fast iterative algorithm within the MM framework. The proposed algorithm admits closed-form updates at each iteration, which leads to a significant reduction in computational time compared to existing methods. From a broader perspective, a substantial body of prior work on beamforming and power allocation can be interpreted through the lens of the MM framework. Motivated by this observation, we provide a unified theoretical analysis of the surrogate function construction in several representative MM-based algorithms, including [9]–[11], [13], together with the proposed method. This analysis reveals the intrinsic relationships among different surrogate functions and highlights the advantages of the surrogate design adopted in this work. Numerical results further demonstrate that the proposed algorithm achieves substantially improved computational efficiency over a range of existing optimization methods across different numbers of users and signal-to-noise ratio regimes.

II. Problem Formulation

We consider a SISO interference channel consisting of K single-antenna base stations (BSs), each serving one single-antenna legitimate user. Let $h_{k,j} \in \mathbb{C}$ denote the downlink channel coefficient from BS j to user k, and let $e_k \sim \mathcal{CN}(0, \sigma_k^2)$ denote the additive white Gaussian noise at user k. We further consider K' eavesdroppers. Without loss of generality, we assume $K' \leq K$. Let $\tilde{h}_{k,j} \in \mathbb{C}$ denote the channel coefficient from BS j to eavesdropper k, and let $\tilde{e}_k \sim \mathcal{CN}(0, \tilde{\sigma}_k^2)$ denote the background noise at eavesdropper k. Let $w_j \in \mathbb{C}$ and $s_j \in \mathbb{C}$ denote the beamforming coefficient and the transmit symbol of BS j, respectively. The received signal at user k is given by

$$y_k = \underbrace{h_{k,k} w_k s_k}_{\text{desired signal}} + \underbrace{\sum_{j=1,\, j\neq k}^{K} h_{k,j} w_j s_j + e_k}_{\text{interference plus noise}}, \quad k = 1, \ldots, K. \tag{1}$$

Similarly, the received signal at eavesdropper k is given by

$$\tilde{y}_k = \underbrace{\tilde{h}_{k,k} w_k s_k}_{\text{desired signal}} + \underbrace{\sum_{j=1,\, j\neq k}^{K} \tilde{h}_{k,j} w_j s_j + \tilde{e}_k}_{\text{interference plus noise}}, \quad k = 1, \ldots, K'. \tag{2}$$

We define the transmit power as $p_j = |w_j|^2$. Each BS j is subject to an individual transmit power constraint

$$|w_j|^2 \leq P_j, \quad j = 1, \ldots, K. \tag{3}$$

We assume that users $k = 1, \ldots, K'$ are each monitored by an associated eavesdropper, while the remaining users are not subject to eavesdropping. For $k = 1, \ldots, K'$, the achievable secrecy rate of user k in the presence of an eavesdropper is given by[1]

$$\begin{aligned} \mathsf{R}_k(\mathbf{p}) = \log\left(1 + \frac{|h_{k,k}|^2 p_k}{\sum_{j=1,\, j\neq k}^{K} |h_{k,j}|^2 p_j + \sigma_k^2}\right) \\ - \log\left(1 + \frac{|\tilde{h}_{k,k}|^2 p_k}{\sum_{j=1,\, j\neq k}^{K} |\tilde{h}_{k,j}|^2 p_j + \tilde{\sigma}_k^2}\right). \end{aligned} \tag{4}$$

[1]In principle, the secrecy rate is $[\mathsf{R}_k(\mathbf{p})]^+ \stackrel{\text{def}}{=} \max\{\mathsf{R}_k(\mathbf{p}), 0\}$. For analytical convenience, we omit the positive-part operator in this paper. Such an operator can be approximated by smooth functions (e.g., the softplus function) or handled using the approach in [14, Proposition 2].

For $k = K'+1, \ldots, K$, where no eavesdropper is associated with user k, the achievable rate is given by

$$\mathsf{R}_k(\mathbf{p}) = \log\left(1 + \frac{|h_{k,k}|^2 p_k}{\sum_{j=1,\, j\neq k}^{K} |h_{k,j}|^2 p_j + \sigma_k^2}\right). \tag{5}$$

The WSSR maximization problem is formulated as

$$\underset{\mathbf{p}\in\mathcal{P}}{\text{maximize}} \quad f(\mathbf{p}) \stackrel{\text{def}}{=} \sum_{k=1}^{K} \omega_k \mathsf{R}_k(\mathbf{p}), \tag{6}$$

where $\mathbf{p} = [p_1, \ldots, p_K]^\top$ denotes the transmit power vector,

$$\mathcal{P} = \{\mathbf{p} \,|\, 0 \leq p_k \leq P_k,\ k = 1, \ldots, K\} \tag{7}$$

denotes the feasible power set with P_k being the transmit power budget at BS k, and $\omega_k \geq 0$ represents the priority weight of user k. The WSSR maximization problem in (6) is nonconvex due to the nonconvexity of the objective function.

III. A Novel MM Algorithm

In the following, we introduce the proposed algorithm based on the MM framework [16]. Observe that for $k = 1, \ldots, K'$, the secrecy rate in (4) can be rewritten as (8), where the first two terms are concave in and the last two terms are convex.

Lemma 1 ([17], [18]). *For* $\log\left(\sum_{i=1}^{n} a_i x_i + \xi\right)$*, the following relation holds* [2]

$$\log\left(\sum_{i=1}^{n} a_i x_i + \xi\right) \leq \frac{\sum\limits_{i=1}^{n} a_i x_i + \xi}{\sum\limits_{i=1}^{n} a_i \underline{x}_i + \xi} - 1 + \log\left(\sum_{i=1}^{n} a_i \underline{x}_i + \xi\right)$$

where the equality is attained at $x_i = \underline{x}_i$.

For $k = 1, \ldots, K'$, applying Lemma 1 to the last two terms in (8), we obtain

$$\begin{aligned} &\mathsf{R}_k(\mathbf{p}) \\ &\geq \log\left(\frac{\sum\limits_{j} |h_{k,j}|^2 p_j + \sigma_k^2}{\sum\limits_{j\neq k} |h_{k,j}|^2 \underline{p}_j + \sigma_k^2}\right) + \log\left(\frac{\sum\limits_{j\neq k} |\tilde{h}_{k,j}|^2 p_j + \tilde{\sigma}_k^2}{\sum\limits_{j} |\tilde{h}_{k,j}|^2 \underline{p}_j + \tilde{\sigma}_k^2}\right) \\ &- \frac{\sum_{j\neq k} |h_{k,j}|^2 p_j + \sigma_k^2}{\sum_{j\neq k} |h_{k,j}|^2 \underline{p}_j + \sigma_k^2} - \frac{\sum_{j} |\tilde{h}_{k,j}|^2 p_j + \tilde{\sigma}_k^2}{\sum_{j} |\tilde{h}_{k,j}|^2 \underline{p}_j + \tilde{\sigma}_k^2} + 2 \\ &\stackrel{\text{def}}{=} \underline{\mathsf{R}}_k(\mathbf{p} \mid \underline{\mathbf{p}}) \end{aligned}$$

Similar to the above derivation, for $k = K'+1, \ldots, K$, based on Lemma 1, we have

$$\begin{aligned} &\mathsf{R}_k(\mathbf{p}) \\ &= \log\left(\sum_{j} |h_{k,j}|^2 p_j + \sigma_k^2\right) - \log\left(\sum_{j\neq k} |h_{k,j}|^2 p_j + \sigma_k^2\right) \\ &\geq \log\left(\frac{\sum_{j} |h_{k,j}|^2 p_j + \sigma_k^2}{\sum_{j\neq k} |h_{k,j}|^2 \underline{p}_j + \sigma_k^2}\right) - \frac{\sum_{j\neq k} |h_{k,j}|^2 p_j + \sigma_k^2}{\sum_{j\neq k} |h_{k,j}|^2 \underline{p}_j + \sigma_k^2} + 1 \\ &\stackrel{\text{def}}{=} \underline{\mathsf{R}}_k(\mathbf{p} \mid \underline{\mathbf{p}}). \end{aligned}$$

[2]In this paper, underlined letters denote variables that are fixed at the current iteration in the MM procedure.

$$\mathsf{R}_k(\mathbf{p}) = \log\left(\frac{\sum_j |h_{k,j}|^2 p_j + \sigma_k^2}{\sum_{j\neq k} |h_{k,j}|^2 p_j + \sigma_k^2}\right) + \log\left(\frac{\sum_{j\neq k} \left|\tilde{h}_{k,j}\right|^2 p_j + \tilde{\sigma}_k^2}{\sum_j \left|\tilde{h}_{k,j}\right|^2 p_j + \tilde{\sigma}_k^2}\right) \tag{8}$$

$$= \log\left(\sum_j |h_{k,j}|^2 p_j + \sigma_k^2\right) + \log\left(\sum_{j\neq k} |\tilde{h}_{k,j}|^2 p_j + \tilde{\sigma}_k^2\right) - \log\left(\sum_{j\neq k} |h_{k,j}|^2 p_j + \sigma_k^2\right) - \log\left(\sum_j |\tilde{h}_{k,j}|^2 p_j + \tilde{\sigma}_k^2\right)$$

Finally, we obtain a surrogate function for f at $\underline{\mathbf{p}}$ as follows:

$$\underline{f}(\mathbf{p} \mid \underline{\mathbf{p}}) = \sum_{k=1}^K \omega_k \underline{\mathsf{R}}_k(\mathbf{p} \mid \underline{\mathbf{p}})$$

which is concave in $\mathbf{p}$. However, with $\underline{f}$ as the objective, the resulting subproblem does not admit a closed-form solution. To obtain closed-form solutions, we introduce the following technique.

Proposition 2. *For* $\log\left(\sum_{i=1}^n a_i x_i + \xi\right)$ *of* $x_i > 0$ *with* $a_i > 0$*, the following relation holds*

$$\log\left(\sum_{i=1}^n a_i x_i + \xi\right) \geq -\frac{1}{\sum_{i=1}^n a_i \underline{x}_i + \xi}\left(\sum_{i=1}^n a_i \frac{\underline{x}_i^2}{x_i} + \xi\right) + \log\left(\sum_{i=1}^n a_i \underline{x}_i + \xi\right) + 1,$$

where the equality is attained at $x_i = \underline{x}_i$.

Proof. The logarithmic function is concave and hence can be upperbounded by its linear expansion around $\frac{1}{\sum_{i=1}^n a_i \underline{x}_i + \xi}$ as follows:

$$\log\left(\frac{1}{\sum_{i=1}^n a_i x_i + \xi}\right) \leq \log\left(\frac{1}{\sum_{i=1}^n a_i \underline{x}_i + \xi}\right) + \left(\sum_{i=1}^n a_i \underline{x}_i + \xi\right)\left(\frac{1}{\sum_{i=1}^n a_i x_i + \xi} - \frac{1}{\sum_{i=1}^n a_i \underline{x}_i + \xi}\right).$$

Then we have

$$\log\left(\sum_{i=1}^n a_i x_i + \xi\right) \geq -\left(\sum_{i=1}^n a_i \underline{x}_i + \xi\right)\frac{1}{\sum_{i=1}^n a_i x_i + \xi} + \log\left(\sum_{i=1}^n a_i \underline{x}_i + \xi\right) + 1.$$

To further decouple the summation in the denominators, we introduce the following lemma.

Lemma 3 ([16])**.** *Assuming* $\mathbf{P} \succ \mathbf{0}$*, the matrix* $\left(\mathbf{A}\mathbf{P}\mathbf{A}^H\right)^{-1}$ *can be upperbounded at* $\underline{\mathbf{P}}$ *as*

$$\left(\mathbf{A}\mathbf{P}\mathbf{A}^H\right)^{-1} \preceq \left(\mathbf{A}\underline{\mathbf{P}}\mathbf{A}^H\right)^{-1}\mathbf{A}\underline{\mathbf{P}}\mathbf{P}^{-1}\underline{\mathbf{P}}\mathbf{A}^H\left(\mathbf{A}\underline{\mathbf{P}}\mathbf{A}^H\right)^{-1},$$

where the equality is attained at $\mathbf{P} = \underline{\mathbf{P}}$.

Particularizing the matrix $\mathbf{P} = \operatorname{diag}(x_1, \ldots, x_n, \xi)$ and $\mathbf{A} = \left(\sum_{i=1}^n a_i \underline{x}_i + \xi\right)^{-1/2}\left[\sqrt{a_1}, \ldots, \sqrt{a_n}, 1\right]$ in Lemma 3, we have

$$\log\left(\sum_{i=1}^n a_i x_i + \xi\right) \geq -\frac{1}{\sum_{i=1}^n a_i \underline{x}_i + \xi}\left[\sqrt{a_1}, \ldots, \sqrt{a_n}, 1\right] \operatorname{diag}\left(\underline{x}_1 x_1^{-1} \underline{x}_1, \ldots, \underline{x}_n x_n^{-1} \underline{x}_n, \xi\right)\left[\sqrt{a_1}, \ldots, \sqrt{a_n}, 1\right]^\top + \log\left(\sum_{i=1}^n a_i \underline{x}_i + \xi\right) + 1$$

$$= -\frac{\sum_{i=1}^n a_i \underline{x}_i^2 x_i^{-1} + \xi}{\sum_{i=1}^n a_i \underline{x}_i + \xi} + \log\left(\sum_{i=1}^n a_i \underline{x}_i + \xi\right) + 1.$$

□

Based on Proposition 2, a further surrogate function can be constructed as in (9). Then, we can solve the WSSR maximization problem by successively solving the following convex problem

$$\underset{\mathbf{p}\in\mathcal{P}}{\text{minimize}} \quad \sum_{i=1}^K \left(\frac{a_i}{p_i} + b_i p_i\right), \tag{10}$$

where

$$a_i = \sum_{k=1}^K \frac{\omega_k |h_{k,i}|^2 \underline{p}_i^2}{\sum_{j=1}^K |h_{k,j}|^2 \underline{p}_j + \sigma_k^2} + \sum_{\substack{k=1\\k\neq i}}^{K'} \frac{\omega_k \left|\tilde{h}_{k,i}\right|^2 \underline{p}_i^2}{\sum_{\substack{j=1\\j\neq k}}^K \left|\tilde{h}_{k,j}\right|^2 \underline{p}_j + \tilde{\sigma}_k^2}$$

$$b_i = \sum_{\substack{k=1\\k\neq i}}^K \frac{\omega_k |h_{k,i}|^2}{\sum_{\substack{j=1\\j\neq k}}^K |h_{k,j}|^2 \underline{p}_j + \sigma_k^2} + \sum_{k=1}^{K'} \frac{\omega_k \left|\tilde{h}_{k,i}\right|^2}{\sum_{j=1}^K \left|\tilde{h}_{k,j}\right|^2 \underline{p}_j + \tilde{\sigma}_k^2},$$

for $i = 1, \ldots, K$. In problem (10), the variables $\{p_i\}$ are separable across indices i. By examining the first-order optimality condition, the unconstrained minimizer of each subproblem is given by $\sqrt{a_i/b_i}$, which is nonnegative since $a_i > 0$ and $b_i > 0$. Taking into account the individual power constraint $0 \leq p_i \leq P_i$, the optimal solution is therefore given by

$$p_i^\star = \min\left\{\sqrt{\frac{a_i}{b_i}},\, P_i\right\}, \quad i = 1, \ldots, K. \tag{11}$$

The convergence guarantee of the derived MM algorithm is presented in Theorem 4.

Theorem 4. *Let* $\{\mathbf{p}^{(t)}\}$ *be the sequence generated by the proposed MM algorithm. Then every limit point of the sequence* $\{\mathbf{p}^{(t)}\}$ *is a stationary point of the problem* (6).

$$\underline{f}\left(\mathbf{p}\mid\underline{\mathbf{p}}\right)=\sum_{k=1}^{K}\omega_k\left(2-\frac{\sum_j\left|h_{k,j}\right|^2\underline{p}_j^2p_j^{-1}+\sigma_k^2}{\sum_j\left|h_{k,j}\right|^2\underline{p}_j+\sigma_k^2}-\frac{\sum_{j\neq k}\left|h_{k,j}\right|^2p_j+\sigma_k^2}{\sum_{j\neq k}\left|h_{k,j}\right|^2\underline{p}_j+\sigma_k^2}\right)$$
$$+\sum_{k=1}^{K'}\omega_k\left(2-\frac{\sum_{j\neq k}|\tilde{h}_{k,j}|^2\underline{p}_j^2p_j^{-1}+\tilde{\sigma}_k^2}{\sum_{j\neq k}|\tilde{h}_{k,j}|^2\underline{p}_j+\tilde{\sigma}_k^2}-\frac{\sum_j\left|\tilde{h}_{k,j}\right|^2p_j+\tilde{\sigma}_k^2}{\sum_j\left|\tilde{h}_{k,j}\right|^2\underline{p}_j+\tilde{\sigma}_k^2}\right)+f\left(\underline{\mathbf{p}}\right) \tag{9}$$

IV. Algorithm Comparison from a Surrogate Function Perspective

In this section, we discuss several MM-based algorithms and clarify their relationships. To this end, we consider the first logarithmic component in the secrecy rate function, which is simplified as

$$f(x,y)=\log\left(1+\frac{x^2}{1+y^2}\right). \tag{12}$$

From a unified perspective, many existing algorithms can be interpreted as instances of the MM framework. In the following, we compare the surrogate functions induced by different MM constructions. For notational simplicity, we omit the arguments in the function notation.

The proposed method: The proposed MM algorithm deploys the following surrogate function f_1:

$$\begin{aligned}f\geq\ &\log\left(1+\frac{\underline{x}^2}{1+\underline{y}^2}\right)+2-\frac{\underline{x}^4}{1+\underline{y}^2+\underline{x}^2}\frac{1}{x^2}\\&-\frac{\left(1+\underline{y}^2\right)^2}{1+\underline{y}^2+\underline{x}^2}\frac{1}{1+y^2}-\frac{1+y^2}{1+\underline{y}^2}\stackrel{\text{def}}{=}f_1,\end{aligned}$$

where $x>0$.

The path-following algorithm in [11]: The surrogate function f_2 is designed as follows:

$$\begin{aligned}f\geq\ &\log\left(1+\frac{\underline{x}^2}{1+\underline{y}^2}\right)+\frac{2\underline{x}^2}{1+\underline{y}^2+\underline{x}^2}\\&-\frac{\underline{x}^2}{1+\underline{y}^2+\underline{x}^2}\left(\frac{\underline{x}}{2x-\underline{x}}+\frac{1+y^2}{1+\underline{y}^2}\right)\stackrel{\text{def}}{=}f_2,\end{aligned}$$

where $x>0$, $\underline{x}>0$, and $2x>\underline{x}$.

The GQMP method in [10]: We have the surrogate function f_3 defined as

$$\begin{aligned}f&=\log\left(1+x^2+y^2\right)-\log\left(1+y^2\right)\\&\geq-\log\left(1+\underline{y}^2\right)+1-\frac{1+y^2}{1+\underline{y}^2}\\&\qquad+\log\left(1-\underline{x}^2-\underline{y}^2+2\underline{x}x+2\underline{y}y\right)\stackrel{\text{def}}{=}f_3,\end{aligned}$$

where $x>0$, $\underline{x}>0$, $y>0$, $\underline{y}>0$, and $2x\underline{x}+2y\underline{y}\geq\underline{x}^2+\underline{y}^2$.

The alternating optimization approach [5] and MM algorithm [9]: The surrogate function is built on

$$f\geq\log\left(1+x^2+y^2\right)-\log\left(1+\underline{y}^2\right)+1-\frac{1+y^2}{1+\underline{y}^2}\stackrel{\text{def}}{=}f_4,$$

which is tighter than f_1 and f_3.

The FP method [13]: The author proposes two FP-based algorithms. The direct FP algorithm gives the following surrogate function:

$$f\geq\log\left(1+\frac{2\underline{x}x}{1+\underline{y}^2}-\underline{x}^2\frac{1+y^2}{\left(1+\underline{y}^2\right)^2}\right)\stackrel{\text{def}}{=}f_5.$$

And the fast FP algorithm gives

$$\begin{aligned}f\geq\ &\log\left(1+\frac{\underline{x}^2}{1+\underline{y}^2}\right)-\frac{\underline{x}^2}{1+\underline{y}^2}+\frac{2\underline{x}x}{1+\underline{y}^2}\\&-\frac{\underline{x}^2\left(1+x^2+y^2\right)}{\left(1+\underline{y}^2\right)\left(1+\underline{x}^2+\underline{y}^2\right)}\stackrel{\text{def}}{=}f_6.\end{aligned}$$

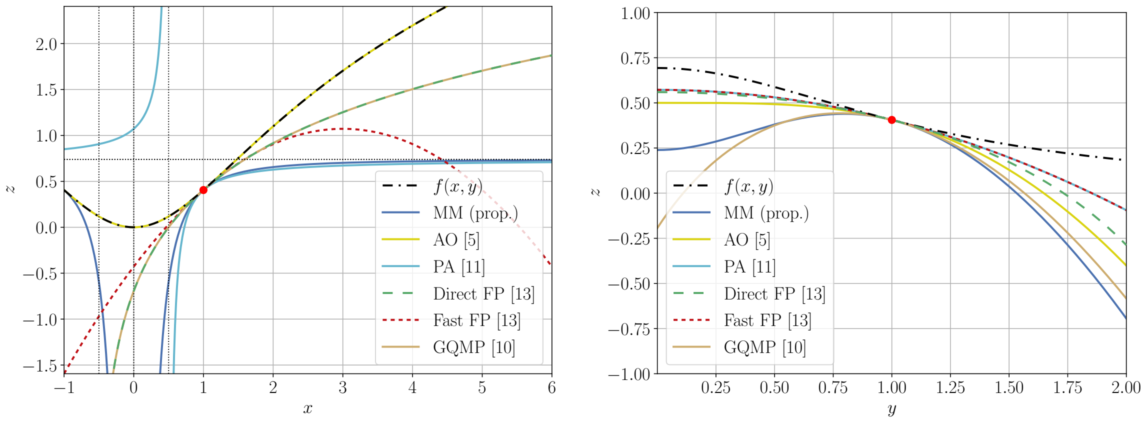
Observe that the surrogate function f_4 corresponds to the first minorization step in Lemma 1, which implies that $f_4\geq f_1$. Furthermore, by linearizing the quadratic form inside the logarithm of f_4, we obtain the surrogate function f_3, and hence $f_4\geq f_3$. From a theoretical perspective, the following relationships hold:

$$f_4\geq f_3,\qquad f_4\geq f_1. \tag{13}$$

Let $\underline{x}=1$ and $\underline{y}=1$. The numerical comparison results are presented in Fig. 1. As illustrated in Fig. 1(a), when y is fixed at $\underline{y}$ and x is treated as the variable, the surrogate function that provides the tightest approximation with respect to x is $f_4\left(x,\underline{y};\underline{x},\underline{y}\right)$. In fact, this surrogate coincides with the original function for all $(x,\underline{y})$. Note that although f_4 is not convex with respect to x, it becomes convex when viewed as a function of x^2. In contrast, as shown in Fig. 1(b), when x is fixed at $\underline{x}$ and y is treated as the variable, the tightest surrogates are given by f_2 and f_6.

V. Numerical Results

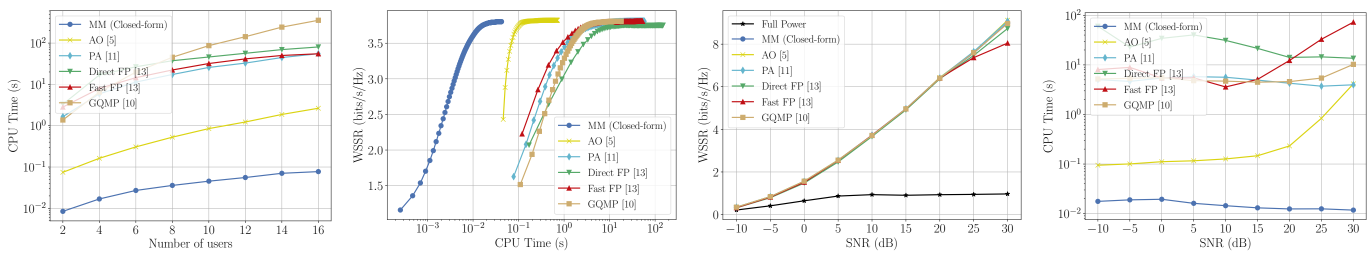
In this section, we conduct numerical simulations to evaluate the performance of the proposed MM algorithm and compare it with existing methods for WSSR maximization. All simulations are carried out in a Python 3.12 environment on a desktop computer equipped with an Intel Xeon W CPU. Convex subproblems are solved using CVXPY with the SCS solver. We consider a system with $K=4$ users and $K'=2$ eavesdroppers, where the transmit power constraints are set as $P_1=\cdots=P_K=P$, the noise variances are given by $\sigma_1^2=\cdots=\sigma_K^2=\sigma^2$ and $\tilde{\sigma}_1^2=\cdots=\tilde{\sigma}_{K'}^2=\sigma^2$, the channel coefficients $h_{i,j}$ are independently drawn from $\mathcal{CN}(0,1)$ for $i,j=1,\ldots,K$, and the eavesdropper channels $\tilde{h}_{i,j}$ are independently drawn from $\mathcal{CN}(0,1)$ for $i=1,\ldots,K'$



(a) Surrogate w.r.t. x

(b) Surrogate w.r.t. y

Fig. 1: Surrogate functions of f from different methods.



(a) WSSR versus K

(b) WSSR versus CPU time

(c) WSSR versus SNR

(d) CPU time versus SNR

Fig. 2: The performance of the proposed MM algorithm (Averaged over 1000 Monte Carlo results).

and $j = 1, \dots, K$. The signal-to-noise ratio (SNR) is defined as $\mathrm{SNR} = P/\sigma^2$. The proposed closed-form MM algorithm is compared with the following benchmark methods: alternating optimization (AO) [5], path-following algorithm (PA) [11], direct fractional programming (Direct FP) and fast fractional programming (Fast FP) [13], and generalized quadratic matrix programming (GQMP) [10]. All results are averaged over 1000 Monte Carlo trials to ensure statistical reliability.

In the first experiment, the SNR was fixed at $10\,\mathrm{dB}$. After 200 iterations, the convergence results and runtime are shown in Fig. 2(a) and (b). In the second experiment, different algorithms were executed over an SNR range from $-10\,\mathrm{dB}$ to $30\,\mathrm{dB}$, with the stopping criterion at the t-th iteration given by

$$|f(\mathbf{p}^{(t+1)}) - f(\mathbf{p}^{(t)})|/f(\mathbf{p}^{(t)}) \leq \epsilon,$$

where $\epsilon = 10^{-4}$. The results are presented in Fig. 2(c) and (d). In Fig. 2(a), as the number of users K increases, the proposed MM (Closed-form) exhibits a stable CPU time, while the other benchmarks show rising trends, indicating superior scalability. Fig. 2(b) demonstrates that for a given WSSR, the proposed method requires less CPU time, highlighting its computational efficiency. Moreover, Fig. 2(c) reveals that the proposed algorithm achieves a higher WSSR across different SNRs. Since the FP-based method [13] requires adding a positive constant to the denominator to avoid numerical issues, it can be observed from the numerical experiments that for high SNR cases, the WSSR obtained by Direct FP and Fast FP will decrease compared to other algorithms. Additionally, Fig. 2(d) shows that the CPU time of the proposed method remains relatively constant with varying SNRs, further confirming its robustness and efficiency. Overall, the proposed MM algorithm outperforms the benchmarks in both performance metrics and computational complexity, making it a compelling solution for practical deployments.

VI. Conclusion

This paper has addressed the challenging problem of weighted sum secrecy rate maximization in SISO interference channels. By developing a novel MM-based algorithm with closed-form updates at each iteration, we have significantly reduced the computational complexity compared to existing approaches that rely on numerical solvers for convex subproblems. The proposed method has demonstrated favorable convergence behavior and superior computational efficiency across a wide range of network configurations and SNR regimes. Numerical results have consistently validated the effectiveness of the proposed approach, showing substantial reductions in computational cost while maintaining competitive secrecy rate performance.

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