COMPARISON OF TECHNIQUES FOR L_2-SENSITIVITY MINIMIZATION UNDER L_2-SCALING CONSTRAINTS IN STATE-SPACE DIGITAL FILTERS

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ABSTRACT

Several techniques which minimize an l_2-sensitivity measure subject to l_2-norm dynamic-range scaling constraints are compared for state-space digital filters. This comparison is performed by solving a numerical example from the viewpoint of the convergence rate and the attained minimum value of an l_2-sensitivity measure.

I. INTRODUCTION

Implementing a fixed-point state-space digital filter with finite word length (FWL), the efficiency and performance of the filter are directly affected by the choice of its state-space filter structure. If a transfer function satisfying specification requirements is designed with infinite accuracy coefficients and realized by a state-space model, the coefficients in the state-space model must be truncated or rounded to fit the FWL constraints. The characteristics of the filter is then altered due to the coefficient quantization, which may turn a stable filter into an unstable one. Therefore, the problem of minimizing the coefficient sensitivity of a digital filter is a significant research topic. Several techniques have been proposed for synthesizing state-space digital filter structures that minimize an l_2-sensitivity measure [1]-[4]. More recently, a few techniques have developed for minimizing an l_2-sensitivity measure subject to l_2-scaling constraints [5]-[7].

We compare the techniques reported in [5]-[7] and a modified version of that in [5] from the viewpoint of the convergence rate and the attained minimum value of an l_2-sensitivity measure. This comparison is carried out through a numerical example.

II. l_2-SENSITIVITY ANALYSIS

Consider a state-space digital filter $(\boldsymbol{A}, \boldsymbol{b}, \boldsymbol{c}, d)_n$ which is stable, controllable and observable

$$\begin{aligned} \boldsymbol{x}(k+1) &= \boldsymbol{A}\boldsymbol{x}(k) + \boldsymbol{b}u(k) \\ y(k) &= \boldsymbol{c}\boldsymbol{x}(k) + du(k) \end{aligned} \tag{1}$$

where $\boldsymbol{x}(k)$ is an $n \times 1$ state-variable vector, $u(k)$ is a scalar input, $y(k)$ is a scalar output, and $\boldsymbol{A}, \boldsymbol{b}, \boldsymbol{c}$ and d are real constant matrices of appropriate dimensions. The transfer function of the state-space digital filter in (1) is given by

$$H(z) = \boldsymbol{c}(z\boldsymbol{I}_n - \boldsymbol{A})^{-1}\boldsymbol{b} + d. \tag{2}$$

Definition 1: Let $\boldsymbol{X}$ be an $m \times n$ real matrix and let $f(\boldsymbol{X})$ be a scalar complex function of $\boldsymbol{X}$, differentiable with respect to all the entries of $\boldsymbol{X}$. The sensitivity function of $f(\boldsymbol{X})$ with respect to $\boldsymbol{X}$ is then defined as

$$\boldsymbol{S}_{\boldsymbol{X}} = \frac{\partial f(\boldsymbol{X})}{\partial \boldsymbol{X}}, \qquad (\boldsymbol{S}_{\boldsymbol{X}})_{ij} = \frac{\partial f(\boldsymbol{X})}{\partial x_{ij}} \tag{3}$$

where x_{ij} denotes the (i, j)th entry of matrix $\boldsymbol{X}$.

Definition 2: Let $\boldsymbol{X}(z)$ be an $m \times n$ complex matrix-valued function of a complex variable z and let $x_{pq}(z)$ be the (p, q)th entry of $\boldsymbol{X}(z)$. The l_2-norm of $\boldsymbol{X}(z)$ is then defined as

$$\|\boldsymbol{X}(z)\|_2 = \left(\mathrm{tr}\left[\frac{1}{2\pi j} \oint_{|z|=1} \boldsymbol{X}(z)\boldsymbol{X}^*(z)\frac{dz}{z} \right] \right)^{\frac{1}{2}}. \tag{4}$$

From (2) and *Definitions 1* and *2*, the overall l_2-sensitivity measure for the state-space digital filter in (1) is defined as

$$\begin{aligned} S &= \left\| \frac{\partial H(z)}{\partial \boldsymbol{A}} \right\|_2^2 + \left\| \frac{\partial H(z)}{\partial \boldsymbol{b}} \right\|_2^2 + \left\| \frac{\partial H(z)}{\partial \boldsymbol{c}^T} \right\|_2^2 \\ &= \left\| [\boldsymbol{F}(z)\boldsymbol{G}(z)]^T \right\|_2^2 + \left\| \boldsymbol{G}^T(z) \right\|_2^2 + \|\boldsymbol{F}(z)\|_2^2 \end{aligned} \tag{5}$$

where

$$\boldsymbol{F}(z) = (z\boldsymbol{I}_n - \boldsymbol{A})^{-1}\boldsymbol{b}, \qquad \boldsymbol{G}(z) = \boldsymbol{c}(z\boldsymbol{I}_n - \boldsymbol{A})^{-1}.$$

The term d in (2) and the sensitivity with respect to it are coordinate-independent and therefore they are neglected here.

It is easy to show that the l_2-sensitivity measure in (5) can be expressed as

$$S = \mathrm{tr}[\boldsymbol{M}(\boldsymbol{I}_n)] + \mathrm{tr}[\boldsymbol{W}_o] + \mathrm{tr}[\boldsymbol{K}_c] \tag{6}$$

where

$$\boldsymbol{M}(\boldsymbol{P}) = \frac{1}{2\pi j}\oint_{|z|=1}[\boldsymbol{F}(z)\boldsymbol{G}(z)]^T\boldsymbol{P}^{-1}\boldsymbol{F}(z^{-1})\boldsymbol{G}(z^{-1})\frac{dz}{z}$$

$$\boldsymbol{K}_c = \frac{1}{2\pi j}\oint_{|z|=1}\boldsymbol{F}(z)\boldsymbol{F}^T(z^{-1})\frac{dz}{z}$$

$$\boldsymbol{W}_o = \frac{1}{2\pi j}\oint_{|z|=1}\boldsymbol{G}^T(z)\boldsymbol{G}(z^{-1})\frac{dz}{z}.$$

The matrices $\boldsymbol{K}_c$ and $\boldsymbol{W}_o$ are called the controllability and observability Gramians, respectively. The Gramians $\boldsymbol{M}(\boldsymbol{P})$, $\boldsymbol{K}_c$ and $\boldsymbol{W}_o$ can be obtained by solving the Lyapunov equations [5]

$$\begin{aligned}\begin{bmatrix} * & * \\ * & \boldsymbol{M}(\boldsymbol{P})\end{bmatrix} &= \begin{bmatrix}\boldsymbol{A} & \boldsymbol{bc} \\ \boldsymbol{0} & \boldsymbol{A}\end{bmatrix}^T \begin{bmatrix} * & * \\ * & \boldsymbol{M}(\boldsymbol{P})\end{bmatrix} \\ &\quad\times \begin{bmatrix}\boldsymbol{A} & \boldsymbol{bc} \\ \boldsymbol{0} & \boldsymbol{A}\end{bmatrix} + \begin{bmatrix}\boldsymbol{P}^{-1} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{0}\end{bmatrix} \qquad (7) \\ \boldsymbol{K}_c &= \boldsymbol{A}\boldsymbol{K}_c\boldsymbol{A}^T + \boldsymbol{b}\boldsymbol{b}^T \\ \boldsymbol{W}_o &= \boldsymbol{A}^T\boldsymbol{W}_o\boldsymbol{A} + \boldsymbol{c}^T\boldsymbol{c}.\end{aligned}$$

If a coordinate transformation defined by

$$\overline{\boldsymbol{x}}(k) = \boldsymbol{T}^{-1}\boldsymbol{x}(k) \tag{8}$$

is applied to the state-space digital filter in (1), then the new realization $(\overline{\boldsymbol{A}}, \overline{\boldsymbol{b}}, \overline{\boldsymbol{c}}, d)_n$ can be characterized by

$$\overline{\boldsymbol{A}} = \boldsymbol{T}^{-1}\boldsymbol{A}\boldsymbol{T}, \quad \overline{\boldsymbol{b}} = \boldsymbol{T}^{-1}\boldsymbol{b}, \quad \overline{\boldsymbol{c}} = \boldsymbol{c}\boldsymbol{T}. \tag{9}$$

From (2) and (9), it is clear that the transfer function $H(z)$ is invariant under the coordinate transformation in (8). The coordinate transformation defined by (8) changes (6) to

$$S(\boldsymbol{P}) = \mathrm{tr}[\boldsymbol{M}(\boldsymbol{P})\boldsymbol{P}] + \mathrm{tr}[\boldsymbol{W}_o\boldsymbol{P}] + \mathrm{tr}[\boldsymbol{K}_c\boldsymbol{P}^{-1}] \tag{10}$$

where $\boldsymbol{P} = \boldsymbol{T}\boldsymbol{T}^T$. Moreover, if the l_2-norm dynamic-range scaling constraints are imposed on the new state-variable vector $\overline{\boldsymbol{x}}(k)$, it is required that for $i = 1, 2, \cdots, n$

$$(\overline{\boldsymbol{K}}_c)_{ii} = (\boldsymbol{T}^{-1}\boldsymbol{K}_c\boldsymbol{T}^{-T})_{ii} = 1. \tag{11}$$

Consequently, the problem of l_2-sensitivity minimization subject to l_2-norm dynamic-range scaling constraints is now formulated as follows: For given $\boldsymbol{A}$, $\boldsymbol{b}$ and $\boldsymbol{c}$, obtain an $n \times n$ nonsingular matrix $\boldsymbol{T}$ which minimizes (10) subject to the constraints in (11).

III. MINIMIZATION TECHNIQUES

In order to minimize (10) over an $n \times n$ symmetric positive-definite matrix $\boldsymbol{P}$ subject to the constraints shown in (11), we define the Lagrange function

$$\begin{aligned} J(\boldsymbol{P}, \lambda) &= \mathrm{tr}[\boldsymbol{M}(\boldsymbol{P})\boldsymbol{P}] + \mathrm{tr}[\boldsymbol{W}_o\boldsymbol{P}] \\ &\quad + \mathrm{tr}[\boldsymbol{K}_c\boldsymbol{P}^{-1}] + \lambda(\mathrm{tr}[\boldsymbol{K}_c\boldsymbol{P}^{-1}] - n)\end{aligned} \tag{12}$$

where λ is a Lagrange multiplier. We compute

$$\begin{aligned}\frac{\partial J(\boldsymbol{P},\lambda)}{\partial \boldsymbol{P}} &= \boldsymbol{M}(\boldsymbol{P}) - \boldsymbol{P}^{-1}\boldsymbol{N}(\boldsymbol{P})\boldsymbol{P}^{-1} + \boldsymbol{W}_o \\ &\quad -(\lambda+1)\boldsymbol{P}^{-1}\boldsymbol{K}_c\boldsymbol{P}^{-1} \\ \frac{\partial J(\boldsymbol{P},\lambda)}{\partial \lambda} &= \mathrm{tr}[\boldsymbol{K}_c\boldsymbol{P}^{-1}] - n\end{aligned} \tag{13}$$

where $\boldsymbol{N}(\boldsymbol{P})$ can be obtained by solving the Lyapunov equation [5]

$$\begin{aligned}\begin{bmatrix}\boldsymbol{N}(\boldsymbol{P}) & * \\ * & *\end{bmatrix} &= \begin{bmatrix}\boldsymbol{A} & \boldsymbol{bc} \\ \boldsymbol{0} & \boldsymbol{A}\end{bmatrix}\begin{bmatrix}\boldsymbol{N}(\boldsymbol{P}) & * \\ * & *\end{bmatrix} \\ &\quad\times\begin{bmatrix}\boldsymbol{A} & \boldsymbol{bc} \\ \boldsymbol{0} & \boldsymbol{A}\end{bmatrix}^T + \begin{bmatrix}\boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{P} & \boldsymbol{0}\end{bmatrix}.\end{aligned}$$

From $\partial J(\boldsymbol{P},\lambda)/\partial\boldsymbol{P} = \boldsymbol{0}$ and $\partial J(\boldsymbol{P},\lambda)/\partial\lambda = 0$, we get

$$\boldsymbol{P}\boldsymbol{F}(\boldsymbol{P})\boldsymbol{P} = \boldsymbol{G}(\boldsymbol{P},\lambda), \qquad \mathrm{tr}[\boldsymbol{K}_c\boldsymbol{P}^{-1}] = n \tag{14}$$

where

$$\begin{aligned}\boldsymbol{F}(\boldsymbol{P}) &= \boldsymbol{M}(\boldsymbol{P}) + \boldsymbol{W}_o \\ \boldsymbol{G}(\boldsymbol{P},\lambda) &= \boldsymbol{N}(\boldsymbol{P}) + (\lambda+1)\boldsymbol{K}_c.\end{aligned}$$

A. Method 1 [5]

Start with initial conditions $\lambda_0 = 0$ and $\boldsymbol{P}_0 = \boldsymbol{I}_n$ and repeat

$$\begin{aligned}\boldsymbol{P}_{i+1} &= \boldsymbol{F}(\boldsymbol{P}_i)^{-\frac{1}{2}}[\boldsymbol{F}(\boldsymbol{P}_i)^{\frac{1}{2}}\boldsymbol{G}(\boldsymbol{P}_i,\lambda_i)\boldsymbol{F}(\boldsymbol{P}_i)^{\frac{1}{2}}]^{\frac{1}{2}}\boldsymbol{F}(\boldsymbol{P}_i)^{-\frac{1}{2}} \\ \lambda_{i+1} &= \frac{\mathrm{tr}[\boldsymbol{P}_i\boldsymbol{F}(\boldsymbol{P}_i)] - \mathrm{tr}[\boldsymbol{N}(\boldsymbol{P}_i)\boldsymbol{P}_i^{-1}]}{n} - 1\end{aligned} \tag{15}$$

where $\boldsymbol{P}_i$ and λ_i are solutions of the previous iteration.

B. Method 2 (A modified version of [5])

Start with initial condition $\boldsymbol{P}_0 = \boldsymbol{I}_n$ and repeat

$$\begin{aligned}\lambda_i &= \frac{\mathrm{tr}[\boldsymbol{P}_i\boldsymbol{F}(\boldsymbol{P}_i)] - \mathrm{tr}[\boldsymbol{N}(\boldsymbol{P}_i)\boldsymbol{P}_i^{-1}]}{n} - 1 \\ \boldsymbol{P}_{i+1} &= \boldsymbol{F}(\boldsymbol{P}_i)^{-\frac{1}{2}}[\boldsymbol{F}(\boldsymbol{P}_i)^{\frac{1}{2}}\boldsymbol{G}(\boldsymbol{P}_i,\lambda_i)\boldsymbol{F}(\boldsymbol{P}_i)^{\frac{1}{2}}]^{\frac{1}{2}}\boldsymbol{F}(\boldsymbol{P}_i)^{-\frac{1}{2}}.\end{aligned} \tag{16}$$

C. Method 3 [6]

Start with initial condition $\boldsymbol{P}_0 = \boldsymbol{I}_n$ and repeat

$$\boldsymbol{S}_{i+1} = \boldsymbol{F}(\boldsymbol{P}_i)^{-\frac{1}{2}}[\boldsymbol{F}(\boldsymbol{P}_i)^{\frac{1}{2}}\boldsymbol{G}(\boldsymbol{P}_i)\boldsymbol{F}(\boldsymbol{P}_i)^{\frac{1}{2}}]^{\frac{1}{2}}\boldsymbol{F}(\boldsymbol{P}_i)^{-\frac{1}{2}}$$

$$\boldsymbol{P}_{i+1} = \frac{\mathrm{tr}[\boldsymbol{K}_c \boldsymbol{S}_{i+1}^{-1}]}{n} \boldsymbol{S}_{i+1} \tag{17}$$

where $\boldsymbol{G}(\boldsymbol{P}_i) = \boldsymbol{G}(\boldsymbol{P}_i, 0)$.

D. Method 4 [7]

Start with initial condition $\boldsymbol{P}_0 = \boldsymbol{I}_n$ and repeat

$$\boldsymbol{P}_{i+1} = \boldsymbol{F}(\boldsymbol{P}_i)^{-\frac{1}{2}} [\boldsymbol{F}(\boldsymbol{P}_i)^{\frac{1}{2}} \boldsymbol{G}(\boldsymbol{P}_i, \lambda_{i+1}) \boldsymbol{F}(\boldsymbol{P}_i)^{\frac{1}{2}}]^{\frac{1}{2}} \times \boldsymbol{F}(\boldsymbol{P}_i)^{-\frac{1}{2}}. \tag{18}$$

Here, λ_{i+1} is obtained using a bisection method so that

$$f(\lambda_{i+1}) = n - \mathrm{tr}[\hat{\boldsymbol{K}}_c(\boldsymbol{P}_i) \hat{\boldsymbol{G}}(\boldsymbol{P}_i, \lambda_{i+1})] = 0 \tag{19}$$

where

$$\hat{\boldsymbol{K}}_c(\boldsymbol{P}_i) = \boldsymbol{F}(\boldsymbol{P}_i)^{\frac{1}{2}} \boldsymbol{K}_c \boldsymbol{F}(\boldsymbol{P}_i)^{\frac{1}{2}}$$
$$\hat{\boldsymbol{G}}(\boldsymbol{P}_i, \lambda_{i+1}) = [\boldsymbol{F}(\boldsymbol{P}_i)^{\frac{1}{2}} \boldsymbol{G}(\boldsymbol{P}_i, \lambda_{i+1}) \boldsymbol{F}(\boldsymbol{P}_i)^{\frac{1}{2}}]^{-\frac{1}{2}}.$$

The above iterative procedures continue until

$$|J(\boldsymbol{P}_{i+1}, \lambda_{i+1}) - J(\boldsymbol{P}_i, \lambda_i)| < \varepsilon \tag{20}$$

is satisfied where ε is a prescribed tolerance.

IV. A NUMERICAL EXAMPLE

Let a state-space digital filter in (1) be specified by

$$\boldsymbol{A} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0.453770 & -1.556160 & 1.974860 \end{bmatrix}$$

$$\boldsymbol{b} = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}^T$$

$$\boldsymbol{c} = \begin{bmatrix} 0.023170 & 0.023020 & 0.79300 \end{bmatrix}$$

$$d = 0.015940.$$

Performing the computation of (7) and the l_2-scaling, the Grammians $\boldsymbol{K}_c$, $\boldsymbol{W}_o$ and $\boldsymbol{M}(\boldsymbol{I}_3)$ were calculated as

$$\boldsymbol{K}_c = \begin{bmatrix} 1.000000 & 0.872501 & 0.562821 \\ 0.872501 & 1.000000 & 0.872501 \\ 0.562821 & 0.872501 & 1.000000 \end{bmatrix}$$

$$\boldsymbol{W}_o = \begin{bmatrix} 0.820741 & -2.035330 & 1.628162 \\ -2.035330 & 5.307276 & -4.264906 \\ 1.628162 & -4.264906 & 3.941493 \end{bmatrix}$$

$$\boldsymbol{M}(\boldsymbol{I}_3) = \begin{bmatrix} 8.921384 & -22.046468 & 17.916293 \\ -22.046468 & 55.671739 & -46.052035 \\ 17.916293 & -46.052035 & 42.522180 \end{bmatrix}.$$

The l_2-sensitivity measure in (6) was computed as

$$S = 120.184738.$$

Applying Method 1 [5] and Method 2 (A modified version of [5]) with $\varepsilon = 10^{-7}$, it took the iterative algorithms 246 and 231 iterations, respectively, to converge to

$$\boldsymbol{P}^{opt} = \begin{bmatrix} 2.307530 & 1.375668 & 0.514401 \\ 1.375668 & 1.103115 & 0.678193 \\ 0.514401 & 0.678193 & 0.666912 \end{bmatrix}$$

which yields

$$\boldsymbol{T}^{opt} = \begin{bmatrix} -0.816495 & 0.220555 & 1.261833 \\ -0.093245 & -0.076884 & 1.043316 \\ 0.437414 & 0.006321 & 0.689595 \end{bmatrix}.$$

In both cases, the l_2-sensitivity measure in (10) was minimized subject to the scaling constraints in (11) to

$$S(\boldsymbol{P}^{opt}) = 8.672129.$$

The l_2-sensitivity performances of 500 iterations for Method 1 [5] and Method 2 (A modified version of [5]) are shown in Fig. 1.

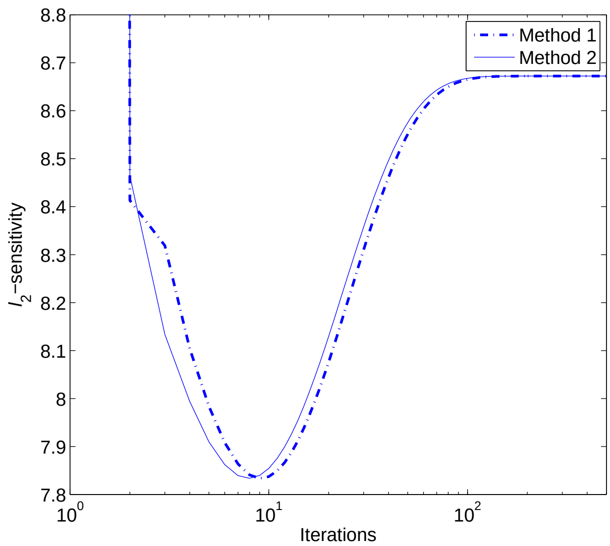

Figure 1: Performances of Methods 1 and 2.

Applying Method 3 [6] with $\varepsilon = 10^{-7}$, it took the iterative algorithm 8 iterations to converge to

$$\boldsymbol{P}^{opt} = \begin{bmatrix} 2.323990 & 1.368404 & 0.507227 \\ 1.368404 & 1.088538 & 0.665792 \\ 0.507227 & 0.665792 & 0.653786 \end{bmatrix}$$

which yields

$$\boldsymbol{T}^{opt} = \begin{bmatrix} -0.811257 & 0.218876 & 1.271985 \\ -0.077911 & -0.069596 & 1.038087 \\ 0.442333 & 0.026430 & 0.676335 \end{bmatrix}.$$

Table 1: Iterations to become less than $\varepsilon = 10^{-7}$

Method	1	2	3	4
Iterations	246	231	8	8

Table 2: Iterations to become less than $\varepsilon = 10^{-8}$

Method	1	2	3	4
Iterations	286	269	10	9

In this case, the l_2-sensitivity measure in (10) was minimized subject to the scaling constraints in (11) to

$$S(\boldsymbol{P}^{opt}) = 8.677268.$$

Applying Method 4 [7] with $\varepsilon = 10^{-7}$, it took the iterative algorithm 8 iterations to converge to the minimum value identical to those obtained by Methods 1 and 2.

The l_2-sensitivity performances of 500 iterations for Methods 3 [6] and 4 [7] are shown in Fig. 2.

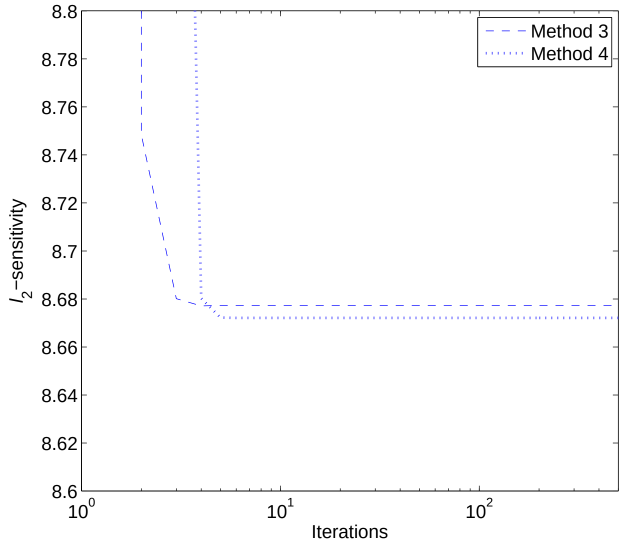

Figure 2: Performances of Methods 3 and 4.

V. CONCLUSION

This paper has compared the techniques reported in [5]-[7] and a modified version of that in [5] from the viewpoint of the convergence rate and the attained minimum value of an l_2-sensitivity measure. This comparison has been accomplished by solving a numerical example. As a result, it has been observed that the modified version of the technique in [5] yields faster convegence than that in [5]. Moreover, the minimum value attained by the technique reported in [6] is higher than those obtained by the other techniques. It is noted that the technique reported in [6] minimizes an l_2-sensitivity measure without l_2-scaling constraints, and then the l_2-scaling is carried out to the resulting solution (filter).

Table 3: Iterations to attain $J(\boldsymbol{P}, \lambda) = 8.672132$

Method	1	2	3	4
Iterations	274	256	Not Applicable	8

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