

# Supplementary Numerical Results

June 15, 2020

## 1 Angular Synchronization Performance in the Presence of Zero Entries

This discussion concerns Theorem 3, which provides recovery guarantees for Algorithm 1. The statement of Theorem 3 assumes that  $\hat{\mathbf{x}}$  is non-vanishing for technical convenience. However, similar results can be derived in the case where  $\hat{\mathbf{x}}$  does vanish, as long as it does not have  $\delta$  consecutive zeros. We verified this by running the angular synchronization algorithm in the case where  $\hat{\mathbf{x}}$  had a small number of zero entries and observed that the algorithm was still effective. A representative numerical simulation is shown in Fig. 1 below, which plots the error in performing angular synchronization (Steps 3–7 in Algorithm 1) in the noiseless setting (for a signal size  $d = 247$ , and with  $\rho = 10$ ), with a random selection of coefficients (not necessarily contiguous) in  $\hat{\mathbf{x}}$  set to zero. As can be seen, the proposed procedure is robust to the presence of a fairly large number of zeros (about 40% of the signal length), with angular synchronization failing only when a large number of zero entries are present.

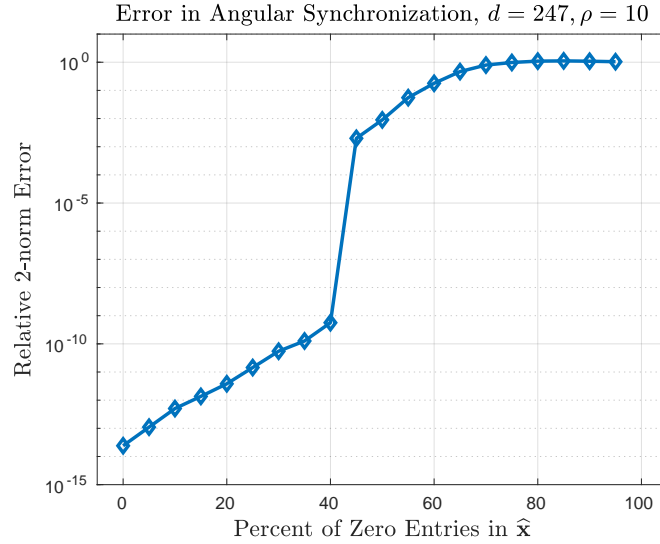


Figure 1: Robustness of Eigenvector-Based Angular Synchronization to the Presence of Zero Entries in  $\hat{\mathbf{x}}$

## 2 More General Masks

We note that the manuscript provides one possible deterministic mask construction for which it is provably true that constants  $\mu_1$  and  $\mu_2$  are strictly positive. Empirically, the conditions that  $\mu_1$  and  $\mu_2$  are strictly positive is fairly mild and is also satisfied if e.g. the nonzero entries of the  $\mathbf{m}$  or  $\hat{\mathbf{m}}$  are generated i.i.d at random. In addition, some empirical results supporting this observation are provided below.

Tables 1 and 2 provide empirically computed  $\mu_1$  values (Mask constant for Algorithm 1) for several different parameter choices and four different types of masks (representative and illustrative plots of these masks are provided in Fig. 2):

1. Random masks (defined in (5.1) in the manuscript),
2. (Deterministic) Exponential masks (defined in (5.2) in the manuscript),
3. Random Symmetric masks – these are defined similar to (5.1), except exhibiting (conjugate) symmetry in the window of support,
4. (Deterministic) Gaussian masks – generated using Matlab’s `gausswin` command and  $\alpha = 2$  (reciprocal of the standard deviation).

As can be observed from the table of  $\mu_1$  values, the proposed method allows for a wide variety of mask prescriptions. Similar results hold for Algorithm 2 and  $\mu_2$  values.

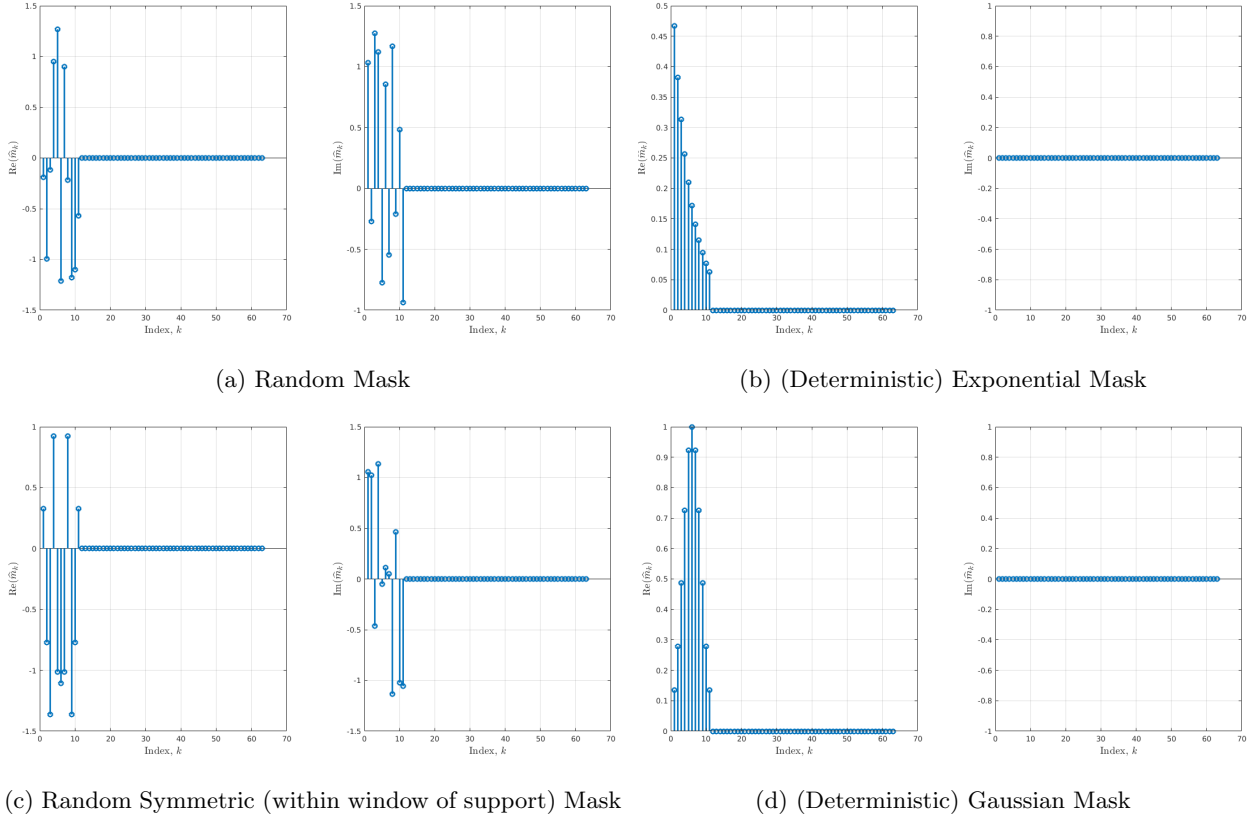


Figure 2: Representative plots (of  $\hat{\mathbf{m}}$ , with  $\rho = 11$ ) for different types of masks. Corresponding mask constants ( $\mu_1$ ) are provided in Table 1.

$(d, \rho)$	Random	Exponential	Random Symmetric	Gaussian
(21, 11)	$1.9720 \times 10^{-1}$	$1.2685 \times 10^{-2}$	$1.3955 \times 10^{-1}$	$1.2011 \times 10^{-3}$
(63, 11)	$1.2140 \times 10^{-1}$	$1.1983 \times 10^{-2}$	$5.5436 \times 10^{-2}$	$3.9680 \times 10^{-4}$
(1029, 11)	$6.3642 \times 10^{-2}$	$1.1892 \times 10^{-2}$	$3.4183 \times 10^{-3}$	$3.4520 \times 10^{-5}$

Table 1: Empirically evaluated  $\mu_1$  (mask constant for Algorithm 1) values for different types of masks (with  $\rho$  fixed and increasing  $d$ ).

$(d, \rho)$	Random	Exponential	Random Symmetric	Gaussian
(63, 2)	$4.0464 \times 10^{-1}$	$2.2827 \times 10^{-1}$	$7.7457 \times 10^{-2}$	$9.1324 \times 10^{-4}$
(65, 3)	$2.1832 \times 10^{-1}$	$1.3767 \times 10^{-1}$	$2.5399 \times 10^{-2}$	$6.5404 \times 10^{-3}$
(63, 4)	$1.9319 \times 10^{-1}$	$9.0640 \times 10^{-2}$	$5.8460 \times 10^{-2}$	$5.4034 \times 10^{-3}$
(63, 5)	$1.7196 \times 10^{-1}$	$6.2255 \times 10^{-2}$	$5.0854 \times 10^{-2}$	$4.0929 \times 10^{-3}$
(65, 7)	$1.4867 \times 10^{-1}$	$3.1409 \times 10^{-2}$	$4.9980 \times 10^{-2}$	$2.6888 \times 10^{-3}$
(57, 10)	$1.4545 \times 10^{-1}$	$1.4018 \times 10^{-2}$	$6.1526 \times 10^{-2}$	$1.1799 \times 10^{-4}$
(69, 12)	$1.2449 \times 10^{-1}$	$1.0398 \times 10^{-2}$	$4.8719 \times 10^{-2}$	$2.4892 \times 10^{-4}$

Table 2: Empirically evaluated  $\mu_1$  (mask constant for Algorithm 1) values for different types of masks (with  $d$  (approximately) fixed (subject to divisibility constraints) and increasing  $\rho$ .)