# Non-negative Super-resolution is Stable

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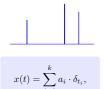


# PROBLEM

Consider the problem of localising k non-negative point sources on the interval [0,1], namely finding their locations  $t_1,\ldots,t_k$  and magnitudes  $a_1,\ldots,a_k\geq 0$  from m noisy samples  $y_1,\ldots,y_m$  which consist of the convolution of the input signal with a known kernel  $\phi$  (e.g. Gaussian  $\phi(t)=e^{-t^2/\sigma^2}$ ) and additive noise  $\eta$  bounded by  $\delta$ . We use the formulation of the problem from [4].

### INPUT SIGNAL

x is the discrete measure we want to reconstruct.



 $t_i$  and  $a_i$   $(i=1,\ldots,k)$  are the locations and magnitudes of the point sources.

Given the source locations  $t_1, \ldots, t_k$ , we define:

•  $\Delta = \min_{i \neq j} |t_i - t_j|$  is the minimum separation of

• For  $\lambda \in [0, \frac{1}{2})$  and for each source  $t_i$ , there exists a sampling location  $s_{l(i)}$  such that  $|s_{l(i)} - t_i| < \lambda \Delta$ 

•  $T_{i,\epsilon} = (t_i - \epsilon, t_i + \epsilon)$  and  $T_{\epsilon}^C = [0,1] \setminus \bigcup_{i=1}^k T_{i,\epsilon}$  for

For a solution  $\hat{x}$  to the Feasibility Problem (1)

and the true measure x, we show that the error

in  $T_{i,\epsilon}$  is bounded and proportional to the noise level  $\delta$  and  $\epsilon$ .

#### MEASURED SIGNAL

 $y_i$  are the samples we use to reconstruct x.



$$y_j = \int_{[0,1]} \phi(t - s_j) x(dt) + \eta_j,$$

where  $s_j$  (j = 1, ..., m) are sampling locations and  $\eta = [\eta_1, ..., \eta_m]^T$  with  $\|\eta\|_2 \le \delta$  is the

# FEASIBILITY PROBLEM

We solve the following problem to find x from y

Find z > 0 subject to

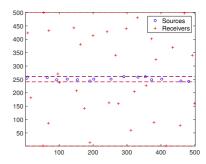
$$\left\| y - \int_{[0,1]} \Phi(t) z(\mathrm{d}t) \right\|_2 \le \delta \quad (1)$$

where

$$y = [y_1, \dots, y_m]^T$$
,  
 $\Phi(t) = [\phi(t - s_1), \dots, \phi(t - s_m)]^T$ .

#### APPLICATION EXAMPLE

We sample at specific points the sound emitted by ships (sources) traveling along a shipping lane in a 2D region of interest and we want to find their locations and the overall sound level, either in a static or in a dynamic setting. The problem is described in more detail in [2].



An example of a receiver and source configuration in the region of interest.

## RESULTS

#### Theorem 1 - General Kernel

Let  $\hat{x}$  be a solution of (1). If  $m \geq 2k+1$ ,  $\phi$  is Lipschitz continuous and, for  $\Delta$ ,  $\lambda$  and  $\epsilon$  defined previously, we have

$$\phi(\lambda \Delta) \ge 2\phi(\Delta - \lambda \Delta) + \frac{2}{\Delta} \int_{\Delta - \lambda \Delta}^{1/2 - \lambda \Delta} \phi(x) dx$$

then, for all  $i \in 1, \ldots, k$ ,

$$\begin{split} \left| \int_{T_{i,\epsilon}} \hat{x}(\mathrm{d}t) - a_i \right| &\leq [2\left(1 + \frac{\phi^\infty \|b\|_2}{\bar{f}}\right) \cdot \delta \\ &+ L \|\hat{x}\|_{TV} \cdot \epsilon] \|A^{-1}\|_\infty \end{split}$$

where

- L is the Lipschitz constant of  $\phi$ ,
- $\phi^{\infty} = \max_{t \in [0,1]} |\phi(t)|,$
- b is the vector of coefficients of the dual certificate, and \(\bar{f}\) is involved in its construction, see below,
- ullet A is the sampling matrix defined below.

#### Theorem 2 - Gaussian Kernel

Let  $\hat{x}$  be a solution of (1) with  $\phi(t) = e^{-x^2/\sigma^2}$ . If  $m \ge 2k + 2$  and for every source we have two samples s, s' such that  $|s - t_i| \le \eta$  and  $|s - s'| \le \eta$  with  $\eta \le \sigma^2$ . If  $\sigma < \frac{1}{\sqrt{3}}, \Delta(T) > \sigma \sqrt{\log \frac{5}{\sigma^2}}$ , then:

$$\left| \int_{T_{1,\epsilon}} \hat{x}(\mathrm{d}t) - a_i \right| \leq \left[ (c_1 + F_2) \cdot \delta + c_2 \frac{\|\hat{x}\|_{TV}}{\sigma^2} \cdot \epsilon \right] F_3,$$

where  $F_2(k,\Delta(T),1/\sigma,1/\epsilon) < c_3 \frac{kC_2(1/\epsilon)}{\sigma^2} \left[\frac{c_4}{\sigma^6(1-3\sigma^2)^2}\right]^k$ ,  $F_3(\Delta(T),\sigma,\lambda) < c_5$  and the universal constants  $c_1,c_2,c_3,c_4,c_5$  and  $C_2(1/\epsilon)$  are given in [1].

### IMPLICATIONS OF THEOREM 2

- Any solution consistent with measurements within  $\delta$  is within  $\delta + \epsilon$  of the true measure in the appropriate notion.
- As  $\delta, \epsilon \to 0$ , the measure x is the unique solution to (1).
- Similar results were previously known only for specific algorithms (e.g. TV-norm minimisation).

## PROOF IDEAS

#### DUAL CERTIFICATE

We use the notion of dual certificate to show that the original signal x is the unique solution of problem (1) with  $\delta=0$ , then extend this notion to  $\delta>0$  to bound the error between the true and the estimated solution. Using ideas from [3], we show that the dual certificate exists if  $\phi$  with different shifts forms a T-System and we construct it. The dual certificate is a function:

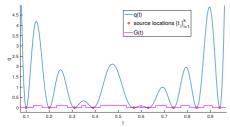
$$q(t) = \sum_{j=1}^{k} b_j \phi(t - s_j)$$

such that

- $q(t_i) = 0, \forall i = 1, \dots, k,$
- $q(t) > 0, \forall t \neq t_i$ .
- $\bullet \ q(t) \geq G(t), \forall t \in [0,1]$

where, for some  $\bar{f} > 0$ ,

$$G(t) = \begin{cases} \bar{f}, \text{ if } t \in T_{\epsilon}^C, \\ 0, \text{ otherwise.} \end{cases}$$



The shape of the dual certificate depends on the locations of the sources and the samples.

## SAMPLING MATRIX

Another important idea is that of diagonally dominance of the matrices A and B defined below. The condition that A is diagonally dominant is related to how close to each source we need the samples to be for a general  $\phi$  in Theorem 1. The determinant of the matrix B appears in the factor  $F_2$  in Theorem 2 for the Gaussian kernel. We bound it by considering bounds on the eigenvalues of B.

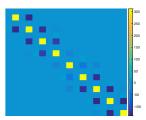
$$A = (a_{ij}) \in \mathbb{R}^{k \times k}$$

$$a_{ij} = \begin{cases} |\phi(s_{l(i)} - t_j)|, & \text{if } i = j, \\ -|\phi(s_{l(i)} - t_j)|, & \text{otherwise.} \end{cases}$$



 ${\it Example \ of \ matrix \ A.}$ 

 $B = (B_{ij}) \in \mathbb{R}^{2k \times 2k}$   $B_{ij} = \begin{bmatrix} \phi(t_i - t_j) & -\phi'(t_i - t_j) \\ \phi'(t_i - t_j) & -\phi''(t_i - t_j) \end{bmatrix}$ 



Example of matrix B.

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