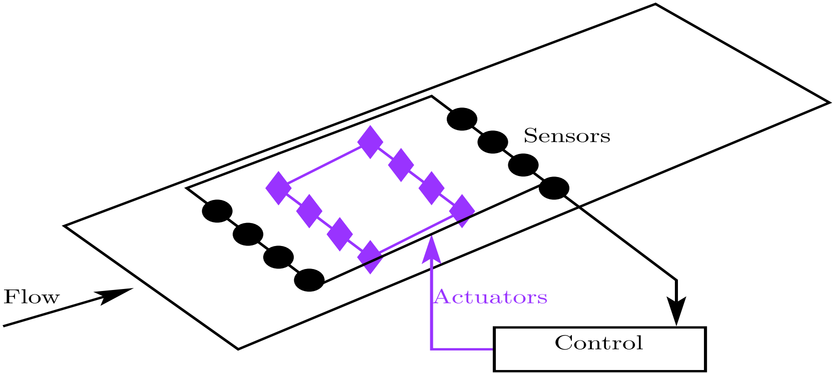
Identifying Disturbance Sources in Shear Flows Using The Degenerate Unmixing Estimation Technique (DUET)

Igal Gluzman, Jacob Cohen & Yaakov Oshman

DEPARTMENT OF AEROSPACE ENGINEERING | TECHNION Israel Institute of Technology

Objectives



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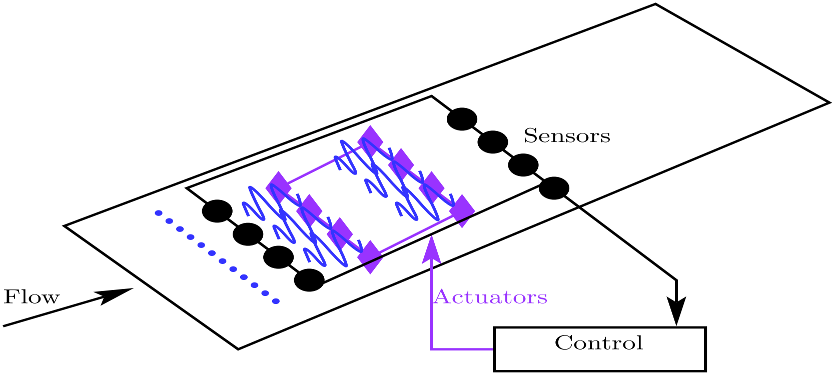

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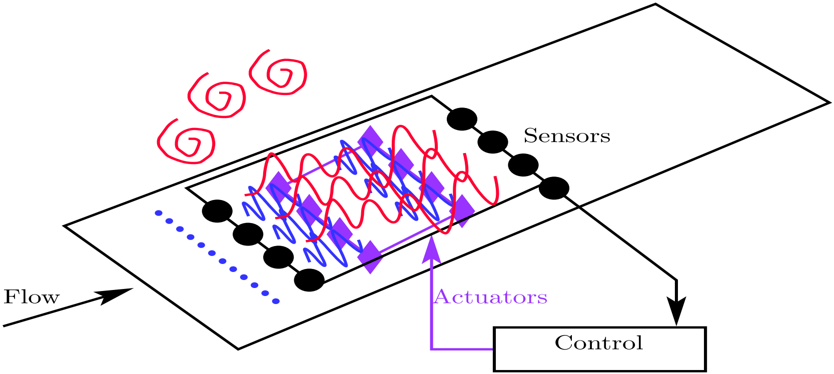

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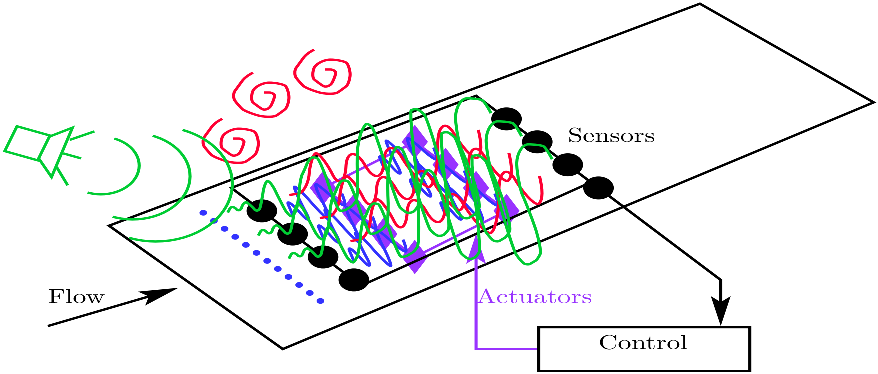

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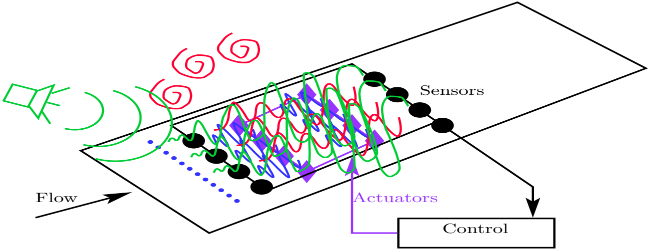
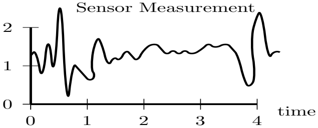
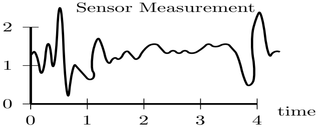

Sensors
Flow
Actuators
Control


Sensor Measurement
0
1
2
0
1
2
3
4
time


Sensor Measurement
0
1
2
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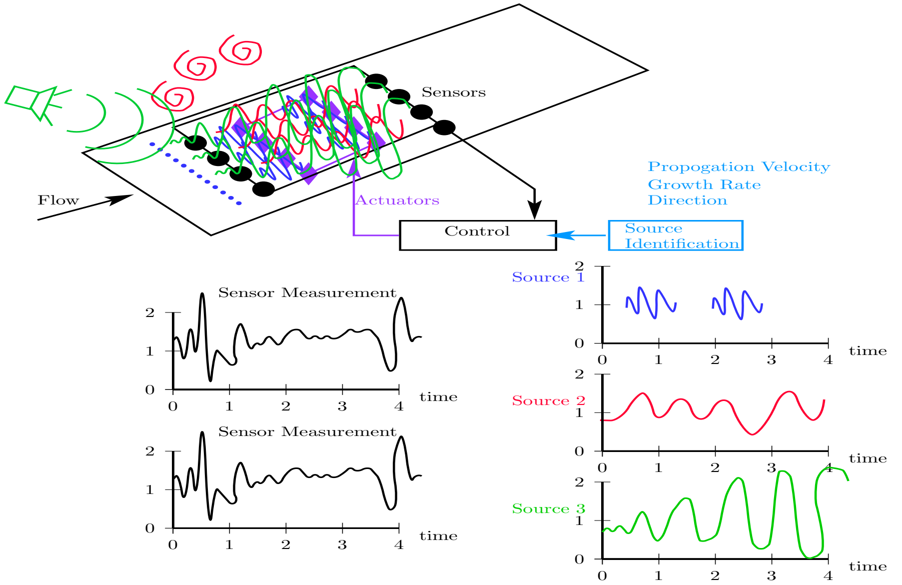
time

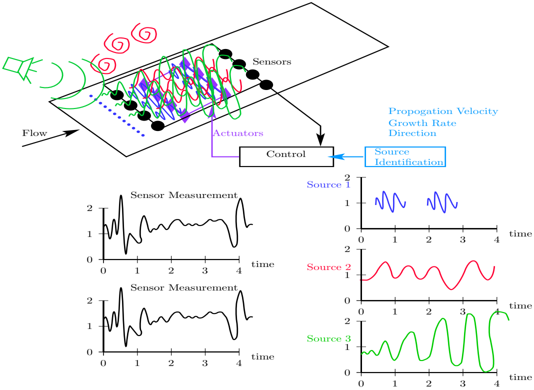
Objectives


Sensors
Flow
Actuators
Control
Propogation Velocity
Growth Rate
Direction
Source
Identification
Sensor Measurement
Sensor Measurement
Source 1
Source 2
Source 3
time
0
1
2
3
4

Objectives

Source Definition

Signal recorded by the sensor due a single physical disturbance source.



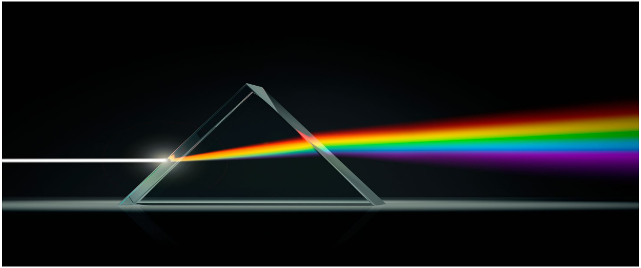
Cocktail-Party Problem

Image source:
https://www.sciencenews.org/blog/science-ticker/3-d-printed-device-cracks-cocktail-party-problem

[Cherry, 1953],[Haykin & Chen, 2005].

Blind Source Separation



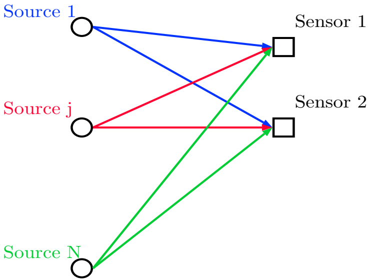
▸ Image sources

The decoupling of unknown signals that have been mixed in an unknown way

Degenerate Mixtures (More sources than mixtures)

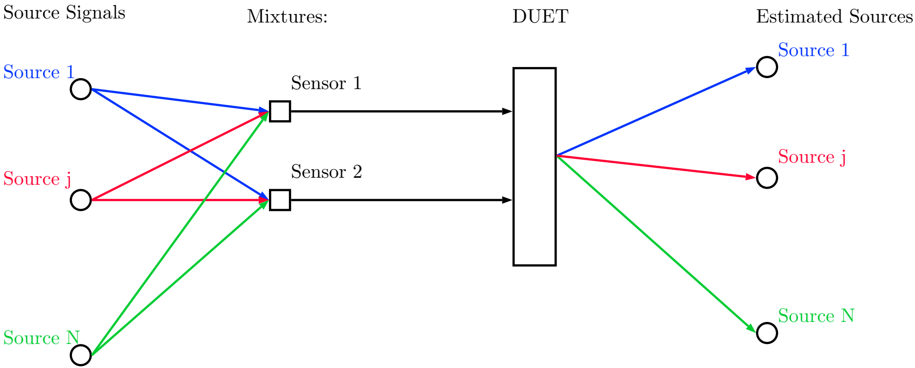
Source Signals

Mixtures:



DUET -Degenerate Unmixing Estimation Technique
[Rickard 2007]

Degenerate Mixtures (More sources than mixtures)

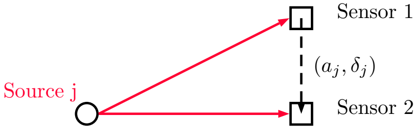


DUET -Degenerate Unmixing Estimation Technique
[Rickard 2007]

DUET Assumptions

Anechoic mixing model

$$x_1(t) = \sum_{j=1}^{N_s} s_j(t)$$
$$x_2(t) = \sum_{j=1}^{N_s} a_j s_j(t - \delta_j)$$



Windowed-disjoint orthogonality

$$\hat{s}_j(\tau, \omega)\hat{s}_k(\tau, \omega) = 0, \quad \forall \tau, \omega, j \neq k.$$

$$\hat{s}_j(\tau, \omega) = F^W[s_j](\tau, \omega) = \frac{1}{2\pi}\int_{-\infty}^{\infty} W(t-\tau)s_j(t)e^{-i\omega t}dt.$$

DUET Assumptions

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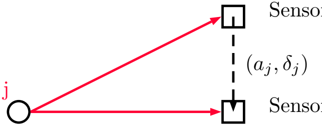
Source j



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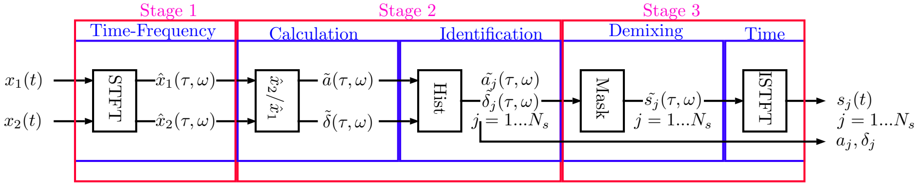
DUET Algorithm



Numerical Study: Linear Stability Model of Measurement

$$x_i = \sum_{j=1}^{N_s} s_{ij}, \quad i = 1, 2, ...N_x \, .$$

The source s_j recorded by sensor x_i is denoted by $s_{ij} \equiv \left[s_j\right]_{x_i}$.

TS wave sources

$$s_{ij} = |\tilde{q}_j([l_y]_{x_i})| e^{-\alpha_{im_j}([l_x]_{x_i} - [l_x]_{s_j})} cos(-\omega_j t + \phi_{t_{ij}}),$$

$$\phi_{t_{ij}} = \alpha_{r_j}([l_x]_{x_i} - [l_x]_{s_j}) + \beta_j([l_z]_{x_i} - [l_z]_{s_j}) + \phi_j([l_y]_{x_i}) + \phi_{t_{0j}}.$$

WP sources

$$s_{ij} = A_{j,[l_y]_{x_i}} \Re \left\{ \sum_{\omega_n=\omega_0}^{\omega_N} \sum_{\beta_k=\beta_0}^{\beta_M} \exp\left\{ i \left[\alpha_{x_{s_j},\omega_n,\beta_k} \left([l_x]_{x_i} - [l_x]_{s_j} \right) + \beta_k [l_z]_{x_i} - \omega_n t \right] \right\} \right\}.$$

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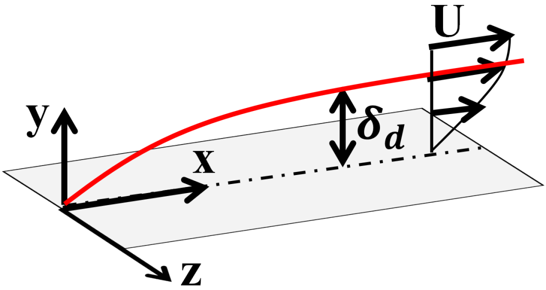
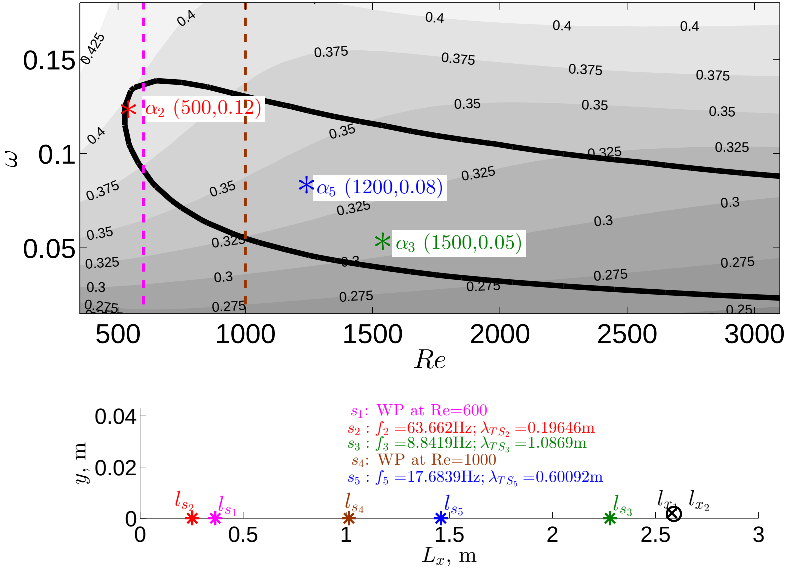
Numerical Study: Blasius Flow

Simulation settings:

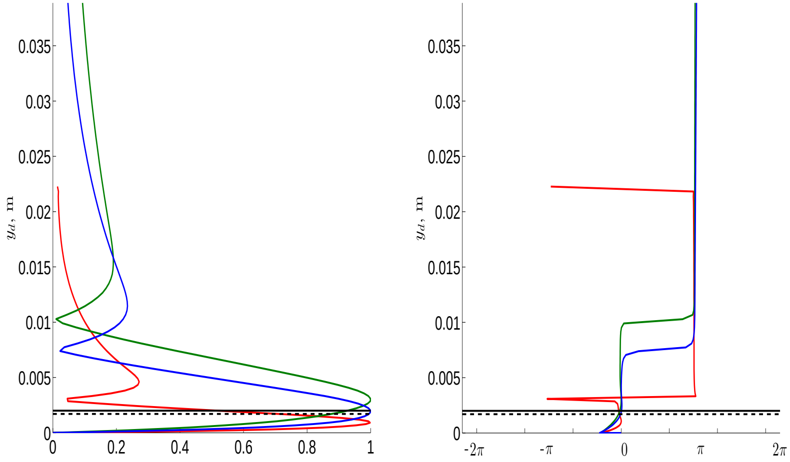
- 2D disturbances
- Spatial case with (complex α and real ω)
- Kinematic viscosity of air ($\nu = 0.15 \cdot 10^{-4}$ m^2/s)
- U=5 m/s



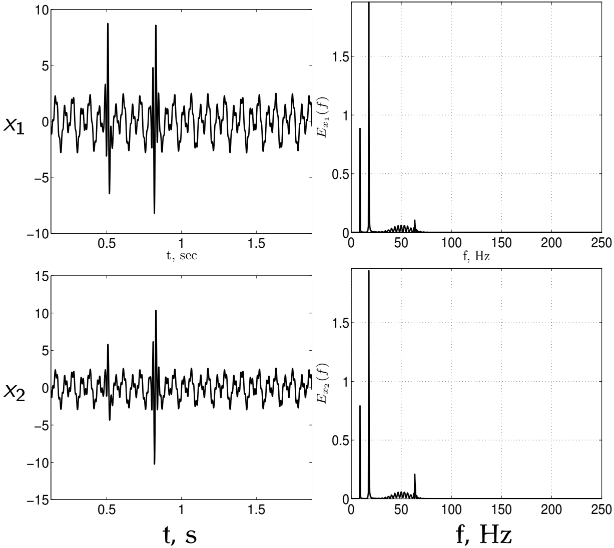
Numerical Study: Blasius Flow



Numerical Study: Blasius Flow



Numerical Study: Simulated Mixtures



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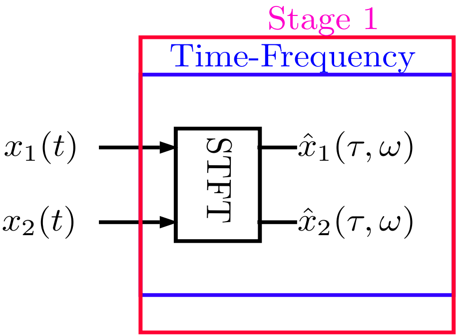

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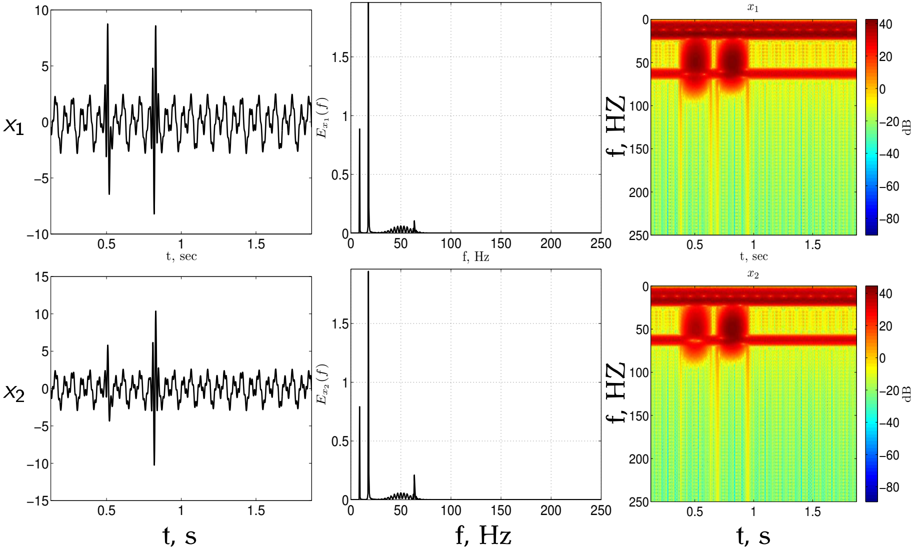
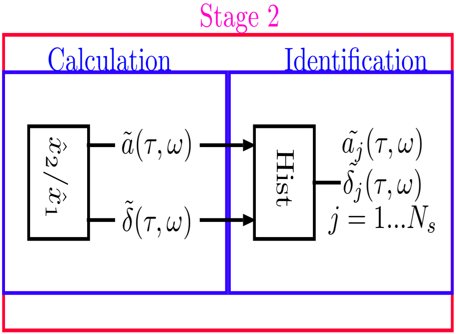


Numerical Study- Identification by DUET



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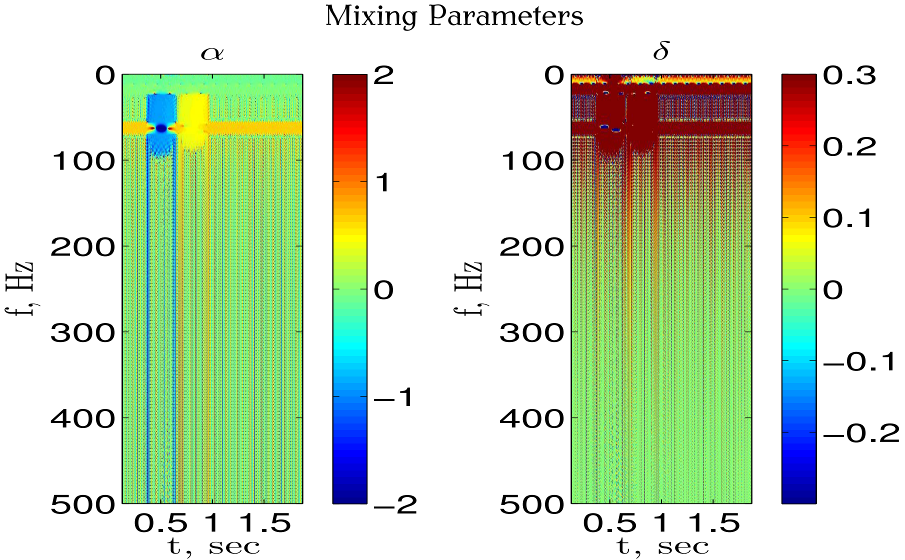
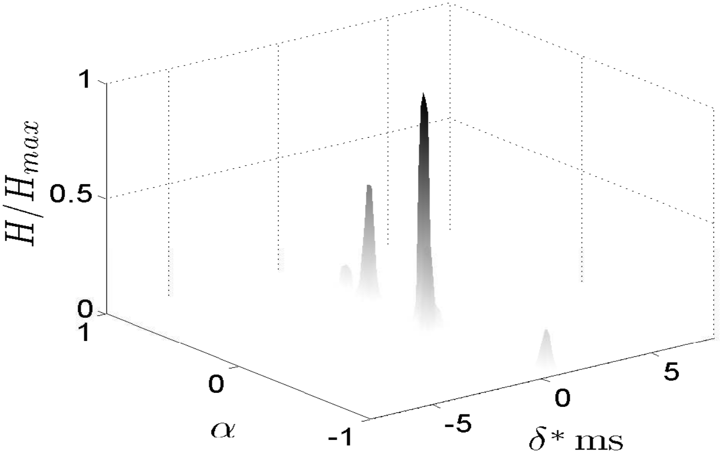


Numerical Study- Identification by DUET

DUET Histogram

$$H(\alpha,\delta) := \iint_{(\tau,\omega)\in I(\alpha,\delta)} |\hat{x}_1(\tau,\omega)\hat{x}_2(\tau,\omega)|^p \omega^q d\tau d\omega.$$



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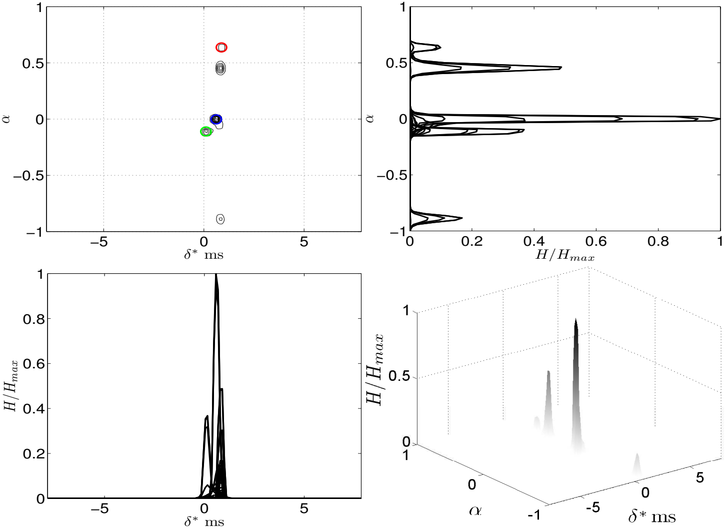
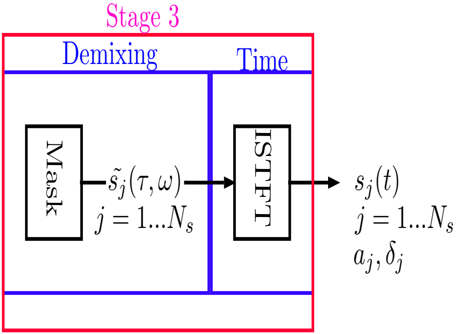


Numerical Study: Estimated sources



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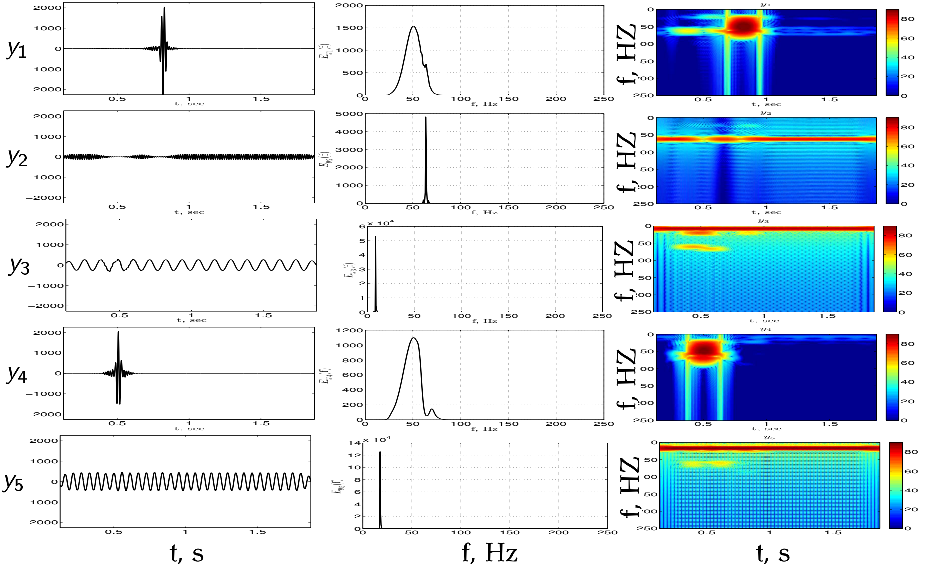
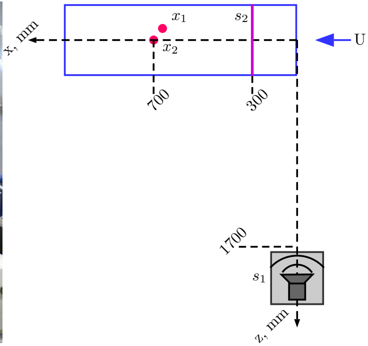


Experimental Study: Experimental Setup



s_1: 60 Hz by the loudspeaker.
s_2: short pulse (50 ms) into an SDBD plasma actuator; L_{s_2}=0.3 m.
U=4.2 m/s.
x_1, x_2: 1 KHz sample rate. L_{x_1}=0.775 m; L_{x_2}=0.8 m; (40 mm spanwise).

Experimental Study: Measured Mixtures

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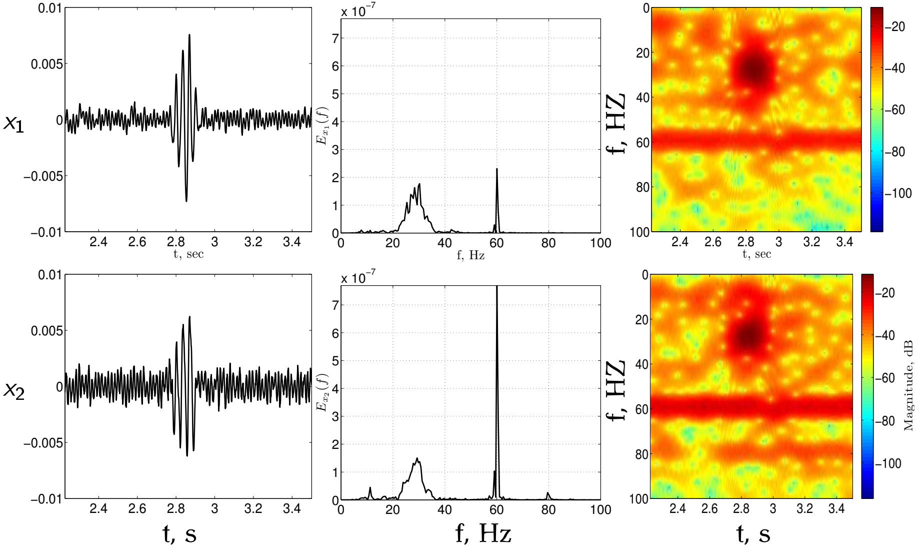
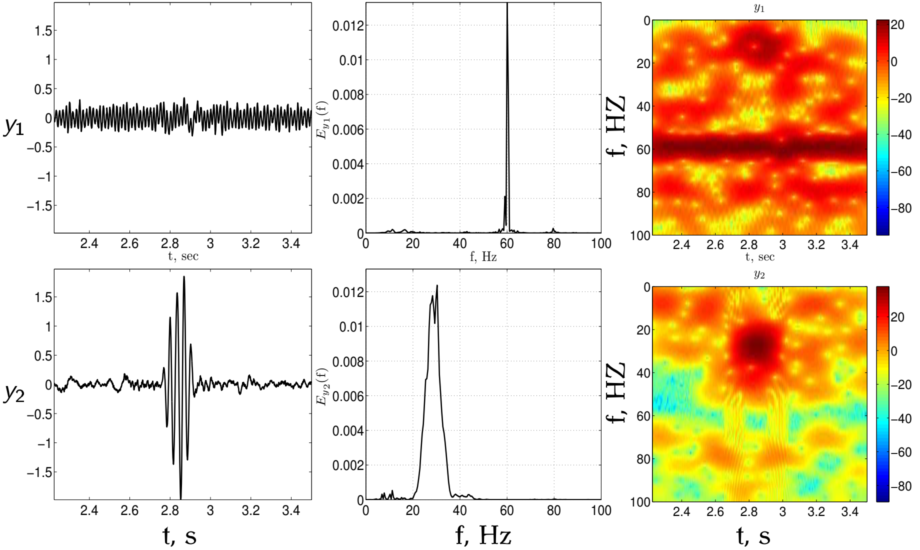
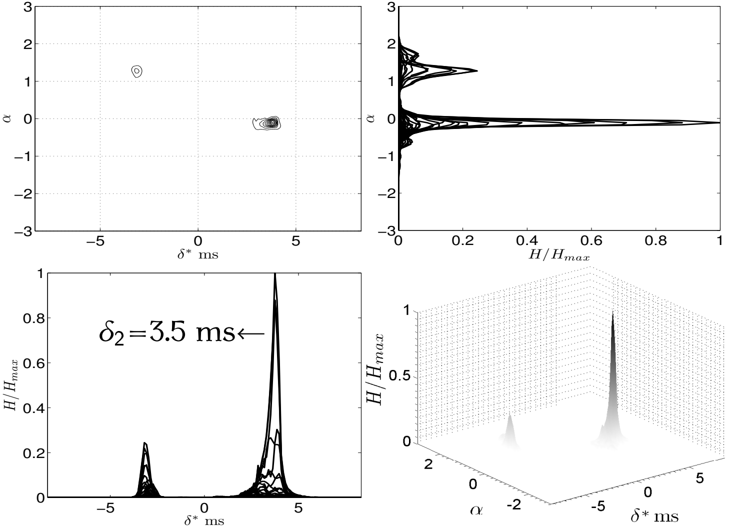


Experimental Study: Estimated sources



Experimental Study: DUET Histogram



$$c_g = \Delta L_x/\delta_2 = 1.43\ m/s = 0.36U$$

leading edge: 0.44U; trailing edge: 0.36U. [Gaster, 1975]

Summary

- Flow state formulated in terms of mixture of sources.
- Sources identified in boundary layer measurements by using DUET.
- DUET can blindly discover any number of sources by using only two sensors.
- Method demonstrated numerically and experimentally.

The End (17:10)

Acknowledgments

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Simon Dolev, Oleg Borochovich

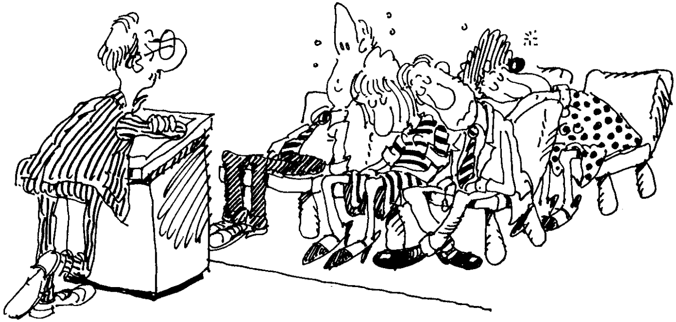

Image source: `http://www.michaelmccurry.net/wp-content/uploads/2010/02/speaker-is-boring.gif`

References

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- S. Haykin and Z. Chen, The cocktail party problem, *Neural Computation*, vol. 17, pp. 1875-1902, Sep 2005.
- Gaster, M., A theoretical model of a wave packet in the boundary layer on a flat plate, *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*. Vol. 347. No. 1649. The Royal Society, 1975.
- Rickard, S., The DUET blind source separation algorithm, *Blind Speech Separation* (2007): 217-237.

BSS-Mathematical framework

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$$x_m(t) = \sum_{n=1}^{N} \sum_{k=0}^{K-1} a_{mnk} s(t-k) + v_m(t), \quad (1)$$

In vector-matrix form, the convolutive model can be written as:

$$\mathbf{x}(t) = \sum_{k=0}^{k-1} \mathbf{A}_k \mathbf{s}(t-k) + \mathbf{v}(t), \quad (2)$$

where,

t- Discrete time index.

$\mathbf{s}(t) = [s_1(t), \ldots s_N(t)]^T$- Source signals.

$\mathbf{x}(t) = [x_1(t), \ldots x_M(t)]^T$- Acquired signals.

$\mathbf{v}(t) = [v_1(t), \ldots v_M(t)]^T$- Sensor noise.

a_{mnk}- Mixing filter coefficients, where $k < \infty$.

$\mathbf{A}_k$- $M \times N$ matrix which contains the k'th filter coefficients.

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1. http://ichef.bbci.co.uk/food/ic/food_16x9_506/recipes/easy_chocolate_cake_31070_16x9.jpg
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