

# Exploiting Diversity and Specialization in Intelligent Systems via Adaptive Combination

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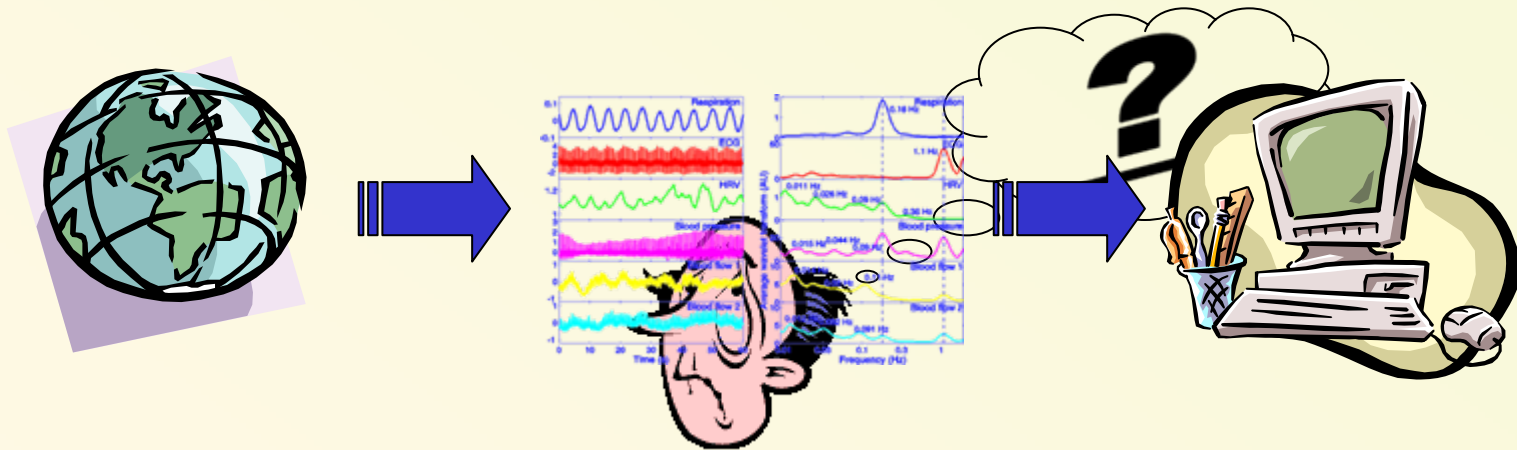
# Outline

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1. Learning from Data
2. Batch vs Sequential Supervised Learning
3. Combination methods in Batch Learning
4. Improving performance in Adaptive Systems via Adaptive Combination
5. Selected Examples
  - Echo cancellation
  - Blind Adaptive Equalization
6. Conclusions and expected future research

# Learning from Data

Aim: To extract information contained (in a not obvious way) in noisy data or signals



Typical Learning Tasks:

- Supervised (Regression, Classification)
- Unsupervised (Clustering, Novelty Detection, Pdf modelling)
- Other (e.g., Collaborative Filtering, Reinforcement Learning)

# Learning from Data (II): Applications

Applications of such Learning Systems are wide, and include, e.g.:

- Text/Video Categorization and Retrieval
- Recommender Systems

• Signal Processing: Equalization, Echo Cancellation, Source Separation, etc. in communication systems (IP telephony, hands-free telephony, ASR)

• Radar detection, array beamforming, soil classification, music genre

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# Learning from Data (III)

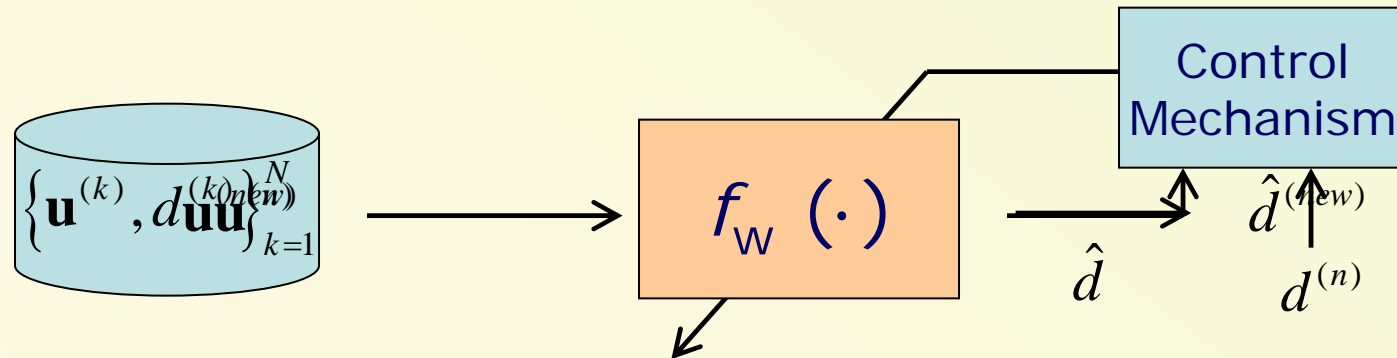
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Keypoints:

- Increasing accessibility to data in digital format (including Internet, companies databases ...)
- Cheaper HW (storage, processing, sensing)
- No statistical information required

The bottom line is “Data is everywhere and we now have the necessary resources (algorithms and hardware) to extract and exploit the information they contain)”

# Batch vs Sequential Supervised Learning



## Batch Learning:

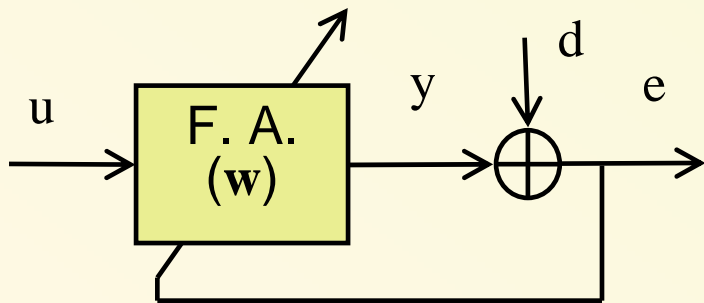
- Training Phase: Available data is used to adjust the weights and free parameters of the system
- Operation Phase: Target values are predicted for new (unseen data)

## Sequential Learning:

- Training examples become available over time  $\{\mathbf{u}^{(n)}, d^{(n)}\}$ , and the system is adapted one sample at a time
- Adaptivity: The system can forget old samples
- Typically, computationally more attractive than batch learning

# Adaptive Signal Filtering

- Systems that carry out transformations on some input signal to optimize some performance goal (typically, squared error)



- If the statistics were known, an optimum filter could be design

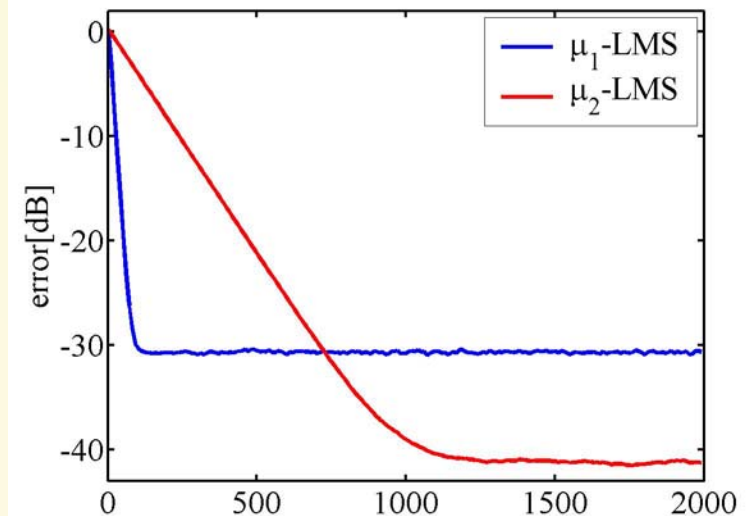
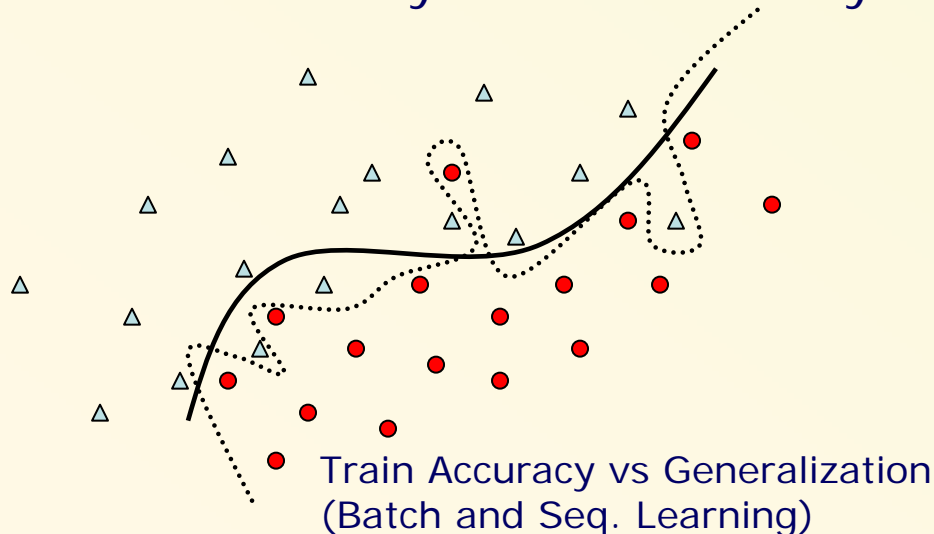
- When this is not the case, or in time varying situations, we can recur to **ADAPTIVE SCHEMES**

- Traditionally, SW and HW constraints (e.g., energy consumption) limited these systems to linear structures and simple algorithms
- Modern Digital Signal Processing (DSP) tools include
  - Powerful algorithms: Particle Filters, Extended Kalman Filter (EKF), Set-Membership Methods ...
  - Non-linear structures: Kernel AF, Volterra Series, ...

# Limitations and Compromises

When designing and applying learning algorithms (both batch and sequential), it is necessary to be aware of several related, and some times conflicting, issues:

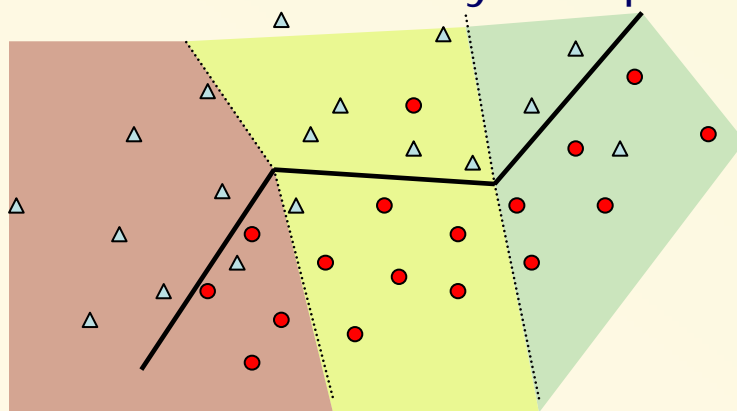
- Difficulty of the learning task
- Expressiveness of the method
- Generalization properties
- Availability of data / Memory
- Algorithm complexity
- Convergence + Tracking
- Accurateness of the solution



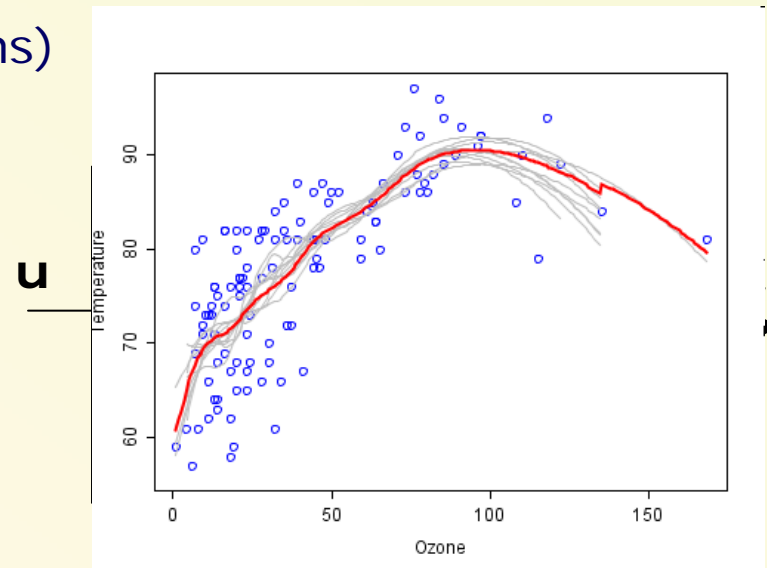
# Exploiting diversity + Specialization

Combination methods have been exploited mostly under the batch learning paradigm. By inducing **diversity** and/or **specialization** among several component networks, the obtained solutions:

- Provide superior performance
- Are conceptually simpler
- Are computationally more affordable (besides distributed implementations)
- Can be more easily interpreted



Exploiting Specialization



Exploiting Diversity

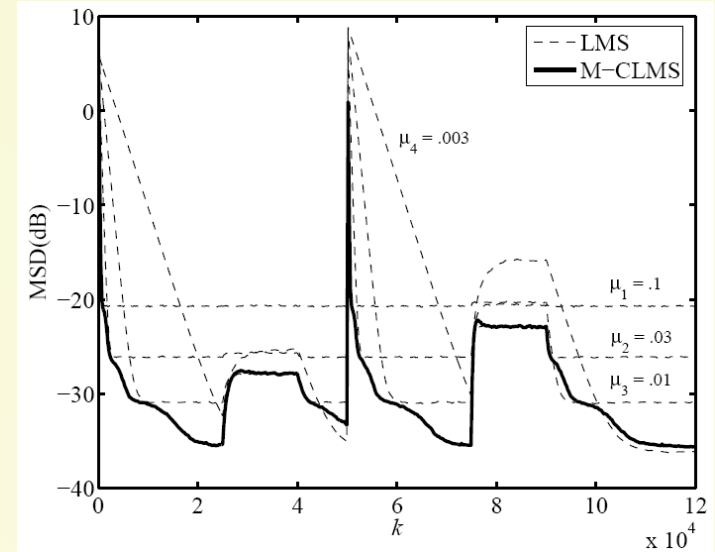
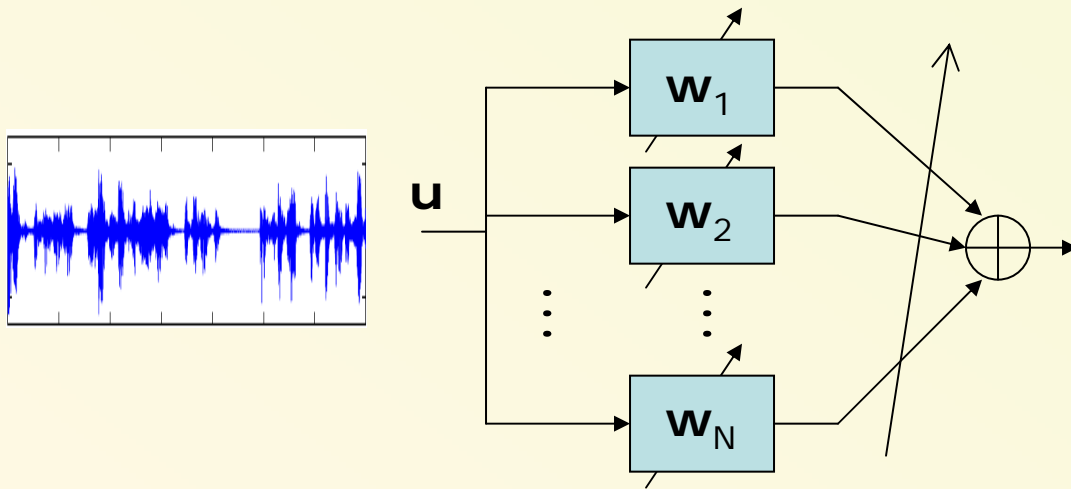
# Some Milestones

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(1990)	R. Schapire: Boosting
(1991)	R. Jacobs et al.: Mixtures of Experts
(1995)	Y. Freund and R. Schapire: Adaboost
(1996)	L. Breiman: Bagging
(2001-2010)	Multi-Classifer Systems Workshop

- Combination methods have been applied to improve the performance of most batch learning methods (NNs, Regression and Classification Trees, SVMs, etc), and in many different applications
- However, apart from the study of some general principles under the sequential learning approach, their application to Adaptive Filtering of signals has mostly been considered over the last five years
- Operation principles are probably sufficiently general to be exported to other engineering fields

# Exploiting diversity + Specialization in Adaptive Systems



- The performance of AF is typically affected by the selection of free parameters, whose optimal selection would require certain knowledge about the filtering scenario
- Working principles are simple: select complementary components (specialization) and update combination parameters to optimize some overall performance goal

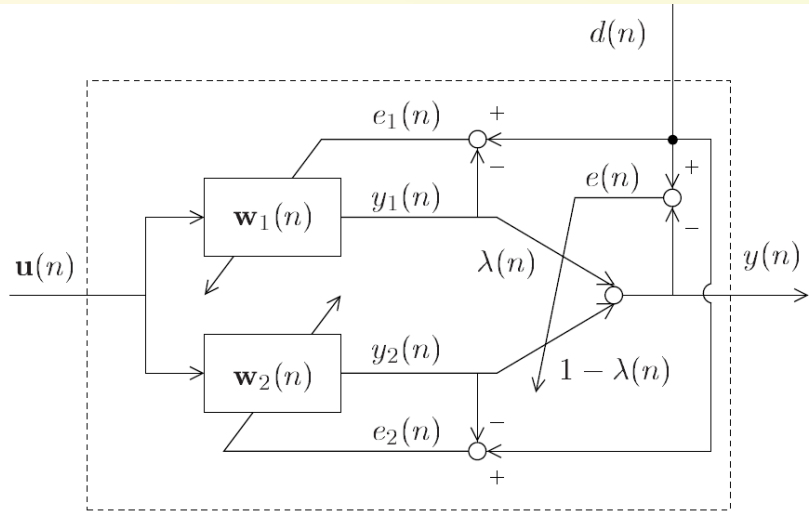
(Singer and Erdogan, 1998)

Model Selection

(Martínez-Ramón et al., 2002)

Speed vs precision (biological inspiration)

# Basic convex combination of two filters



- Component filters are independently adapted according to their own rules and error signals

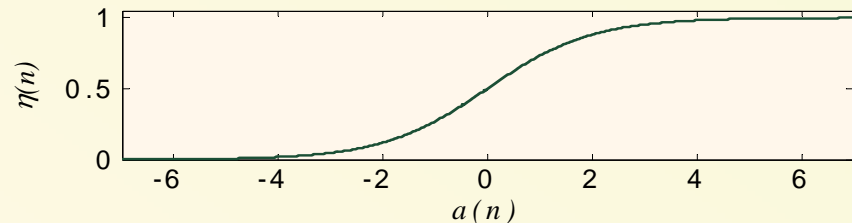
$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mathbf{f}_i[\mathbf{w}(n), \mathbf{u}(n), d(n), \mathbf{q}_i(n)]$$

- Combination output is obtained as

$$y(n) = \lambda(n)y_1(n) + [1 - \lambda(n)]y_2(n)$$

- For the convex combination case  $\lambda(n) \in [0, 1]$ , it is convenient to define

$$\lambda(n) = \text{sigm}[a(n)] = \frac{1}{1 + \exp^{-a(n)}}$$



- Mixing parameter is adapted to minimize overall error, e.g.,:

$$a(n+1) = a(n) - \mu_a \frac{\partial e^2(n)}{\partial a(n)}$$

# Theoretical results (Arenas et al., 2006)

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It can be shown that, if properly designed, the combination will be operating in one of the following two regimes

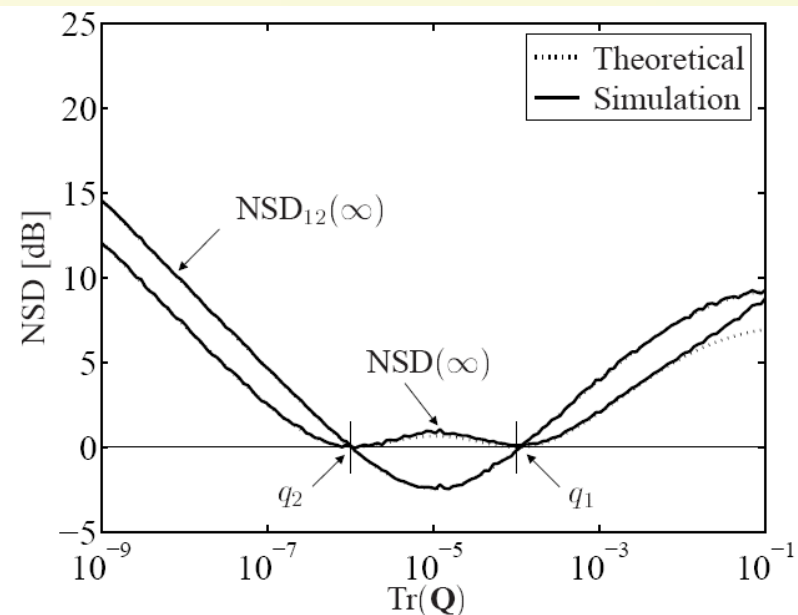
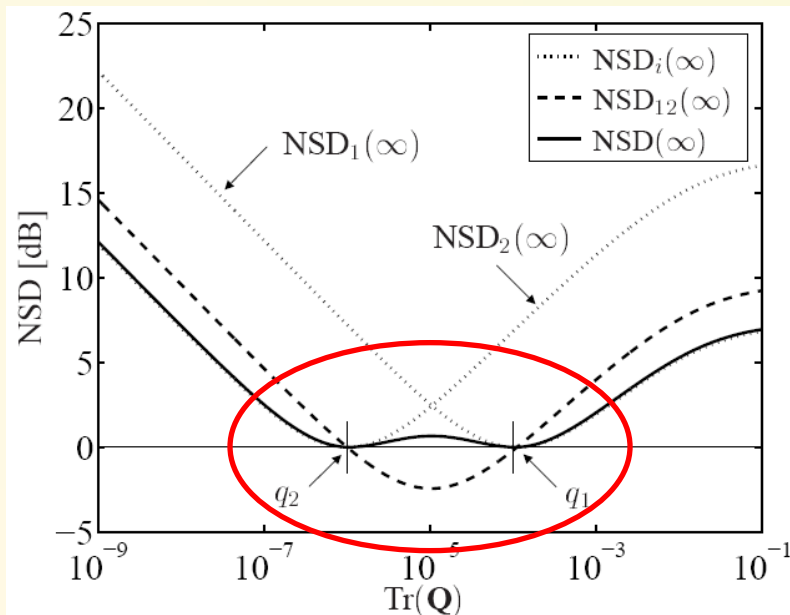
- CASE 1: when the cross-correlation between filter errors is in between mean square errors, then the combination performs like the best operating filter (specialization)
- CASE 2: when the cross-correlation between filter errors is smaller than mean square errors, then the combination outperforms both component filters (diversity)

This “better-than-universal” behavior appears, e.g.,

- In tracking situations with fast and slow filters
- When combining heterogeneous filters (e.g., LMS and RLS)
- Combinations of proportionate filters with different asymmetry factors (echo cancellation applications)
- ?

# Theoretical results (II)

For instance, when combining filters with different memories, the following behavior is observed in a tracking situation (the optimal solution continuously changes with speed  $\text{Tr}(\mathbf{Q})$ ):



# Combination Methods + Analysis

(Kozat and Singer, 2000)	Unconstrained combination of M filters
(Arenas-García et al., 2006)	Convex combination of 2 filters
(Arenas-García et al., 2005)	Convex combination of M filters
(Bershad et al., 2008)	Affine combination of 2 filters
(Azpicueta-Ruiz et al., 2008)	Normalized convex combination of 2 filters
(Nascimento and Silva, 2008)	Tracking analysis of convex combinations
(Arenas-García et al., 2009)	Block-based combination of M filters
(Nascimento et al., 2010)	Convergence analysis
(Kozat et al., 2010)	Steady-state analysis (unifying framework)

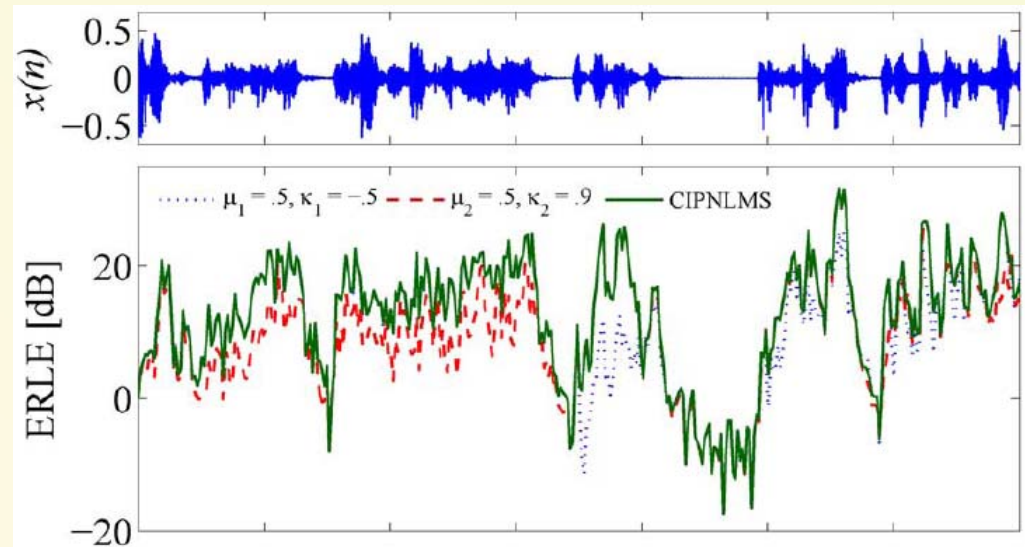
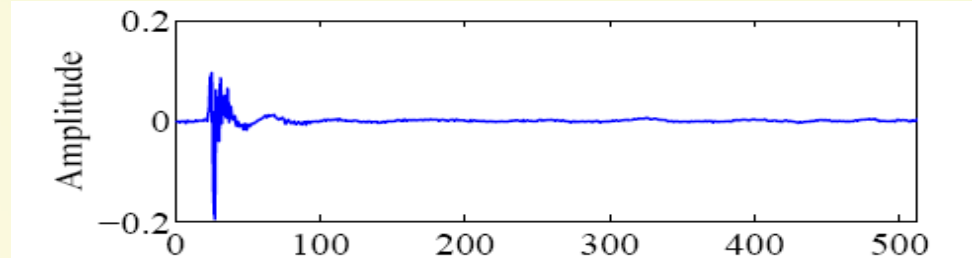
Adaptive Filtering issues that have already been tackled with “general purpose” combinations schemes:

- Model Selection
- Convergence vs steady-state error tradeoff
- Tracking capabilities
- Robustness to non-Gaussian noise
- Stability

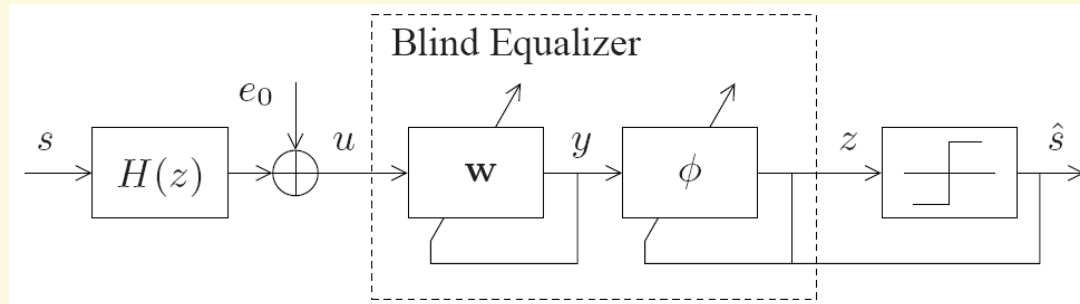
# Selected examples: acoustic echo cancellation

In the context of echo cancellation, combinations have been applied to:

- Improve robustness to unknown or varying SNR
- Improve the identification of sparse channels
- Managing the linear-non-linear cancellation trade-off with Volterra Filters
- Learning the size of Volterra kernels in non-linear echo cancellation

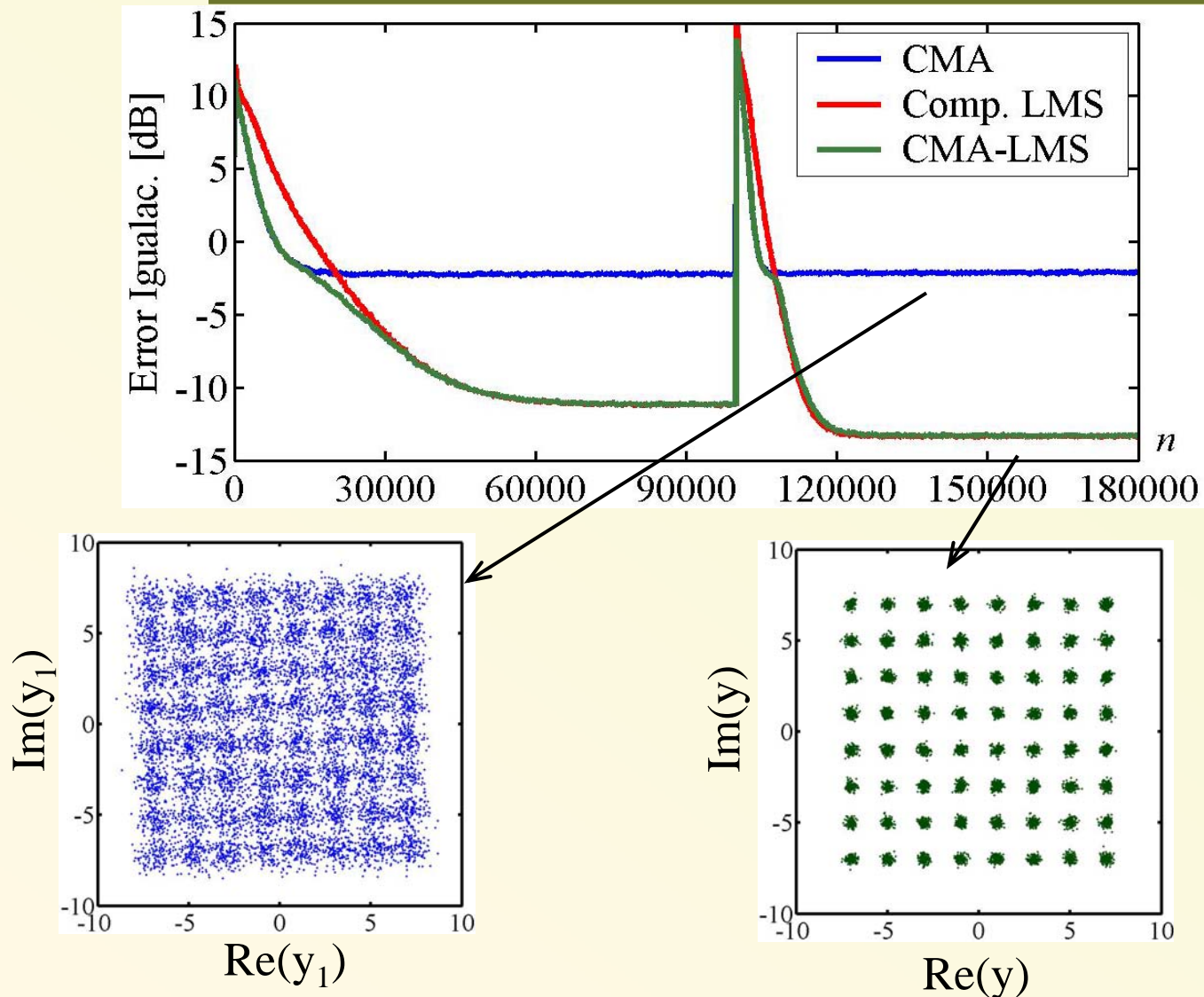


# Selected examples: blind equalization



- Essentially a classification problem (which symbol was transmitted?)
- The goal of the equalizer is to compensate the distortion introduced by the channel
- Supervised Adaptive Filters can be applied, but require a training sequence to converge
- Blind Adaptive Filters do not need such sequence, thus saving wideband; on the downside, they incur in larger steady-state error
- Running both kinds of algorithms in parallel and combining their outputs allow no training sequence + accurate solution

# Selected examples: blind equalization (II)



# Conclusions: Advantages of the approach

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We have presented a general approach to improve the properties of virtually any Adaptive Filter or Sequential Learning Scheme:

- No assumptions are imposed on the component filters. Conceptually very simple
- Completely general  
(although “ad hoc” combination strategies can be derived for particular applications)
- “Better than universal” performance is possible
- An effective approach to fight against the lack of knowledge about the learning task

The approach exploits a very general principle:

“Adaptively combining complementary (specialized) and diverse solutions can lead to improved solutions in an easy way”

# Conclusions: Next results in AF

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Some guesses on what we will see in the near future in Adaptive Filtering:

- Studying combinations based on new algorithmic components, and new combination rules
- Incorporation into other DSP applications
- Enforcing low-correlation among components by design
- Fight other performance trade-offs:
  - Topology selection (e.g., kernel or kernel parameter selection in Kernel Adaptive Filtering, active learning)
  - Generalization control in non-linear adaptive filtering
  - Semi-supervised learning
- Implementation in distributed scenarios (sensor networks)

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Thank you



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