How to Swallow a Mouthful of Data and Avoid Indigestion

Barry M. Wise, Ph.D.
President
Eigenvector Research, Inc.

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Outline

- The process monitoring data problem
- Example data set
- Approaches to preprocessing
  - Variable means
  - Warping for multi-way
  - Data summary
- Comparison of results
- Conclusions

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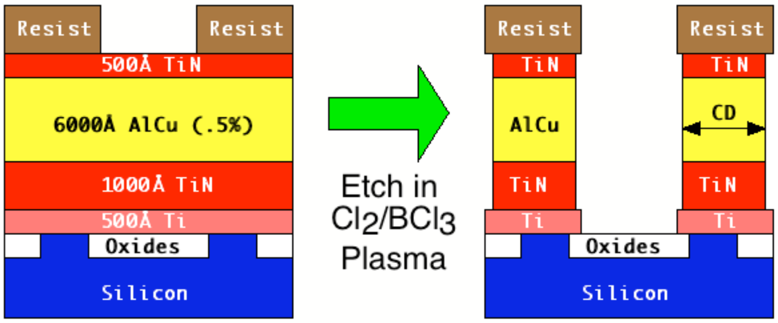
Plasma Metal Etch



- Linewidth (Critical Dimension) Control
  - Constant linewidth reduction run to run and across wafer
  - Constant linewidth reduction for every material in stack
- Minimal damage to oxide

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Metal Etch Data Set

This data has been used many times and is available at www.eigenvector.com. A few examples:

- Barna, G.G., White, D., Wise, B.M., Gallagher, N.B., Sofge, D., “Development of Robust Fault Detection and Classification Techniques/SEMATECH J-88E Project at TI”, SEMATECH AEC/APC Workshop VIII, Santa Fe, New Mexico, Oct. 27-30, 1996.
- White, D., Barna, G.G., Butler, S.W., Wise B., and Gallagher, N., "Methodology for Robust and Sensitive Fault Detection," Electrochemical Society Meeting, Montreal, May, 1997.
- Gallagher, N.B.,Wise, B.M., Butler, S.W., White, D., and Barna, G.G., "Development and Benchmarking of Multivariate Statistical Process Control Tools for a Semiconductor Etch Process: Improving Robustness Through Model Updating", IFAC ADCHEM'97, Banff, Canada, 78–83, June, 1997.
- Wise, B.M., Gallagher, N.B., Butler, S.W., White, D., and Barna, G.G., "A Comparison of Principal Components Analysis, Multi-way Principal Components Analysis, Tri-linear Decomposition and Parallel Factor Analysis for Fault Detection in a Semiconductor Etch Process," *J. Chemometr.*, **13**, 379–396 (1999).
- Wise, B.M., Gallagher, N.B., Butler, S.W., White, D., and Barna, G.G., "Development and Benchmarking of Multivariate Statistical Process Control Tools for a Semiconductor Etch Process: Impact of Measurement Selection and Data Treatment on Sensitivity", IFAC SAFEPROCESS'97, 35–42, Kingston Upon Hull, U.K., Aug., 1997.
- Wise, B.M., Gallagher, N.B., and Martin, E.B., “Application of PARAFAC2 to Fault Detection and Diagnosis in Semiconductor Etch,” *J. Chemometr.*, **15**(4), 285–298 (2001).
- Wise, B.M., Gallagher, N.B., "Multi-way Analysis in Process Monitoring and Modeling," *AIChE Symposium Series*, **93**(316), 271–274 (1997).
- Warren, J. and Gallagher, N.B., “Heuristic and Statistical Methods for Fault Detection: Complementary or Competing Approaches?”, SEMATECH AEC/APC Symposium XVIII, Westminster, CO, Sept. 30-Oct. 5 (2006).

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Available Measurements

- Equipment has SECS-II Port
  - Provides traces with time stamp and step number
- Regulatory controller setpoints & controlled variable measured values
  - gas flows, pressure, plasma powers
- Regulatory controller manipulated variables
  - exhaust throttle valve, capacitors
  - mass flow controller do not provide valve position
- Additional process measurements
  - endpoint intensity (plasma emission at particular frequency)
  - impedance measurements
- ~~Optical emission spectra~~
- ~~RF plasma variables~~

Sensitivity of MSPC Models

- Three experiments performed with 21 “induced” faults on:
  - TCP top power
  - RF bottom power
  - Cl2 flow
  - BCl3 flow
  - Chamber pressure
  - Helium chuck pressure
- Goal: Compare ability of models considered for detecting faults

Global and Local Models

- Global models based on data over long period of time with considerable variance due to drift
- Local models build over narrower time windows, less drift variance

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Generating Faults

- Setpoints were changed for controlled process variables
- Data for the controlled variable was adjusted to have the original desired mean
- Result is data that looks like a sensor has developed a bias

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Batch Process Monitoring Data Problem

- Messy-typically includes start-up and shut-down phases that are not of interest
- Periods of “steady-state” where not much is changing
- Variable record lengths
- Lots of data!
- Reduce to a set of more compact descriptors?

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Mean of Each Variable over Wafer Processing Time

- Take mean of each variable
- Pros:
  - Easy, conceptually simple
  - Large data reduction
  - No problem with variable record length
- Cons:
  - May miss some types of fault
  - Completely lose time information

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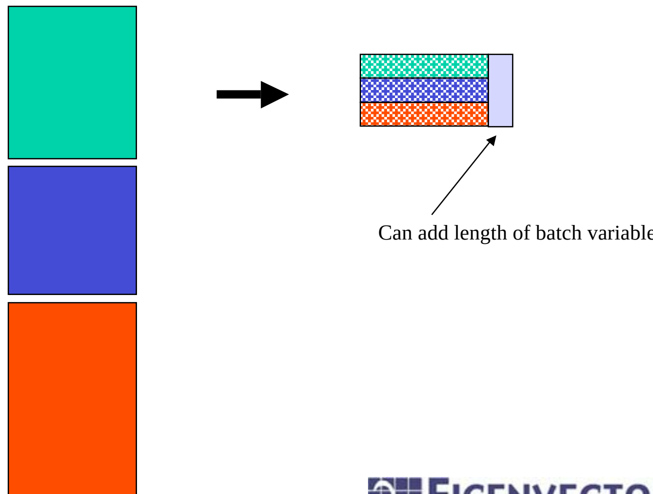
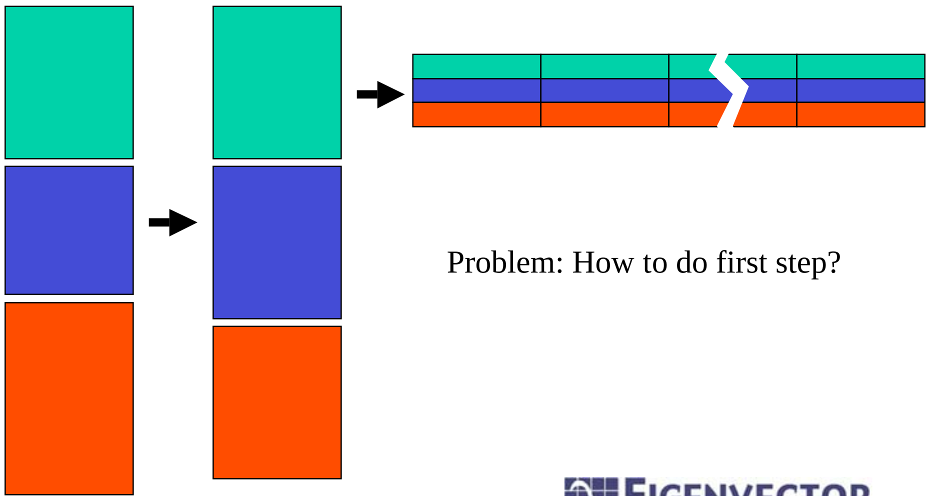
Mean Procedure



Arrangement of Data for Multiway Analysis

- Records must be the same length (except PARAFAC2)
- Requires some combination of alignment, truncation or warping
- Pros
  - Retains time information
- Cons
  - Results in many variables (parsimony problem)
  - Complex preprocessing step, requires interpolation
  - Model interpretation issues

Alignment for Multi-way



Problem: How to do first step?

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Alignment and Warping Methods

- A veritable smorgasbord of methods available
  - Dynamic Time Warping (DTW)
  - Correlation Optimized Warping (COW)
  - Indicator variable/step number
  - Linear interpolation
  - Align and truncate
  - Combinations and variations of the above
  - Etc.

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Correlation Optimized Warping

- Piecewise preprocessing method
- Allows limited changes in segment lengths, controlled by slack parameter
- Linear interpolation over segments
- Dynamic programming used to optimize correlation between warped sample and reference
- Less flexible than DTW (unless constrained)

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COW References

- N.P.V Nielsen, J.M. Carstensen and J. Smedsgaard, "Aligning of single and multiple wavelength chromatographic profiles for chemometric data analysis using correlation optimized warping," *J. Chromatogr. A*, **805**, 17-35, 1998.
- G. Tomasi, F. van den Berg and C. Andersson, "Correlation Optimized Warping and Dynamic Time Warping as Preprocessing Methods for Chromatographic Data," *J. Chemometrics*, **18**, 231-241, 2004.
- G. Tomasi, T. Skov and F. van den Berg, Warping Toolbox, see: http://www.models.life.ku.dk/source/DTW_COW/index.asp

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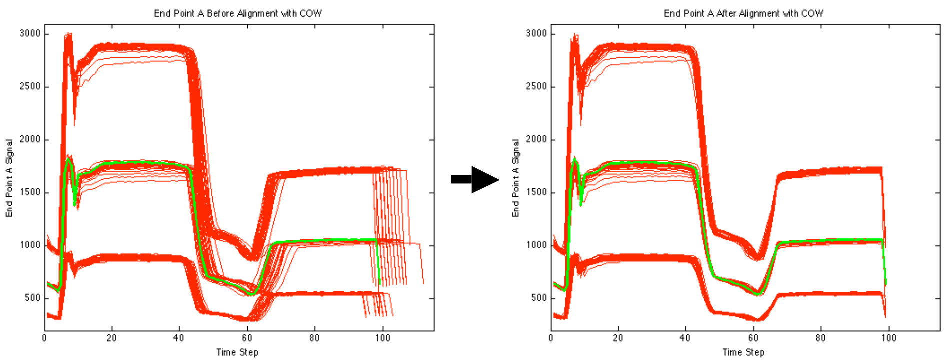
Example: COW

COW breaks signals into segments and linearly expands or contracts them to optimize correlation



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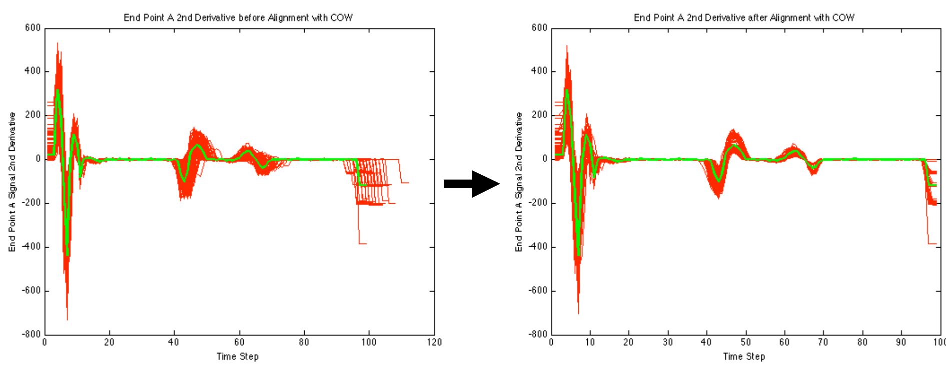
Hints on COW

May be better to calculate warp with 2nd derivative
Apply calculated warp to other variables
Calculate warp on PCA scores or other latent variable



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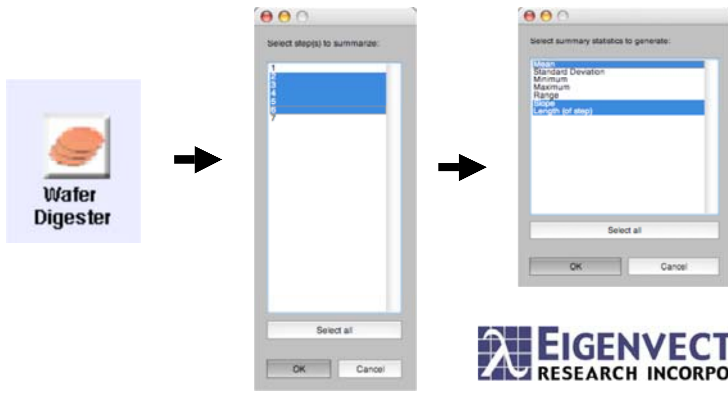
Data Summary Approach

- Convert data into alternate set of descriptors
- If process has multiple steps, calculate parameters that describe each step



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Summary Variables

- Pros
  - Conceptually simple
  - Some time information retained
  - Noise reduction
  - Reduces number of variables (vs. MPCA)
- Cons
  - Further from original data
  - May not have step numbers to work with

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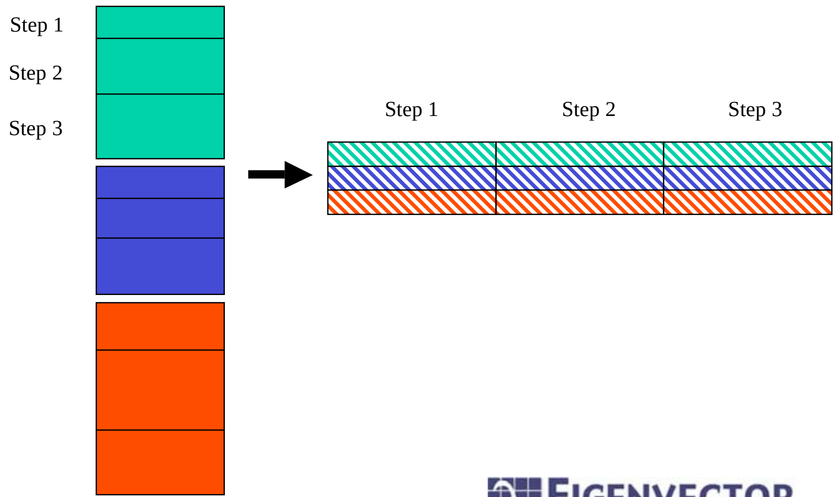
Summary Variables



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Creation of Pseudo-steps

- Break reference process trace into "sensible" segments (manually)
- Assign step numbers
- Warp new data onto reference
- Reverse warp reference step numbers into new data
- Use summary variables

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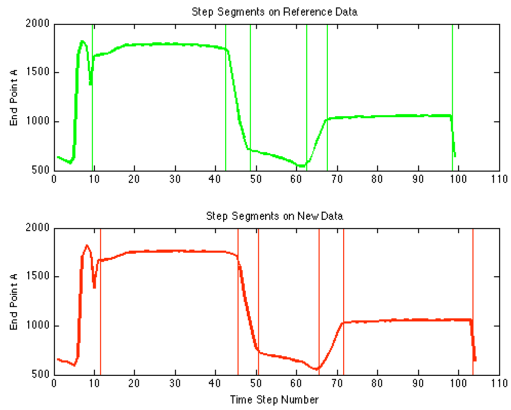
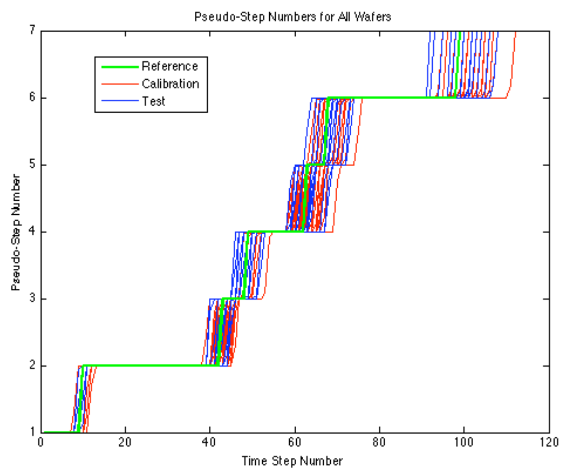
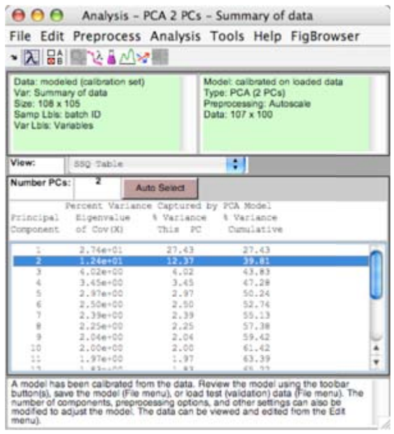
Example of Step Creation

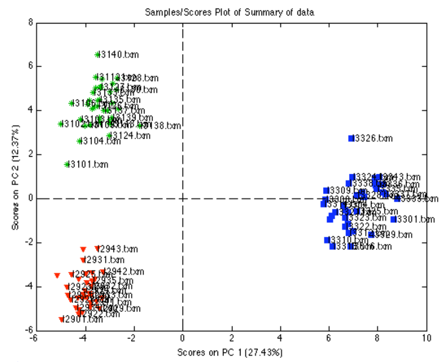


Variation in Step Length



PCA on Summary Variables





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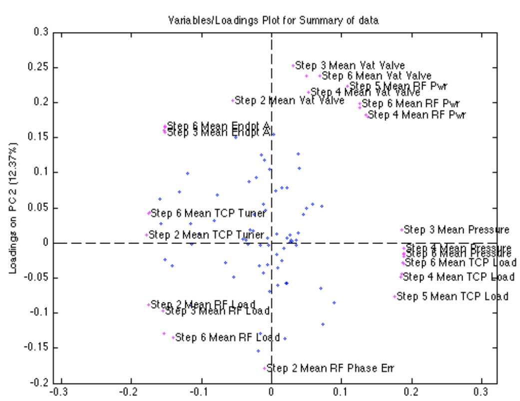
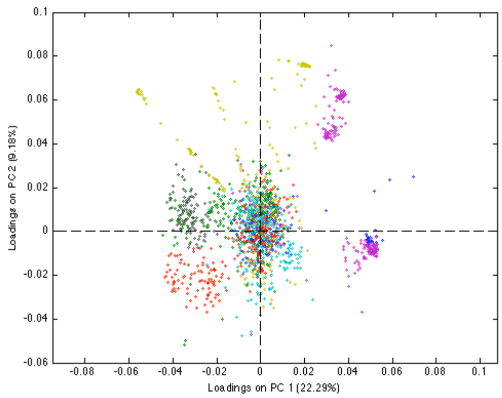
Loadings for PCA Model



Decluttered

Compare to MPCA Loadings



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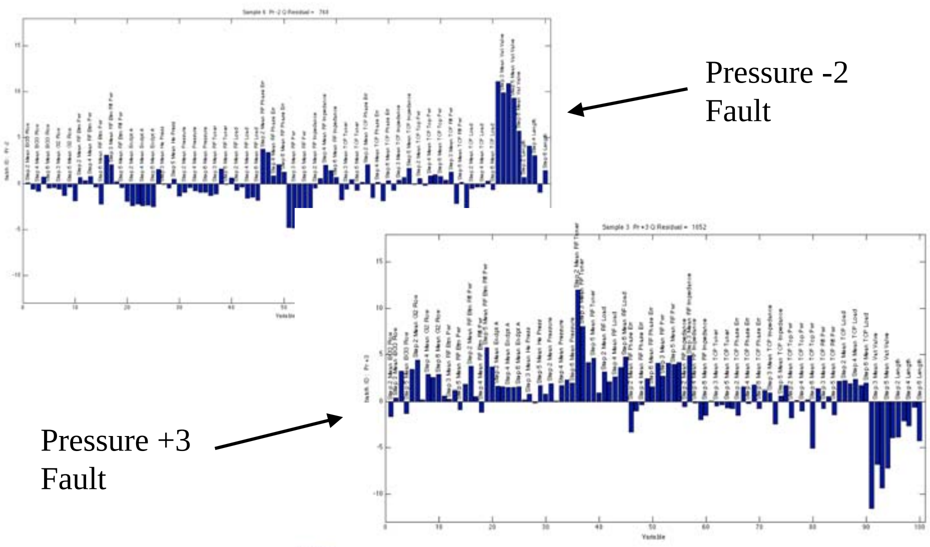
Contribution Plots



Pressure -2 Fault

Pressure +3 Fault

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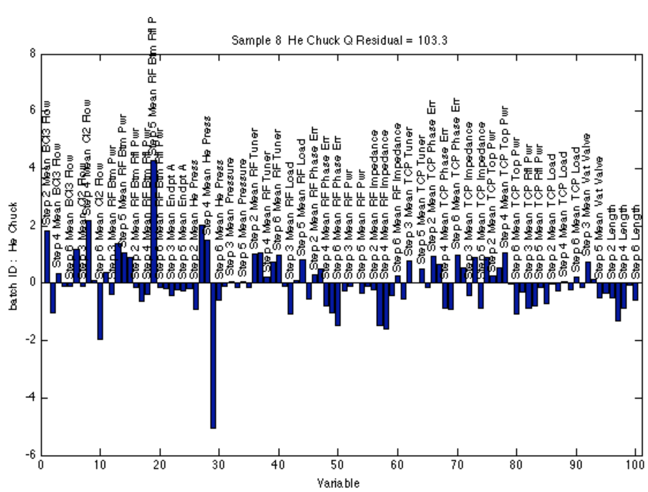
Results

Faults Caught by PCA on Summary Variables Compared with TLD, PARAFAC, MPCA, PCA on the Means and PARAFAC2.

	TLD	PARAFAC	MPCA	PCA/Means	PARAFAC2	Summary
Global	11	12	10	10	7	**14**
Local	14	17	11	16	13	**18**

He Pressure Fault



Summary

- Digestion into summary variables creates smaller, more manageable and interpretable data sets
- Segments can be based on process steps
- Warping techniques such as COW can be used to create pseudo-steps
- Models based on summary variables at least as sensitive as MPCA but easier to work with

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