INFORMS 2005

"DEVELOPMENT OF RECONFIGURABLE AUTOMATED VISUAL INSPECTION SYSTEMS"

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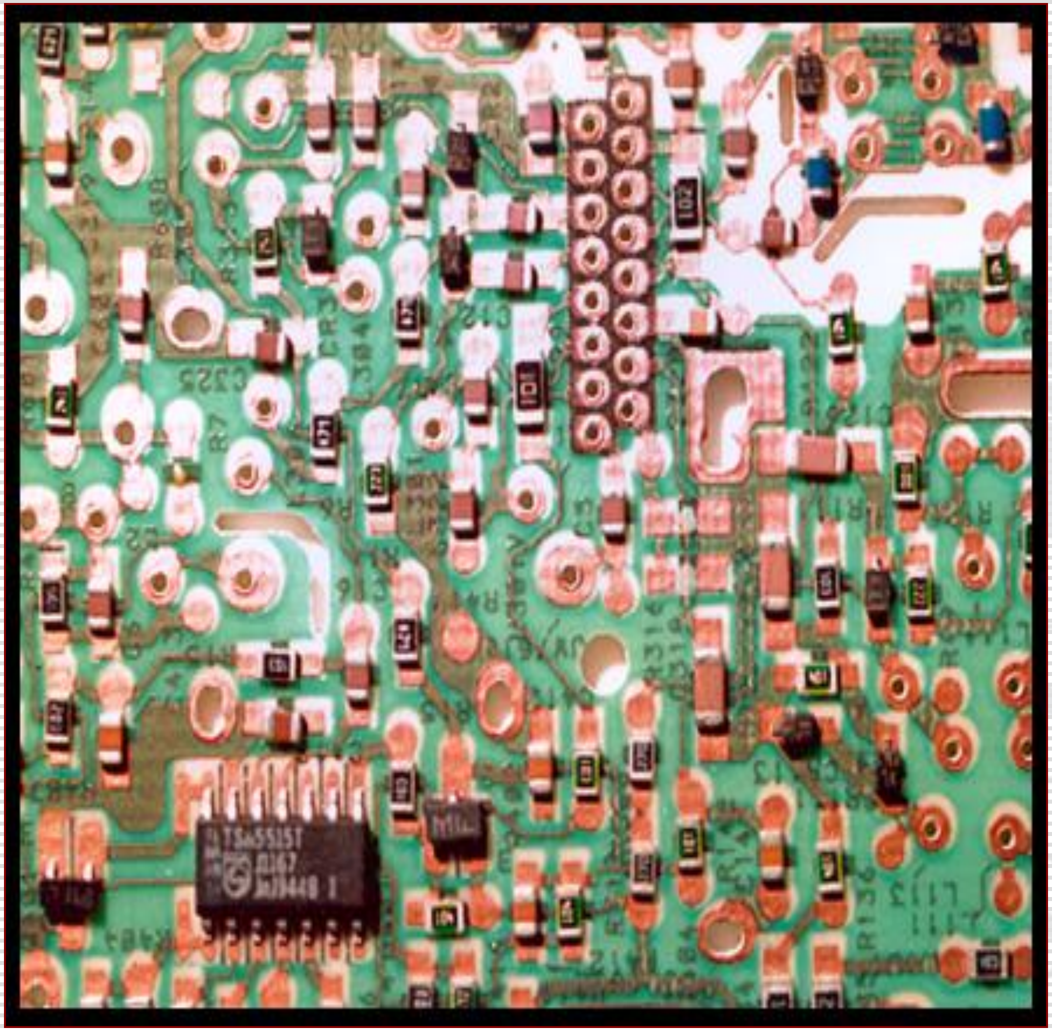
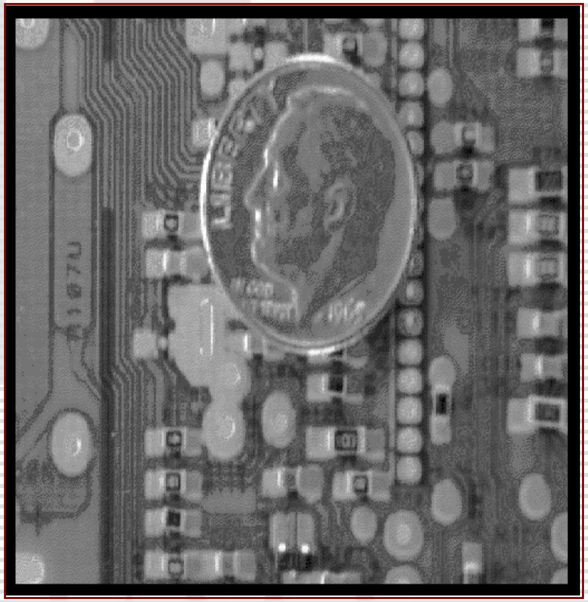
Agenda

- Introduction
- Problem Context
- Envisioned Reconfigurable Environment
- Modules Description
- General Overview of Reconfiguration Methodology
- Conclusion

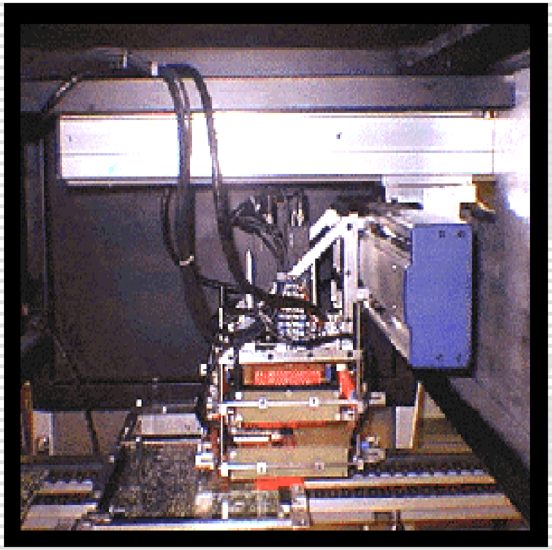
Printed Circuit Board

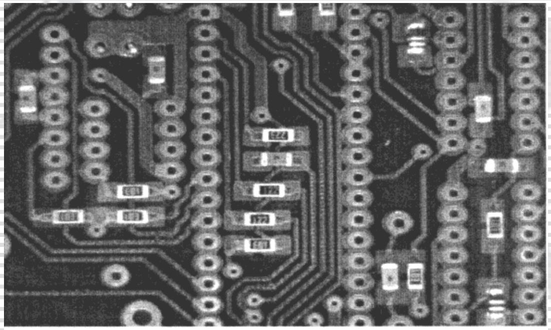




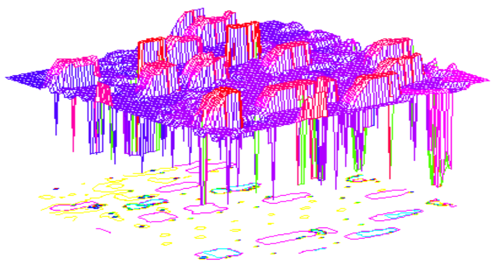
Inspection Systems

2 - D System



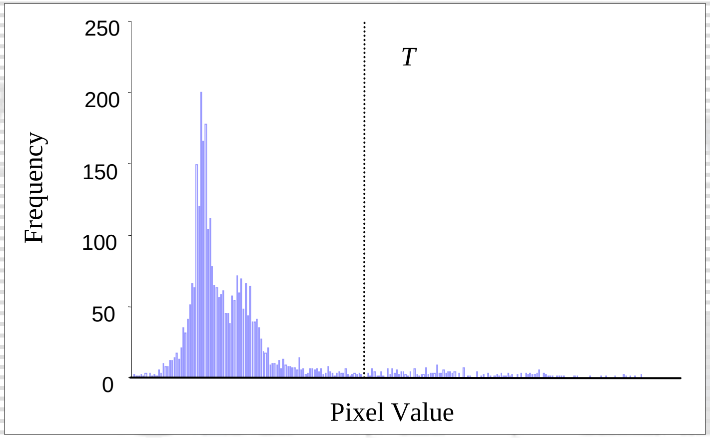


3 - D System

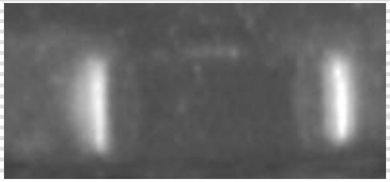


Feature Definition

- A feature in our context is usually a prominent or distinctive characteristic that can be extracted from a digital image of an SMD component.
- Each feature acts as a function whose domain is the digital image and whose range is the real line.
- In our case we have six features: Energy (E), Correlation (C), Diffusion (D), Fenergy (F), Blob (B) and Texture (T).



Energy Feature for Image with SMD Present



Original Component Image

Binarized Image Using Calculated

Problem Statement

- The lack of flexibility, combined with the rapid introduction and retirement of electronic products, has deterred equipment manufacturers and the electronic assembly industry from investing in the development of AVI systems more convenient for process improvement.

- It is necessary to build AVI systems that are more easily adaptable to new electronic products.

  - AVI Systems should not be rendered obsolete by minimum changes in component technology or change of product designs.

Envisioned Reconfigurable Environment

- In order to achieve the objective of developing self-reconfigurable AVI systems we need to decompose the overall problem into simpler sub-problems. The modules of this reconfigurable environment are:

1. An Automated Feature Generation and Optimization Module
2. A Decision Module
3. A Feature Selection Module
4. An Inspection Performance Assessment Module
5. An Inspection Refinement Module

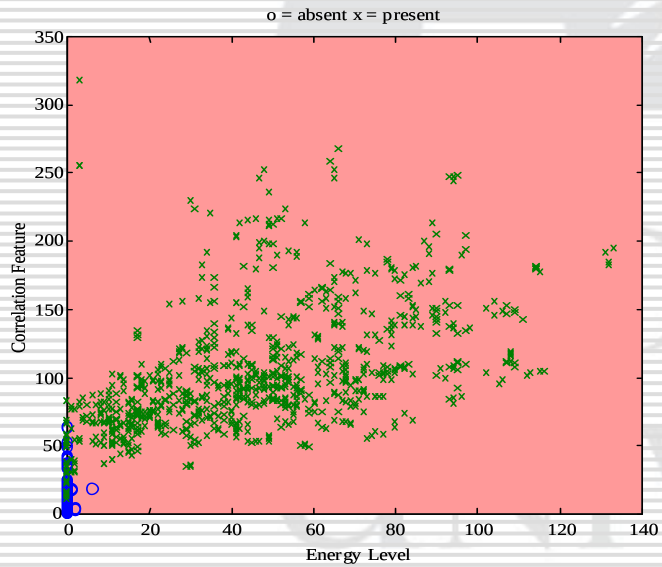
1. Feature Generation and Optimization Module

- The objective of this module is to generate without (or minimal) human intervention the features to be used to inspect the new component/product.

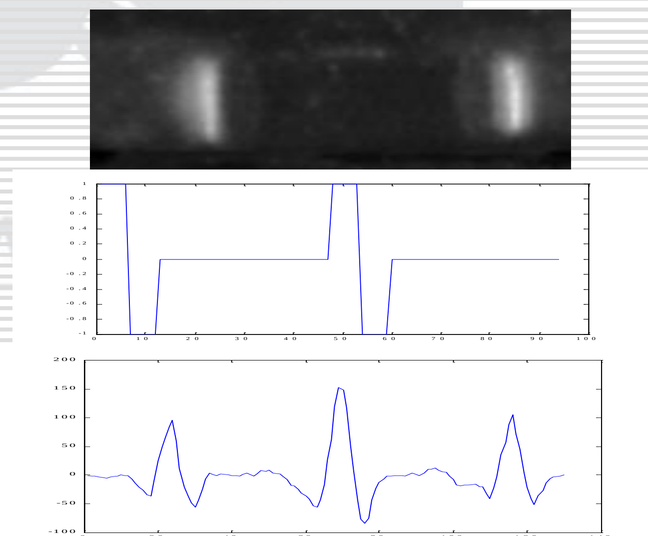
- Once that the potential inspection features have been generated; the next step is to optimize them to render the best individual discrimination possible.

1.1 Feature Generation

- We are planning to start from traditional approaches for feature generation by basing our development on features that have:
  - Common characteristics
  - Computationally inexpensive and simple enough to accommodate new components by just changing their parameters.



Energy and Correlation Features

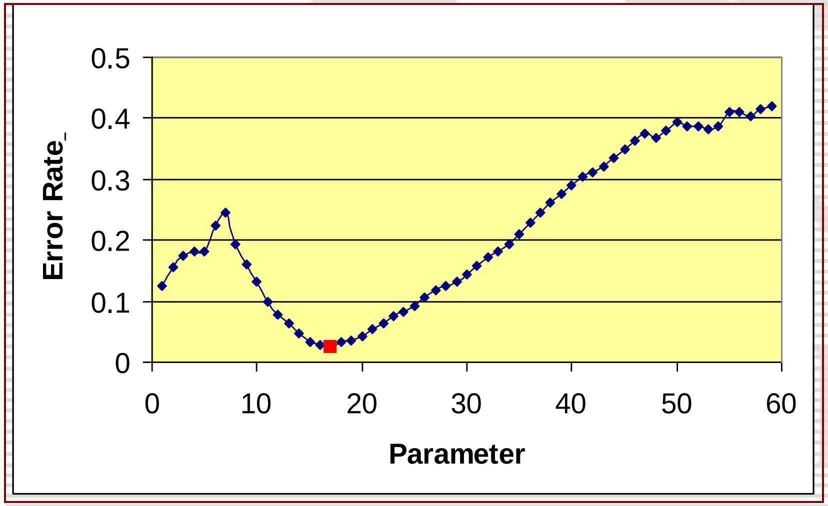


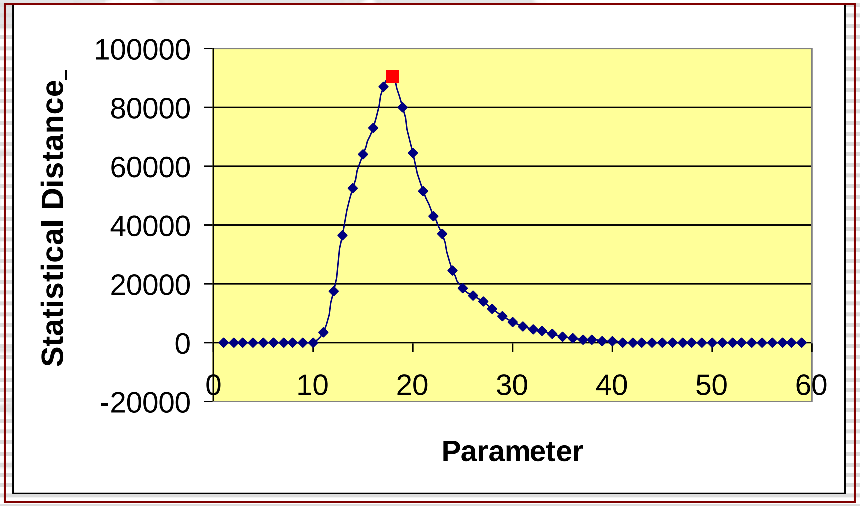
Correlation Feature

1.2 Individual Feature Parameters Optimization

- The objective is to set the parameters of each feature independently such that the discrimination between the defective and non-defective populations is maximized.

- We will explore a heuristic-iterative approach to search for good levels of discrimination between the populations.





2. **Decision Module**

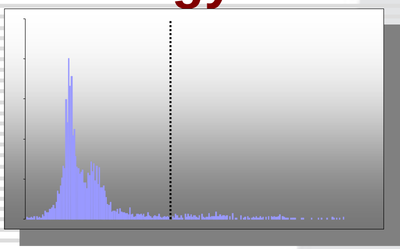
- ✓The objective is to have a classifier easy to use with a great power of discrimination between the populations.

- ✓The characteristics should be
  - ✓Easily expandable and changeable to include other features in addition to the pre-existing ones.
  - ✓The robustness of the features used in the classifier.

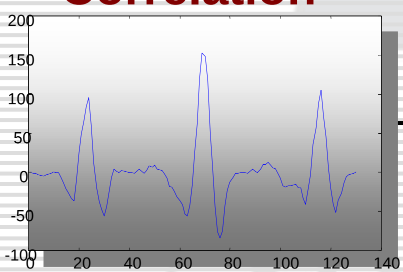
2.2 Quadratic Classification Function

The QCF assigns a vector observation under consideration to the most likely of two populations (in our case denoted as π_0, “non-defective” and π_1, “defective”).

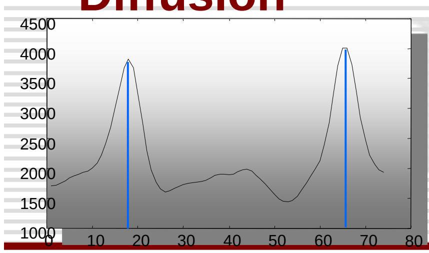
Energy



Correlation



Diffusion



$$R_1 : -\frac{1}{2}\mathbf{x}'\left(\mathbf{S}_1^{-1} - \mathbf{S}_2^{-1}\right)\mathbf{x} + \left(\mu_1'\mathbf{S}_1^{-1} - \mu_2'\mathbf{S}_2^{-1}\right)\mathbf{x} - k \geq c$$

$$R_2 : -\frac{1}{2}\mathbf{x}'\left(\mathbf{S}_1^{-1} - \mathbf{S}_2^{-1}\right)\mathbf{x} + \left(\mu_1'\mathbf{S}_1^{-1} - \mu_2'\mathbf{S}_2^{-1}\right)\mathbf{x} - k < c$$

$$k = \frac{1}{2}\ln\left(\frac{|\mathbf{S}_1|}{|\mathbf{S}_2|}\right) + \frac{1}{2}\left(\mu_1'\mathbf{S}_1^{-1}\mu_1 - \mu_2'\mathbf{S}_2^{-1}\mu_2\right)$$

$$c = \ln\left[\left(\frac{c(1\,|\,2)}{c(2\,|\,1)}\right)\left(\frac{p_2}{p_1}\right)\right]$$

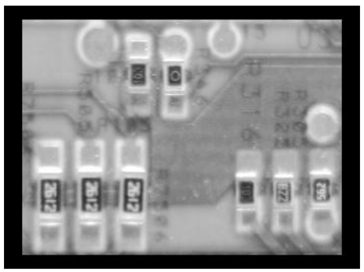
Result

Component is Present or Absent

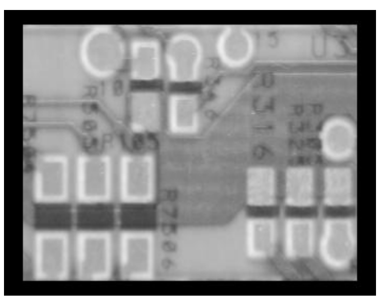
2.3 Training Sample Size Determination

Boards

Populated



Empty



Training Phase

Mean Vector of Features

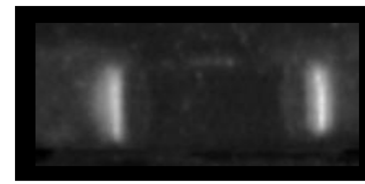
Energy, Correlation, Diffusion, Fenergy, Blob, and Texture

Covariance Matrix

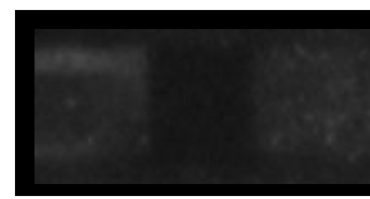
Vector Response

Inspection Phase

Present



Absent



2.3 Training Sample Size Determination

- Analytical determination of the minimum number of training sample required to ensure statistical reliability in the parameter estimation.

- Some of the approaches are,
  - Specify the desired width of a **confidence interval** and determine the sample size that achieves that goal.
  - **Bayesian approach** can be used where we optimize some utility function.
  - Another approach involving the **power of a test** of hypothesis.

3. Feature Selection Module

- The goal of this module is to automatically select a subset of features among the larger set of features known to provide the greatest level of discrimination.

The problem of feature selection is as follows:

"Given a set of *p* features, select a subset of size *m* that leads to the smallest classification error; given the existing time constraints".

Example of Feature Selection

Rank	Features	MER
1	Correlation	0.0125
2	Diffusion	0.0196
3	Energy	0.0392
4	Fenergy	0.0819
5	Texture	0.2847
6	Blob	0.3719

Table - MER for each Feature

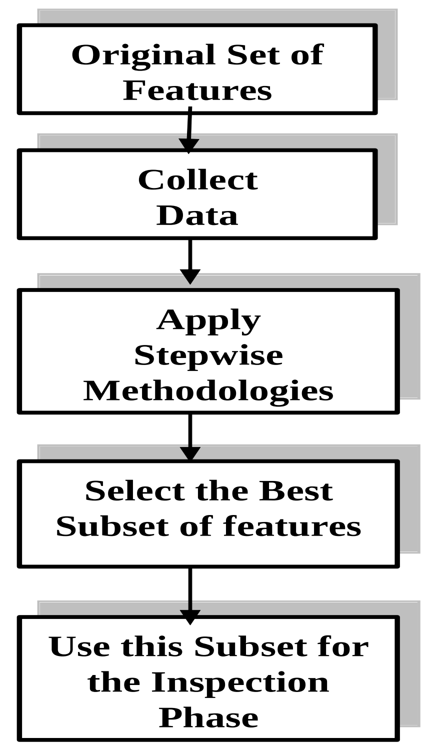
Features	Energy	Correlation	Diffusion	Fenergy	Blob	Texture
Energy	1.00	0.84	0.90	0.83	0.52	0.50
Correlation	0.84	1.00	0.93	0.82	0.42	0.53
Diffusion	0.90	0.93	1.00	0.83	0.49	0.55
Fenergy	0.83	0.82	0.83	1.00	0.33	0.53
Blob	0.52	0.42	0.49	0.33	1.00	0.27
Texture	0.50	0.53	0.55	0.53	0.27	1.00

Table - Cross-Correlation between Features

Stepwise Discriminant Analysis (SDA)

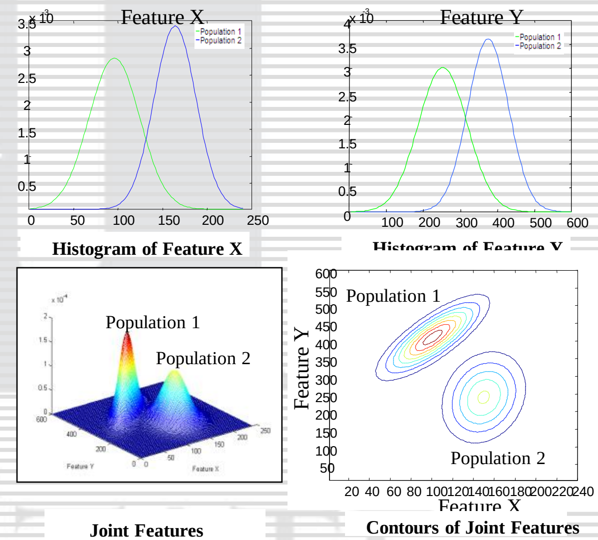
- In order to expedite the feature selection process, we explored the use of Multivariate Stepwise Discriminant methods such as:
  - Wilks'Λ
  - Mahalanobis Distance
  - Unexplained Variance
  - Smallest Distance
  - Rao's V

Figure 2. Feature Selection General Approach



4. Inspection Performance Assessment Module

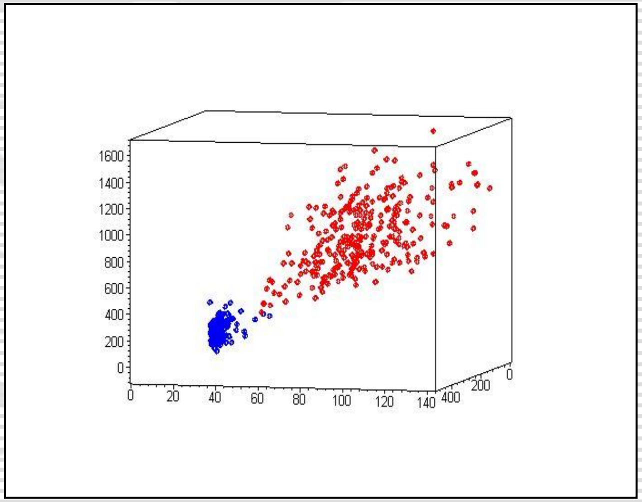
- The objective of the Inspection Performance Assessment Module is to measure the performance of the AVI system
  - In the training phase.
  - In the inspection phase.



- Although it is relatively “easy” to measure current performance, projections of future performance become more complex and less reliable if the populations are no stable.

4.1 Classifier Performance Measurements

- We use three non-parametric statistics that measure the level of discrimination through the Misclassification Error Rate (MER). These methods are:
  - The **APER** is a biased estimator of the probability of errors as it is evaluated on the training data.
  - The **EAER** is a nearly unbiased estimate of the expected true error rate of the population (this statistic is calculated using cross-validation of size one).
  - The **IER** is an unbiased estimator of the true error rate because the used data is independent from the training data utilized to build the QCF.



4.2 Prediction of the AVI System

- **Regression Analysis** is used to predict the AVI performance.
- The dependent variable of the equation is the MER.
- It is necessary to determine the independent variable. We have explored methods such as
  - Wilks' Lambda Value,
  - Hotelling-Lawley Trace Value
  - Statistical Distance between Populations $D_{A\text{-}P}$

4.2.1 Wilks' Lambda Value

- This **is a measure of the difference between populations** of the centroid (vector) of means on the independent variables.

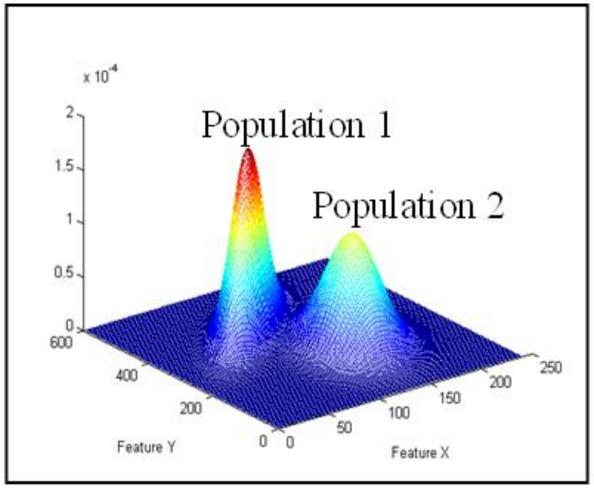
- The smaller the value of lambda, the greater the difference between the populations.

- The likelihood ratio test statistics can be expressed as;

$$\Lambda = \frac{|\mathbf{W}|}{|\mathbf{B}+\mathbf{W}|} = \prod_{i=1}^{s} \frac{1}{1+\lambda_i}$$

Experimental Results

Statistics	MER	Wilks	Hotelling	D_{1-2}
MER	1.000	0.953	-0.739	-0.745
Wilks	0.953	1.000	-0.894	-0.901
Hotelling	-0.739	-0.894	1.000	0.983
D_{A-P}	-0.745	-0.901	0.983	1.000



Method	Regression Analysis		Model Adequacy			Analysis of Variance	
	Constant	Coefficient	R^2	PRESS	$R^2_{prediction}$	F Value	P Value
Wilks	-0.081	0.473	0.91	0.031	0.874	615.77	0
Hotelling	0.172	-0.038	0.55	0.137	0.439	73.43	0
D_{1-2}	0.186	-0.017	0.55	0.137	0.439	76.17	0

5. Inspection Refinement Module

- The objective is to continuously improve the performance of the AVI system.
- This module includes a methodology for;
  - **Eliminating the Noise** present in the training data.
  - **Joint Optimization** of the parameters of the features used in the inspection.
  - **Constructing New Features** based on the current performance of the system.

5. 1 Cluster Formation and Elimination of Outliers

- The second step of the methodology is the creation of the function to identify the outliers.
- Some of the methods that we will explore to create the function to eliminate outliers are based on the
  - Classification Boundary
  - Chi-Square Distribution
  - Mahalanobis Distance

5.1.3 Mahalanobis Distance

- This measure standardizes the distance between two vectors with the inverse of the covariance matrix:

$$\boxed{T^2 = n(\bar{\mathbf{x}} - \boldsymbol{\mu}_0)'\mathbf{S}^{-1}(\bar{\mathbf{x}} - \boldsymbol{\mu}_0)}$$

- This test can be used to determine which elements can be classified as outliers.

$$\boxed{T_{Pi}^2 = \left(\bar{\mathbf{x}}_P - \mathbf{x}_i\right)' \mathbf{S}_P^{-1}\left(\bar{\mathbf{x}}_P - \mathbf{x}_i\right)}$$

$$\boxed{T_{Ai}^2 = \left(\bar{\mathbf{x}}_A - \mathbf{x}_i\right)' \mathbf{S}_A^{-1}\left(\bar{\mathbf{x}}_A - \mathbf{x}_i\right)}$$

- If T_{Pi}^2 or T_{Ai}^2 ≥ $T_{\alpha,p,n-1}^2$, the element *i* is considered as an outlier.

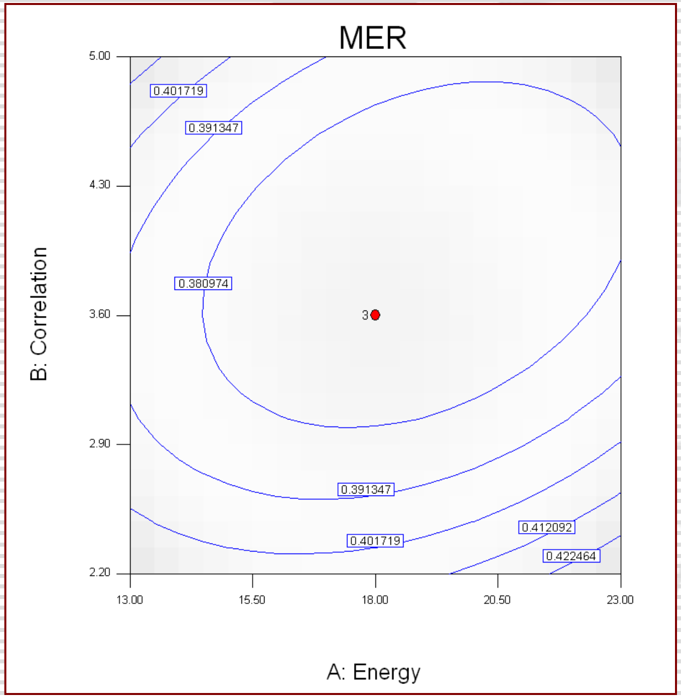
Experimental Results

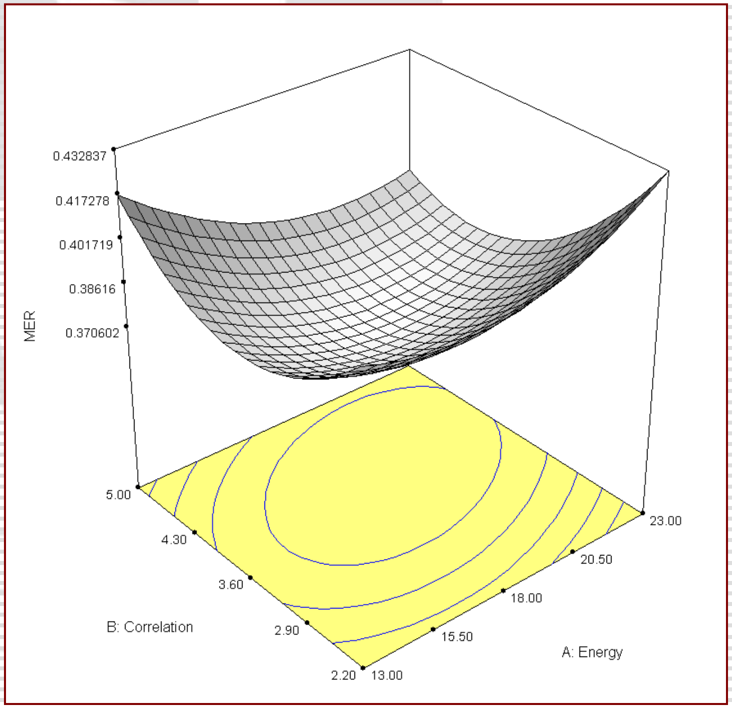
SCENARIOS	Inspection Data With Outliers	Inspection Data With Outliers	Inspection Data Without Outliers
Training Data With Outliers	**A**		
Training Data Without Outliers		**B**	**C**

Scenarious	A			B				C			
Features	**Elements**	**MER**	**Value**	**Elements**	**Method**	**MER**	**Value**	**Elements**	**Method**	**MER**	**Value**
ECDFBT	281	APER	0.0196	281	D_{PA}	APER	0.0000	281	D_{PA}	APER	0
	281	EAER	0.0196	281		EAER	0.0000	281		EAER	0
	2810	IER	**0.0178**	2810		IER	0.0224	2810		IER	**0**
				263	**Hotelling's T^2**	APER	0.0019	263	**Hotelling's T^2**	APER	0.0019
				263		EAER	0.0038	263		EAER	0.0038
				2810		IER	0.0178	2630		IER	0.0036
				281	**CHI-SQUARE**	APER	0.0019	281	**CHI-SQUARE**	APER	0.0019
				281		EAER	0.0038	281		EAER	0.0038
				2810		IER	**0.0176**	2810		IER	0.0036

5.2 Multi-Feature Parameters Re-Optimization

- Optimizing a single parameter might not result in the global maximization of that feature's response.
- The approach is based on factorial design and multiple response surface methodologies.





5.3 Feature Construction

- Feature construction is a process that discovers missing information about the relationships between features and augments the space of features by inferring or creating additional features.

- For example, assuming there are *n* original features A_1, A_2,…, A_n", after feature construction, we may have the additional *m* features $A_{n+1,}$ A_{n+2}, ... , A_{n+m}.

- Another example: a two-dimensional problem (say, A_1=width and A_2=length) may be transformed into a one-dimensional problem (B_1 = area) after B_1 is constructed.

General Overview of Reconfiguration Methodology

1. Create features for the AVI system.
2. Optimize the features independently.
3. Determine the training sample size.
4. Obtain images with defective and non-defective components.
5. Apply the predefined features to the images to obtain the multivariate information.
6. Based on the multivariate information, estimate the parameters for the defective and non-defective global populations.
7. Determine the best subset of features for each component.
8. Estimate the AVI performance in the training stage and for the functioning in the factory floor.

General Overview of Reconfiguration Methodology

9. Create new features to improve the classification for those components whose performance values are outside the acceptable level of discrimination.
10. Determine the clusters of components and eliminate the outliers from them.
11. Optimize the parameters jointly for each subset of features.
12. Identify those components for which, given the current set of features, neither global nor local classification is possible. Term these components special cases.
13. Create additional features for the classification of special cases.

Conclusion

- The resulting development framework will
  - Significantly shorten the development time for inspection algorithms.
  - Minimize the intervention of human developers.
  - Improve the AVI systems in two dimensions of flexibility;
    - Introduction of new products and
    - Rapid product changeovers.

- While the envisioned resulting methodology will be of immediate application in the electronics assembly industry, its impact goes beyond of this application.
  - Medical Diagnostic
  - Solder Paste Inspection
  - Inspection of Textile Products