COMPOSITE TECHNOLOGIES FOR INTELLIGENT INDUSTRIAL LASER PROCESSING

prof. VINCENZO PIURI
Department of Information Technologies, University of Milan
via Bramante 65, 26013 Crema (CR), Italy

EU Project SLAPS
Self-Tuning and User-Independent
Laser Material Processing Units

PHILIPS

Information Sources

Partners in IMS/Brite-Euram Project SLAPS

- **Philips-CFT**
- **Laser Zentrum Hannover**
- **Odense Steel Shipyard LTD.**
- **Jurca Opto-elektronik**
- **Fiat-CRF**

- **Trumpf**
- **Lasag AG**
- **Politecnico di Milano**
- **Ecole Politechnique Federale de Lausanne - IOA**
- **University of Vienna**

Contributions to the Tutorial: Prof. Cesare Alippi, Politecnico di Milano, Italy
Dr. Toon Bloom, Philips CFT, The Netherlands

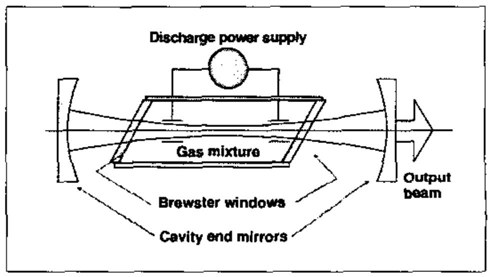
Laser Processing

Applying energy to a work piece
in the form of (high intensity) light beam

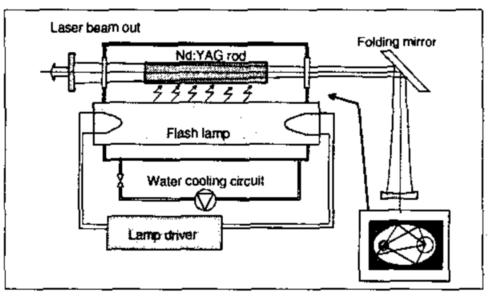
- Laser seam welding
- Laser cutting
- Laser spot welding
- Laser drilling
- Laser cladding
- Laser marking
- Laser adjustment
- ......

Carbon Dioxide Laser

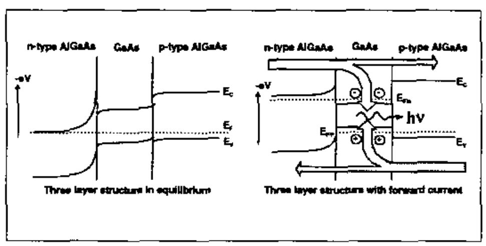
Typical gas laser construction



Nd:YAG Laser

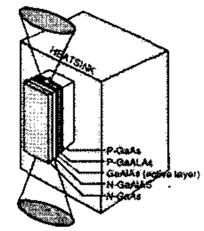


Solid State Laser Diode

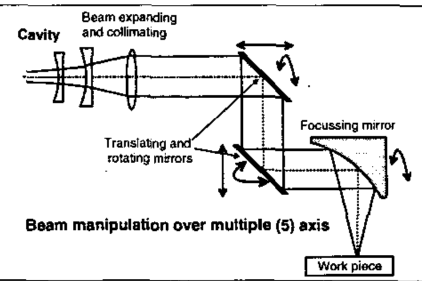


Solid State Laser Diode

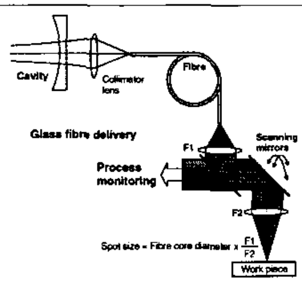
- Low output power
- Laser diode arrays for processing
- Low beam quality
- Good control qualities
- High efficiency



Beam Delivery

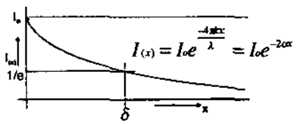


Beam Delivery



Absorption, Reflection, Transmission

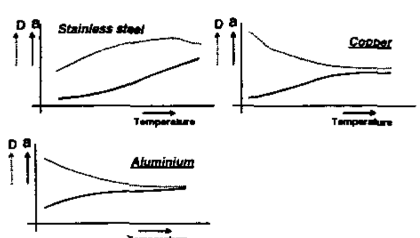
- Kirchhoff: Absorption +reflection+transmission = 1
- Extinction of the penetrating light wave



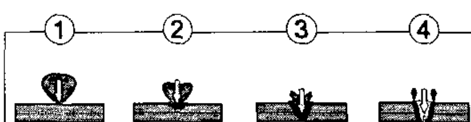
$$I_{(x)} = I_0 e^{\frac{-4\pi k x}{\lambda}} = I_0 e^{-2\alpha x}$$

- Penetration depth: $\delta = \frac{1}{\alpha} = \frac{\lambda}{2\pi k} \approx \frac{\lambda c \varepsilon_0}{\pi \sigma} = \frac{\lambda}{\pi \sigma c \mu_0} = \frac{1}{\pi \sigma \mu_0 f}$

Absorption and Heat Diffusion = F(T)

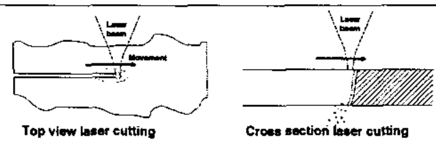


Process Phases



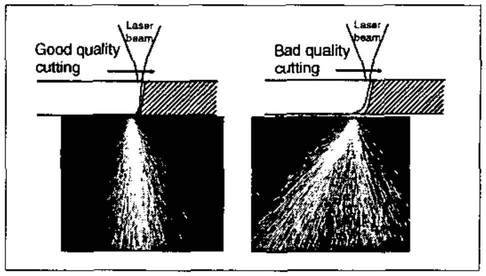
- 1: Heating: Absorption, heat diffusion
- 2: Phase transition of top material, change of properties
- 3: Vaporisation, recoil pressure pushes liquid metal aside
- 4: Liquid level reaches bottom and is blown out

Laser Cutting

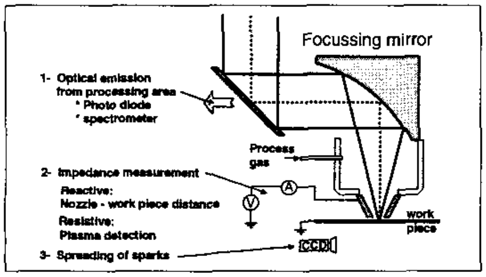


- Medium to high power CW lasers (CO_2)
- Process gas, reactive (O_2 extra reaction energy) or not (N_2), to blow out molten material
- Wave guide kind of energy transfer through the cutting slit

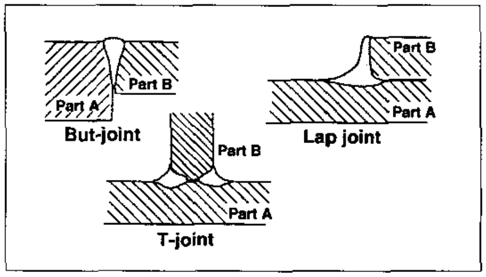
Spark Pattern During Laser Cutting



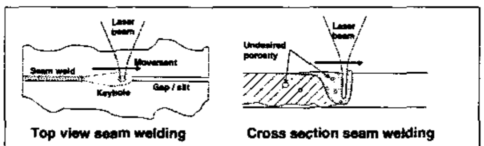
Process Monitoring



Laser Seam Welding



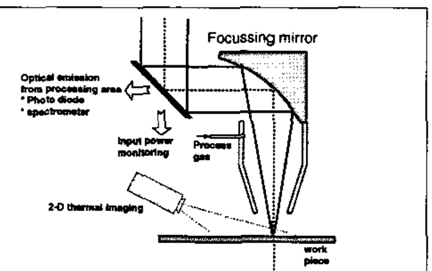
Laser Seam Welding



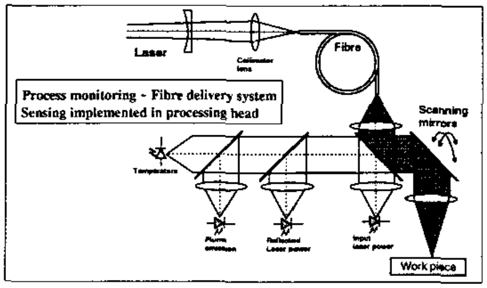
- Battery casings, Pace maker casings
- Car bodies, Transmission parts
- Sub assemblies in ship building
- Plastics (overlap penetration welding)

Laser Seam Welding

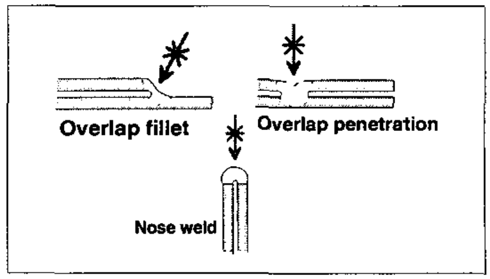
Process monitoring - Direct delivery system



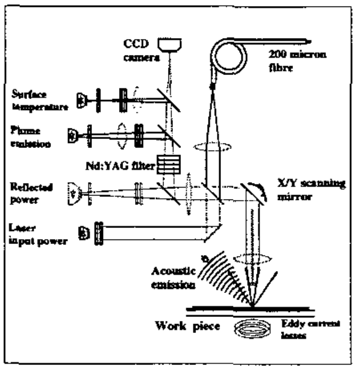
Laser Seam Welding



Spot Weld Geometries

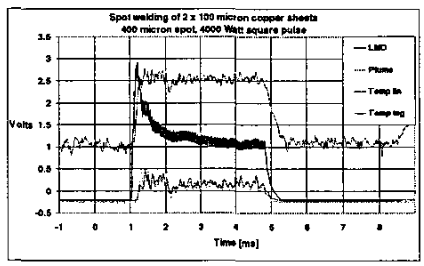


Process Monitoring in spot welding



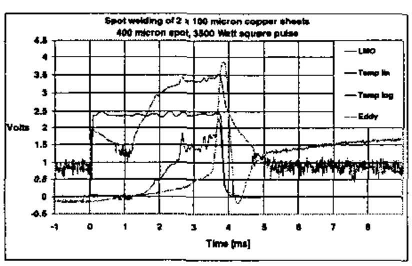
Signal Processing

Example of measured signals



Signal Processing

Example of measured signals



Automatic Classification

based on multi sensor process monitoring

- The complete set of sensors provides
  a broad information range
  about the performance of the process
- Realisation of data reduction by extraction
  of specific features from the recorded signals
- The features are recognised as being related
  to certain process events
- The relations between features and
  a good or bad performing process
  have to be established through a large set
  of verification experiments

Requirements

- Accuracy
  - It measures the performance of the final solution according to a figure of merit to be defined
- In general, accuracy is not the unique goal to be pursued
- Computational load
  - Real time processing requirements
    - HW (HW Latency, Throughput)
    - SW *(Flops, Worst case analysis)*

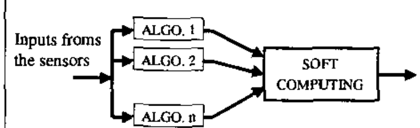
Requirements

- Modularity
  - Module reuse
  - Easy module up-grade
  - Homogeneity within the system
- Complexity of the Algorithm
  - Simplicity of the final solution
  - Latency
  - Easy implementation on a target dedicated processor (CISC,RISC,VLIW)
  - *Easy HW implementation (ASIC, FPGA)*

Requirements

- Robustness (Sensitivity)
  - It measures the ability of the final algorithm to tolerate classes of perturbations
    - Fluctuations in the inputs (e.g., noise, non-stationarity of the process)
    - Perturbations affecting the computation (e.g., finite precision representations)
      - General purpose processor (Floating point representation)
      - *DSP/Dedicated HW (Fixed point representation)*
      - Analog implementation

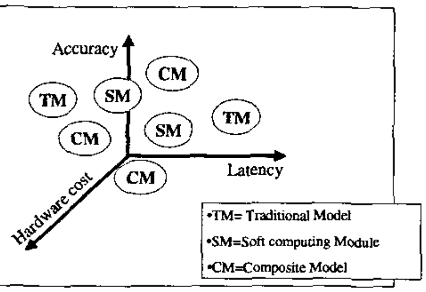
A Composite System



Feature extraction

High level processing (classification, modeling, ...)

Models and Requirements Space



Starting with Simple Models

- I would rather start with linear models
  - generally they are the simplest models
    - Linear regression (static)
    - AR(X), ARMA(X),Kalman Filters, etc (dynamic)
- Test the solution accuracy
  - *with an appropriate figure of merit (e.g., MSE)*
  - inspect the nature of the residual error
    - Anderson whiteness test
    - Kolmogorov Test
- Decide whether to accept the model/consider more complex/nonlinear models

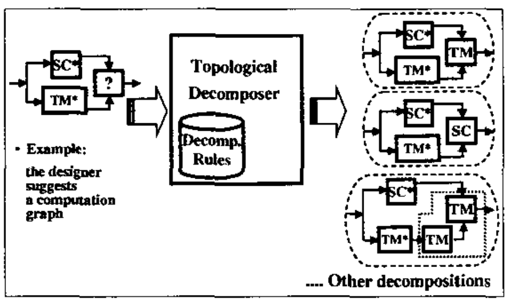
Move Towards Complex Models

- Non-linear models:
  - Leitmotiv: simplicity!
  - Static models
    - Supervised:
      - Feedforward NN, RBF
      - ...
    - Unsupervised
      - SOM, LVQ
      - ...
  - Note that predictive models not requiring the concept of state are considered to be static

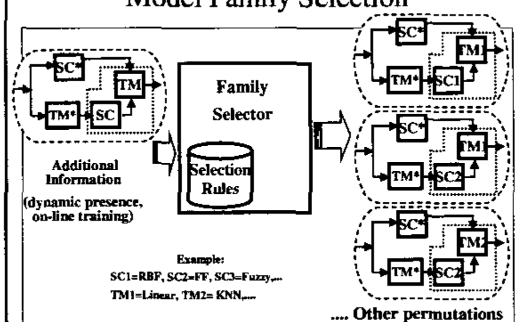
Equation-based Models

- Equation-based Models
  - Most of times we forget that we can generate equation based models from physical/chemical principles.
  - We could start considering very simple models and test accuracy/ residual errors
  - More sophisticated models can be considered when necessary
    - Keep anyway in mind that we are in a constrained environment and there is the "time to market" concept.

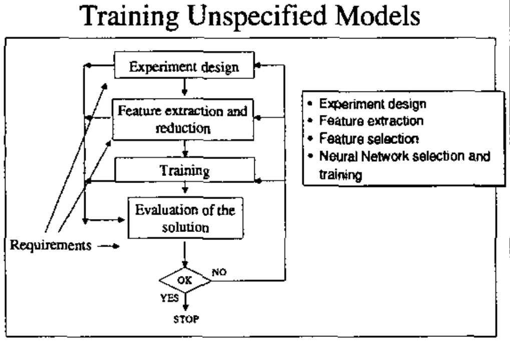
Decomposition and Partitioning



Model Family Selection



Training Unspecified Models



Feature Extraction

•We need features to represent the information present in the sensorial signals in a compact way

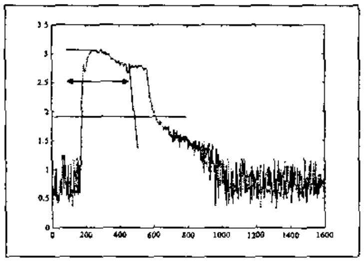
•Advantages:
- Information compression (less data to be further processed)
- Input data reduction

•Disadvantages:
- Additional computational load in the feature extraction step

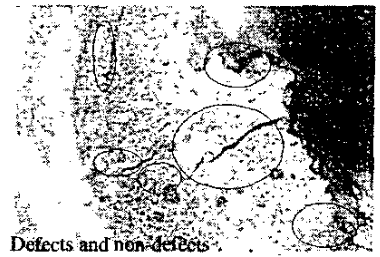
We want relevant and easy to be generated features.

Not always relevant features are computationally intensive

Features Extraction: Example



Edge Detection in Images



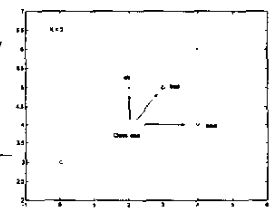
Features Selection

- Each classifier needs
  - a training phase
  - a validation phase to estimate its performance
- A "traditional" parameter adjusting procedure is not acceptable
- The problem can be solved with a heuristic based on the KNN classifiers

KNN Classifiers: Philosophy

- KNN = K Nearest Neighbours
- Basic Idea:

  a pattern is classified based on the majority of the K nearest training patterns close to it



KNN Classifier

- It is an approximation of the optimal Bayes classifier ($N \to \infty$).
- The probability distributions are locally estimated based on each point
- KNN does not need a true training phase, since it "emerges" from available patterns once the parameters have been dimensioned
- Degrees of freedom:
  - number of class K
  - neighbourhood norm
  - selection of the K neighbourhood

The Algorithm: Description

0. U = set of all the features, n = 1
1. Build all the S_i subsets of U containing N features
2. For each S_i estimate the LOO performance of all the KNN classifiers with S_i as inputs (all combinations of preprocessings and K values up to a minimum)
3. Select those S_i which yield a performance better than a threshold; if only one S_i is selected goto 5...
4. ... else build their union U, increase n, and goto 1
5. Greedily grow S_i with the other features one by one, until no further performance improvement is scored
6. Select the best performing classifier

The Algorithm: Example

- Starting with 33 features:

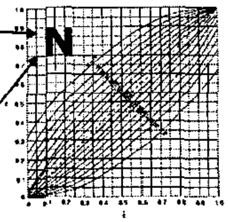
Iteration	Classifier Error	Feature sets selected (K=1,3,5)
1	< 35%	3; 8; 20; 21; 23; 24; 32
2	< 25%	(3,8); (3,20); (3,32); (8,20); (8,24); (8,32); (20,32)
3	< 20%	(3,8,32); (3,20,32); (8,20,32)
4	-	(3,8,20,32)

- Adding all the other features to (3,8,20,32) one by one did not introduced further performance improvements
- Best KNN classifier:
  - inputs = (3,8,20,32), K = 5, estimated error = ~ 8-18%

Models Trained on Data

The parameterized models are tuned (Trained) using experimental data

ACCURACY
Cross-validation
(Some examples are used to test the performance of the model)



Interval of Accuracy with 95% confidence A±a
Based on the Bayesian Optimum Classifier

System Validation

- The system validation must be carried out by using
  - the whole system
  - the available (input,output) pairs
  - LOO (too expensive globally)
  - CV to be preferred instead
- If final performances do not satisfy the requirements we have to iterate the procedure by considering a different composite system

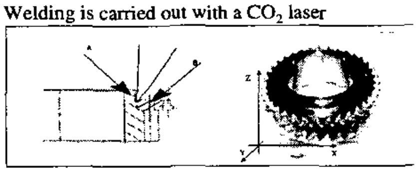
LASER WELDING FOR AUTOMOTIVE COMPONENTS

This research has been carried out in collaboration with

Fiat Research Centre, Turin, Italy

The Application

- The gear is built by joining two separated rings (a light syncronization gear and the principal gear)
- Welding is carried out with a CO_2 laser



- Every product is tested using ultrasonic waves after welding for quality control

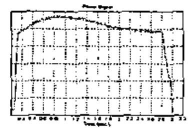
The Application

- We wish on-line monitoring for
  - welding quality assessment
  - welding process monitoring (control)
- Welding problems are related to:
  - Penetration depth
  - Misalignment of coupling in mounted samples
  - Porosity
  - Power decrement up to 10%
  - Power lack up to 10 ms

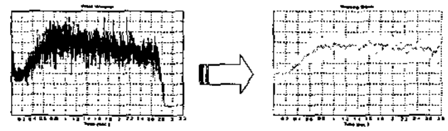
The Application Requirements

- The error categories can be grouped in three classes:
  - Power Loss
  - Mounting
  - Porosity
- Requirements:
  - High monitoring performance
  - Low computational load

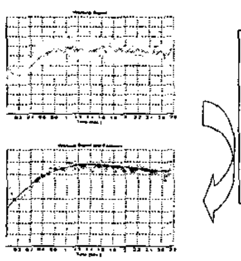
Signal Pre-Processing



- Simple Processing
  - Amplitude Demodulation
  - Low Pass Filtering
- Fast Processing
  - 15K samples

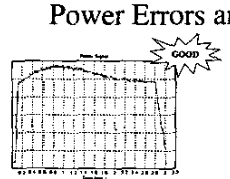


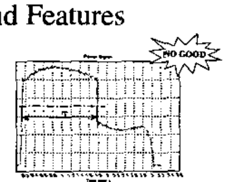
Feature Extraction



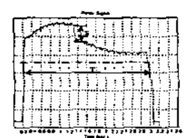
- Reference construction
  - a Cubic line has been considered to interpolate the relevant interval of the weld watcher signal
- Processing
  - 1805697 Flops

Power Errors and Features

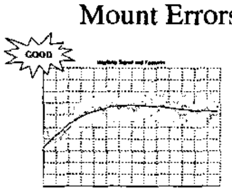


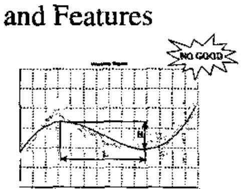


- Power Loss Errors
  - Short Duration of Welding Process
  - Laser Power Fluctuation
- Features
  - T: Duration of Effective Laser Power
  - F: Maximum Power Fluctuation



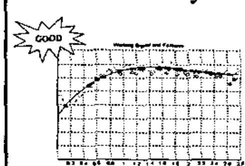
Mount Errors and Features

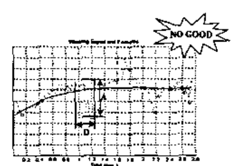




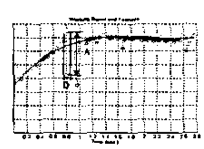
- Mount Errors
  - Modulation in Weld Watcher Signal
- Features
  - Parameters of the Cubic line
  - H-L: Cubic line Features

Porosity Errors and Features





- Porosity Errors
  - Variations wrt to the reference signal
- Features
  - A: Amplitude of the discrepancy
  - D: Time duration of the discrepancy

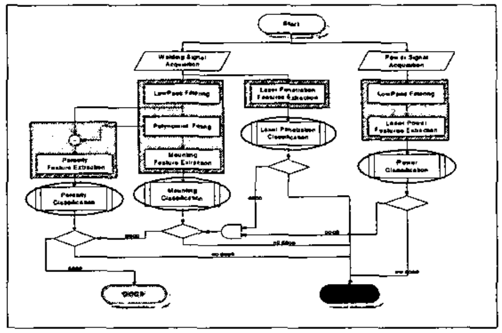


Remarks

- Few samples are available to configure the solution
- Not all samples can be classified by the operator
- The distribution of samples for the different error typologies is unknown

	Good	No Good	Not Classified	Total
Depth Error	31	9	29	69
Power Error	29	40	0	69
Mount Error	47	8	14	69
Porosity Error	275	10	60	345

The Proposed Algorithm



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Experimental Results

	Classifier	Training	Cross Validation	Error of best classifier	Accuracy Interval	Notes
Depth	KNN	40 samples (100%)	39 samples (~100%)	0 %	~ 0 –10 %	K= 1
	FF-NN	28 samples (70%)	12 samples (30%)	0 %	~ 0 – 10 %	Neurons= 2 (Best over 100)
Power	KNN	69 samples (100%)	68 samples (~100%)	0 %	~ 0 – 8 %	K= 1
	FF-NN	48 samples (70%)	21 samples (30%)	0 %	~ 0 – 8 %	Neurons= 4 (Best over 100)
Mount	KNN	55 samples (100%)	54 samples (~100%)	1.8 %	~ 0 – 10 %	K= 1
	FF-NN	39 samples (70%)	16 samples (30%)	0 %	~ 0 – 8 %	Neurons= 2 (Best over 100)
Porosity	KNN	215 samples (100%)	214 samples (~100%)	0.35 %	~ 0 – 4 %	K= 1
	FF-NN	199 samples (70%)	86 samples (30%)	0 %	~ 0 – 4 %	Neurons= 4 (Best over 100)

Vincenzo Piuri, SIcon/02, Houston, TX, USA, 19-21 November 2002

SPARKS ANALYSIS FOR LASER CUTTING

This research has been carried out in collaboration with

TRUMPF, Ditzingen (Stuttgart), Germany

Vincenzo Piuri, SIcon/02, Houston, TX, USA, 19-21 November 2002

The Application

- Laser cutting of steel/stainless steel is a complex process
- It is expected that monitoring of the sparks dynamic associated with the cutting process can provide hints about
  - The internal nature of the cutting process
  - Indications for subsequent process monitoring and control

Vincenzo Piuri, SIcon/02, Houston, TX, USA, 19-21 November 2002

The Application Requirements

- There are three cutting error categories:
  - Good
  - No Good
    - Discontinuous cut
    - Pearls of metal
  - Ambiguous
- Requirements:
  - High Accuracy
  - Low computational load

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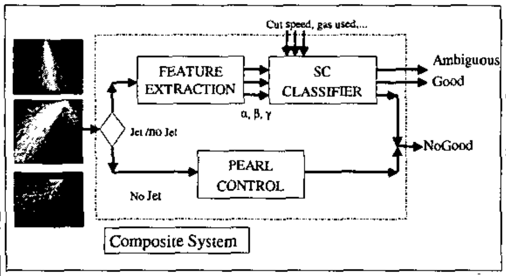
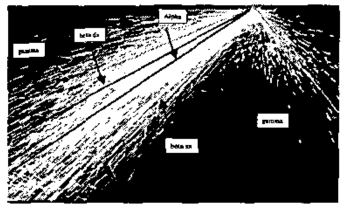
Composite System Partitioning

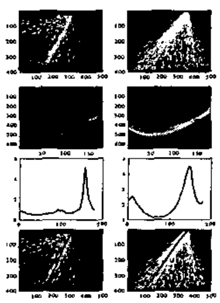


Features Extraction



α : inclination angle
β : opening angle of the main jet
γ : opening angle of the whole jet

Finding the Jet Starting Point

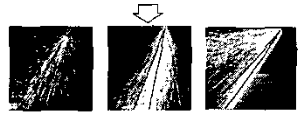


Radon transform
Profile extraction
Direction of the main jet

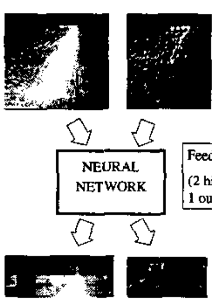
Estimating the Angles

THE γ AND β ANGLES

- Median filtering
- Threshold binarization
- Cumulate intensity in rows
- Find left/right edges of the spark
- Separated left/right linear regression passing trough the vertex

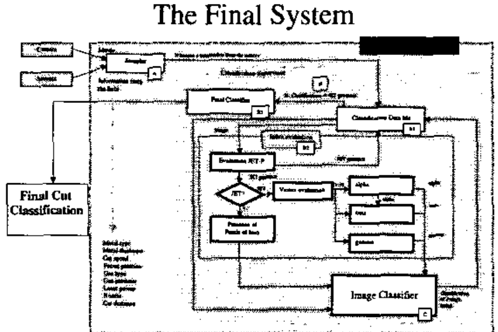


Pearl Identification



FeedForward Neural Network
(2 hidden units,
1 output good/no good unit)

The Final System



Performance

	Performance	Note
processing α, β, γ	Error < 3°	Using human estimates over 121 images the behavior of the angles-processing module fits suitably the sparks
Pearls	30/30	Using validation images
Classification good/no good/ambiguous	84/84	

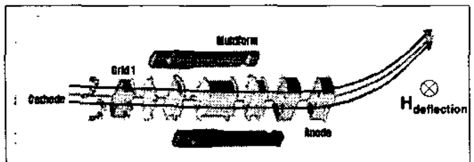
LASER SPOT WELDING FOR ELECTRONIC COMPONENTS

This research has been carried out in collaboration with

PHILIPS
Philips Centre for Industrial Technology

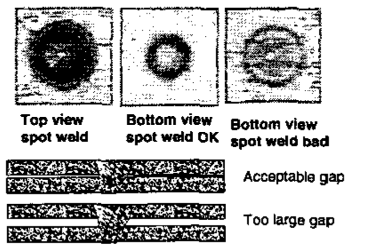
Philips CFT - Centre for Industrial Technology

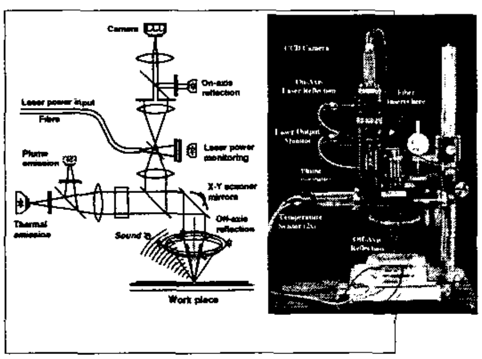
Electron Gun for Cathode Ray Tube



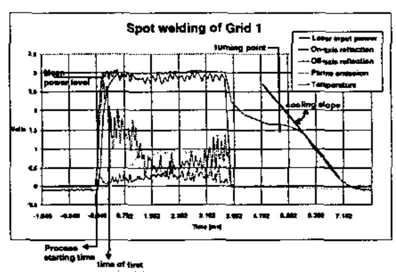
1 - Generation of free electrons by cathode
2 - Beam shaping using 'electric field lenses'
3 - Acceleration of electrons

Manual Classification





Feature Extraction



Automatic Classifiers

	Pros	Cons
Neural Networks	High accuracy	[redacted]
K-Nearest Neighbor Classifier	No training required Does not necessarily lead to classifications	[redacted]

Results from the Nearest Neighbour Classifier

	1NN		2NN		
	O.K.	N.O.K.	O.K.	??	N.O.K.
Strip	98.15	1.85	95.74	3.24	1.02
Strip (3)	97.67	2.33	95.63	3.20	1.17
Bracket	75.92	24.08	61.53	25.43	13.04
Bracket(15)	75.44	24.56	62.25	25.04	12.71
Curamik	84.86	15.14	73.06	19.64	7.30
Curamik(18)	86.04	13.96	75.01	17.14	7.85
MAI (32)	78.65	21.35	64.22	23.73	12.05
MAI (18)	77.37	22.63	63.70	24.75	11.55