Evolving Intelligent Systems

Lecture 3: Applications

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Lecture 3 Applications

1. Process industries (eSensors)
   - a) predicting quality in oil refineries (CEPSA)
   - b) modelling polymerisation (The Dow Chemicals, TX)
2. Robotics, SLAM, landmarks
3. Security and video-analytics
4. Automotive industry (Dr. D. Filev)

Recommended Readings

- P. Angelov, Evolving Rule-based Models: A Tool for Design of Flexible Adaptive Systems, Physica-Verlag: Heidelberg, February 2002, ISBN 3-7908-1457-1.
- N. Kasabov, Evolving Connectionist Systems: Methods and Applications in BioInformatics, Brain Study and Intelligent Machines, Springer, London, 2003, ISBN: 1-85233-400-2.
- P. Angelov, D. Filev and N. Kasabov (Eds.), Evolving Intelligent Systems: Methodology and Applications, 484pp., John Willey and Sons, IEEE Press Series on Computational Intelligence, April 2010, ISBN: 978-0-470-28719-4

Applications of eSensors

- Quality of oil refinery products (CEPSA-Total, Spain; Dr. J. Macias)
- Polypropylene and other chemical products (The Dow Chemical, TX, USA; Dr. A. Kordon)
- NOx emissions in exhaust gases of car engines estimation (Dr. E. Lughofer, University of Linz, Austria

Inferential (soft) Sensors

- ✓ Inferential (soft) sensors – since '80s in chemical, process industries etc.
- ✓ Product quality on-line monitoring
- ✓ 'Black-box methods', NN, PCA, PLS, SVM
- ✓ They often provide a valuable advantage over the conventional approaches that rely on manual intervention and laboratory tests

Soft/Intelligent Sensors

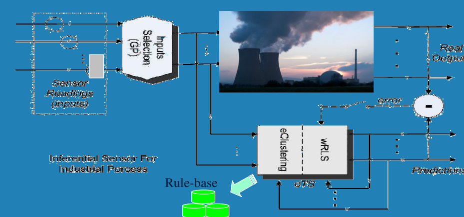
- However, they are *costly to build and maintain:*
- the operation of industrial plants is subjected to a continuous change:
  - raw materials alter in quality
  - catalysts deactivate and must be exchanged, and
  - equipment is subject to wear or contamination and has to be maintained or replaced.
- Even minor process changes outside the conditions used off-line can lead to performance deterioration which may become inadequate to the changing environment.

Soft/Intelligent Sensors

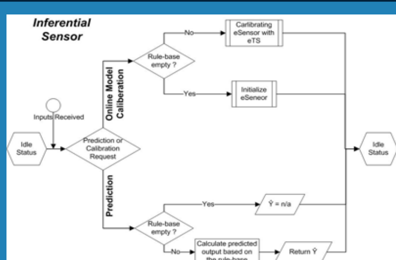
- This requires maintenance and frequent model/ sensor re-design, including derivation of entirely new model structure and human expert involvement as well as re-calibration
- As a result, maintenance costs form a significant proportion of the life-cycle costs
- Another serious deficiency of current soft sensors is their inability to incorporate process knowledge

eSensor – the concept

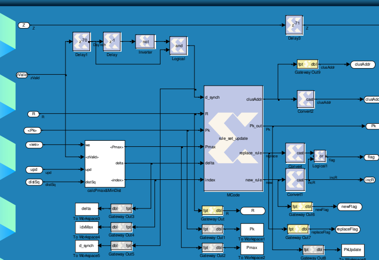
- ✓ eSensor (evolving intelligent sensor) concept is based on eTS (including on-line inputs selection)

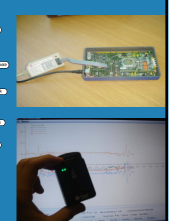


eSensor flow chart



eTS on FPGA - XtremeDSP





Monitoring Quality of products in oil refineries

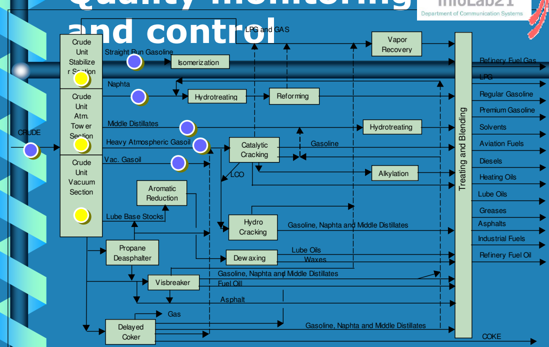
courtesy of Dr. J. M. Hernandez, CEPSA, Spain

- **Crude Distillation Tower Quality Control**
  - ASTM D86, Abel In flammability.
  - Lab samples Once a day
  - Crude Switching 2-3 days
  - On-line analyzers availability
- **Statistical methods**
  - To cope for differences Lab / On-line analyzers
  - To reduce monitoring and unit control budget

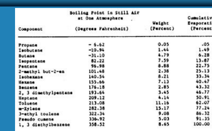
State of the art 2

- Statistical models used
  - Based on simplified engineering models of the tower. Strong but do not account for instrument readings drifts and failures.
  - Multivariate calibration models, PLS. Strong, protected versus co linearity but do not solve adaptation either.
  - Feed forward Neural Networks. Very powerful Black box models but difficult to explain to the operators and process engineers. Recalibration required.
- Need for adaptation

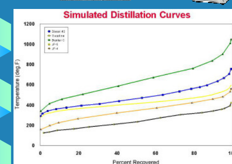
Quality monitoring and control

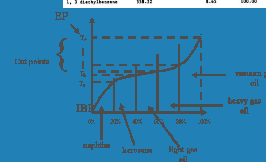


ASTM D86

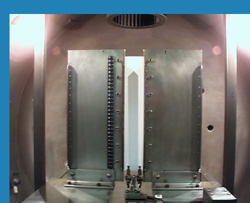


Component	Boiling Point in Still Air at One Atmosphere (Degrees Fahrenheit)	Weight (Percent)	Cumulative Evaporation (Percent)
Propane	- 6.62	0.05	.05
Isobutane	-10.94	1.44	1.49
Butane	-31.10	4.79	6.28
Isopentane	82.22	7.59	13.87
Pentane	96.98	8.88	22.75
2-methyl but-2-en	101.48	2.38	25.13
Isohexane	140.54	8.21	33.34
Hexane	155.66	7.13	40.47
Benzene	176.18	2.85	43.32
2, 3 dimethylpentane	193.64	3.45	46.77
Heptane	209.12	4.14	50.91
Toluene	213.08	11.16	62.07
m-Xylene	282.38	15.17	77.24
3-ethyl toulene	322.34	9.08	86.32
Pseudo cumene	336.92	5.03	91.35
1, 3 diethylbenzene	358.52	8.65	100.00





Inflammability Test



Industry's Application Requirements

- ✓ Strong (good prediction, low error) model
- ✓ Safe on prediction outside calibration horizon
- ✓ Able to adapt to instrument drifts, crude quality characteristics, etc.
- ✓ Automatic adaptation
- ✓ Easy to explain to operators and process engineers

Data Characteristics

- Once a day lab sample and Lab data results in the same day few hours later
- Hourly average instrument readings of temperatures, flow rates and pressures of the distillation tower.
- Data for Calibration and prediction 450 samples or days. More than one year operation to account for mostly crudes processed at the refinery and have instruments drifts, shutdowns, etc.
- The data is taken from normal operation values, i.e. it has a narrow operating window that makes it difficult for prediction.
- Process dynamics in raw data

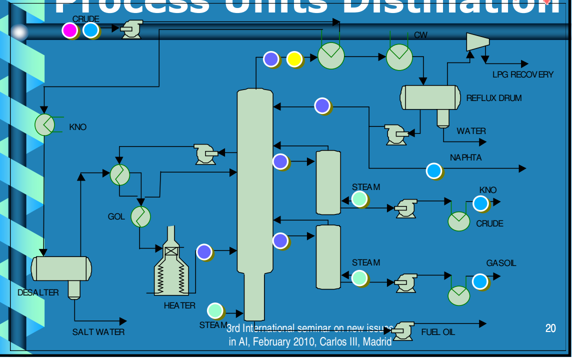
Crude Oil Distillation Tower

- 80000 b/d, 47 trays, 5.2m top diameter, 2.4m bottoms.
- 5 side streams
  - Heavy Naphtha (HN)
  - Kerosene (KN)
  - Light Gas oil (LGO)
  - Medium Gas oil (MGO)
  - Heavy Gas oil (HGO).
- Side stream strippers with steam and bottoms stripping steam
- Top, bottoms and Side stream Temperatures
- Pressure Top and Reflux drum
- Side stream Flow rates
- Steam flow rates
- Crude density

Properties of interest

- 95% ASTM D86 heavy naphtha, depends on
  - The pressure of the tower, *p, kg/cm2g*
  - The amount of the product taking off, *P, %*
  - The density of the crude, *d, g/l*
  - Temperature of the column overhead, *Tco, oC*
  - Temperature of the naphtha extraction, *Tne, oC*
- 95% ASTM D86 kerosene
  - The pressure of the tower, *p, kg/cm2*
  - Amount of product taking off, naphtha and kerosene oil, *P, %*
  - Density of the crude, *d, g/l*
  - Temperature of the column overhead, *Tco, oC*
  - Steam introduced in GOL stripper, *SGK, kg/h*
  - Temperature of the Kerosene Extraction, *Tke, oC*
  - Temperature of the Naphtha Extraction, *Tne, oC*

Process Units Distillation



Properties of interest

- Abel in flammability KNO
  - The pressure of the tower, *p, kg/cm2g*
  - Amount of product taking off, *P, %*
  - Density of the crude, *d, g/l*
  - Temperature of the column overhead, *Tco, oC*
  - Temperature of the Naphtha Extraction, *Tne, oC*
  - Steam introduced in Kerosene stripper, *SkK, kg/h*

Properties of interest

- 85% ASTM D86 GOL
  - The pressure of the tower, *p, kg/cm2g*
  - Amount of product taking off, *P, %*
  - Density of the crude, *ρ, g/l*
  - Temperature of the column overhead, *Tco, oC*
  - Steam introduced in GOM stripper, *SgG, kg/h,*
  - Temperature of the GOL Extraction, *TGOL, oC*
  - Temperature of the Kerosene Extraction, *Tke, oC*
  - Temperature of the Naphtha Extraction, *Tne, oC*

Experimental results: Oil refinery

Results for Predicting Quality of the Crude Oil Distillation

Method	Rules	inputs	RMSE	*e*
Neural Network (**off-line**)	-	7	2.87	3.43
ANFIS (**off-line**)	29	7	**2.15**	**2.25**
DENFIS	29	7	2.46	-
eSensor (A+B)	5	7	2.29	2.37
eSensor (A,B,F)	9	**5**	2.30	2.38
eSensor (A-E)	3	7	2.19	2.28
Full eSensor (A-F)	**3**	**6**	**2.18**	**2.27**

Experimental results: Oil refinery

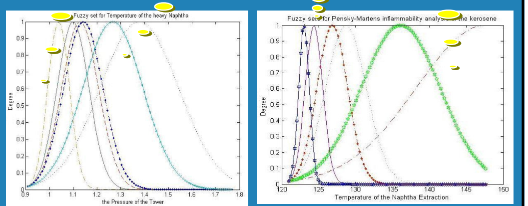
Final Rule base in the Abel inflammability test

R_1: ***IF*** *(P is 5.4%)* ***AND*** *(T^{co} is 323.3 ^oC)* ***AND …AND*** *(T^{ne} is 126.8 ^oC)* ***THEN*** *(A^1=20.2 + 92.7P + … + 0.12 T^{ne})*

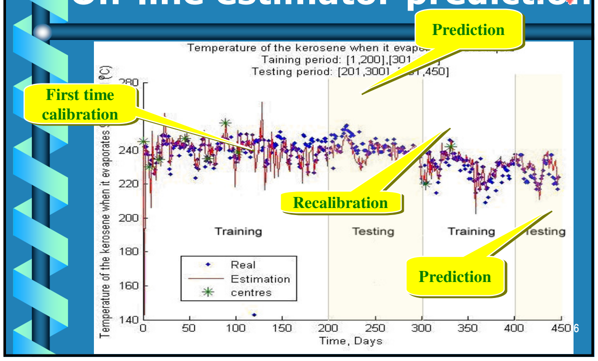
R_2: ***IF*** *(P is 11.7%)* ***AND*** *(T^{co} is 365.0 ^oC)****AND …AND*** *(T^{ne} is 147.6 ^oC)* ***THEN*** *(A^2=42.1 + 63.4P + … + 0.10 T^{ne})*

R_3: *IF (P is 5.4%)* ***AND*** *(T^{co} is 335.14 ^oC)* ***AND…AND*** *(T^{ne} is 136.1 ^oC)* ***THEN*** *(A^3=25.2 + 71.9P + … + 0.19 T^{ne})*

eTS Fuzzy Models (snapshot)



On-line estimator prediction



Chemical Industry

courtesy of Dr. A. Kordon, The Dow Chemical, TX

- ✓ Compositions 1-3 and Propylene distillation
- ✓ Large number of input variables, noise, sudden change of the process state (catalyzer change)

4 case studies

General Information for the 4 data sets

	Comp1	Comp2	Comp3	Propylene
All measured inputs	6	47	47	22
Selected Inputs	2	2	7	2
No of Samples	309	308	308	3000
Noise	Yes	no	Yes	Yes
Operating regime change at sample	127	113	113	Broad range of operations

Composition 1

- ✓ Case 1 is to model the product composition in a distillation tower.
- ✓ The process data is retrieved from 6 physical (‘hard’) sensors used as inputs to the inferential sensor applying hourly averages for every *8* hours.
- ✓ The product composition (real output) is estimated by a laboratory analysis.
- ✓ The estimation of the product composition contains noise due to the nature of the analysis.
- ✓ A significant operating condition change has taken place after sample *127*.

Composition 2

- ✓ The second case concerns product composition in the **bottom** of the distillation tower.
- ✓ A list of *47* related variables are initially included as the inputs, some of them are very loosely related to the product composition.
- ✓ Similarly, lab analysis has been used to obtain the real output, which is less noisy than the output for the other *3* datasets.
- ✓ There is a significant operation change around data sample *113*.

Composition 3

- ✓ The third case is very similar to the previous case (Composition *2*).
- ✓ The only difference is that the level of noise in this problem is much higher.

Propylene

- ✓ The fourth case concerns the Propylene that is in the top of the distillation tower.
- ✓ *22* different physical ('hard') sensors and respectively inputs for the inferential sensor are measured.
- ✓ The data for this, fourth case contains *3000* data points measured every 15 minutes using gas chromatography.
- ✓ They cover a very broad range of operating conditions.

Experimental results: Propylene

- The propylene data set is collected from a chemical distillation process run at The Dow Chemical Co., USA.
- The data set consists of *3000* readings from *23* sensors that are on the plant.
- They are used to predict the propylene content in the product output from the distillation.
- Some of the inputs may be irrelevant to the model and thus bring noise.

Experimental results: Propylene

Results for Predicting Propylene Content of Distillation

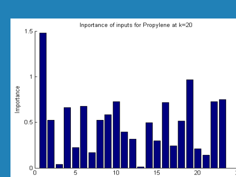
Method	**Rules**	**inputs**	**RMSE**	**correl**
NN (**off-line**) -	-	23	0.11	0.963
ANFIS (**off-line**)	29	23	0.11	0.972
DENFIS	235	23	0.11	0.979
eSensor (A &B)	23	23	0.10	0.981
eSensor (A,B,F)	23	**2**	0.09	0.982
eSensor (A-E)	14	23	0.12	0.974
eSesnor (A-F)	**7**	**2**	**0.09**	**0.983**

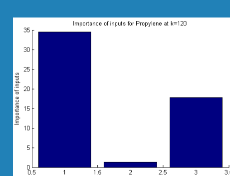
Experimental results: Propylene

Final Rule-base for Propylene:

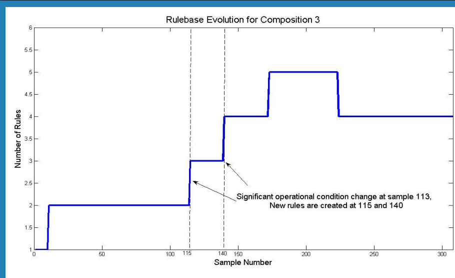
R_1: ***IF*** *(x_1 is 24.6)* ***AND*** *(x_2 is 26.3)* ***THEN*** ($\bar{y} = -0.039 + \bar{x}_1 - 0.324\bar{x}_2$)
R_2: ***IF*** *(x_1 is 39.0)* ***AND*** *(x_2 is43.5)* ***THEN*** ($\bar{y} = -0.615 + 4.77\bar{x}_1 - 0.340\bar{x}_2$)
R_3: ***IF*** *(x_1 is 46.2)* ***AND*** *(x_2 is 49.5)* ***THEN*** ($\bar{y} = -0.679 + 1.090\bar{x}_1 + 0.450\bar{x}_2$)
R_4: ***IF*** *(x_1 is 45.9)* ***AND*** *(x_2 is 49.9)* ***THEN*** ($\bar{y} = -1.340 + 5.570\bar{x}_1 - 3.320\bar{x}_2$)
R_5: ***IF*** *(x_1 is 36.2)* ***AND*** *(x_2 is 43.5)* ***THEN*** ($\bar{y} = -0.002 + 0.320\bar{x}_1 - 0.065\bar{x}_2$)
R_6 ***IF*** *(x_1 is 31.6)* ***AND*** *(x_2 is 38.7)* ***THEN*** ($\bar{y} = -0.007 + 0.366\bar{x}_1 - 0.129\bar{x}_2$)
R_7 ***IF*** *(x_1 is 40.6)* ***AND*** *(x_2 is 39.5)* ***THEN*** ($\bar{y} = -0.527 + 0.406\bar{x}_1 - 0.345\bar{x}_2$)

Experimental results: Propylene





Evolution of the fuzzy rules



Experimental results: NOx emissions

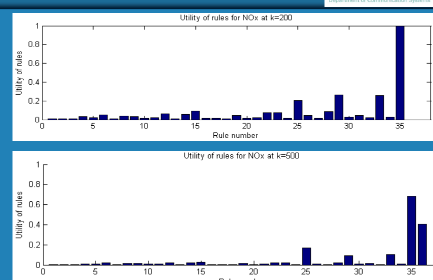
- The last data set was collected from car engines to estimate the NOx content in the emissions that they produce.
- It is based on the variables that are easy to measure, such as pressure in the cylinders, engine torque, rotation speed, etc.
- In total as much as *180* input variables are considered as potential inputs

Experimental results: NOx emissions

Results for NOx Car Emission Analysis

Model	Rules	inputs	RMSE	correl
NN (off-line)	-	180	0.15	0.934
ANFIS (off-line)	32	180	0.15	0.932
DENFIS	113	180	0.17	0.917
eSensor (A,B)	22	180	0.17	0.914
eSensor (A,B,F)	36	101	0.13	0.947
eSensor (A-E)	14	180	0.17	0.908
eSensor (A-F)	13	7	0.15	0.935

Experimental results: NOx emissions



Features of eSensor

- ✓ Intuitive models
- ✓ Adaptation and automatic recalibration
- ✓ Predictions are within acceptable values
- ✓ On-line application to be implemented
  - ✓ OPC connection to DCS
  - ✓ Lab data results interface
  - ✓ Automatic procedure.
  - ✓ On-line optimization of the model/sensor structure! Incl. inputs selection, fuzzy rules, sets, all parameters etc.

eSensor

- ✓ On-line inferential sensor with evolving structure
- ✓ Self-calibrating
- ✓ Detects *shifts* and *drifts* in the data pattern
- ✓ Adaptive, non-linear, robust, linguistically interpretable, computationally light
- ✓ Input selection – on-line

What do we gain?

- A new approach to TS FS structure adaptation on-line including
- On-line inputs (feature) sensitivity analysis and selection
- Utility of fuzzy rules monitoring and rule-base simplification
- Concept *shift* detection using derivative of age of the cluster/rule
- Applied to various problems with improved results

Algorithm Analysis

- Maintenance costs and lab samples (manual work) – reduced significantly
- No problem-specific or user-specific parameters → generic
- Can start from an a priory models structure (expert-based or off-line) and evolve (adapt and improve)
- Extracts knowledge automatically
- Detects anomalies automatically (low P)
- computationally very light, can be implemented on chip and embedded

SLAM

- Joint classification & classifier design
- Classifier needs adaptation (structure/rules, number of classes)
- Start from 'scratch' (unsupervised learning for situation awareness, # of classes/landmarks unknown beforehand)
- Recursive ⇒ computationally efficient
- On-line, autonomous, visual self-localisation and mapping
- Very often absolute coordinates – unavailable or unreliable

Landmarks

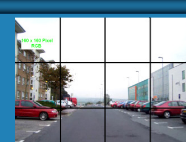
- Novelty Detection
  - The ability to differentiate between common sensory stimuli and perceptions never experienced before
- Landmark Recognition (trees, rocks, contours, other static objects)
  - With Novelty Detection, robot can select aspects of the environment that are unusual and therefore can be used as landmarks for self-localization
- Vital to survive and operate in a completely unknown environment and for Terrain Navigation

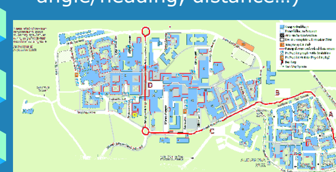
Landmark recognition

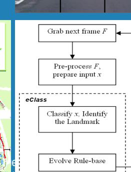
- Explore unknown environment
- No communication link (no GPS, maps…)
- Fully unsupervised (no pre-training, no model structure assumed)
- Indoor, and
- Outdoor experiments

Outdoor experiment

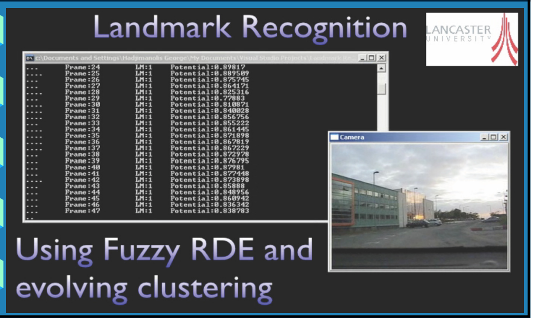
- Frames grabbed in RT, demo
- Features – colour intensity (also may be rotation angle/heading, distance…)







Outdoor experiment



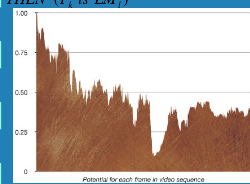
Outdoor experiment

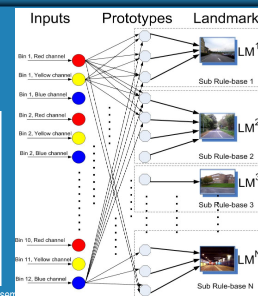
$R_1^1 : IF\,(\mu_{11}{}^R \textit{ is close to } 0.5407)$

$AND\ (\mu_{11}{}^G \textit{ is close to } 0.5548)\cdots$

$AND\ (\mu_{34}{}^B \textit{ is close to } 0.3374)$

$THEN\ \ (F_k \textit{ is } LM_l)$





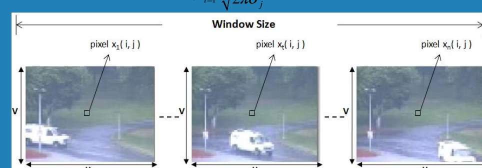
Fast RDE for detection

- Traditional off-line methods require a large amount of computer storage for archiving video streams
- The main challenge is to develop autonomous systems requiring little processing time and memory storage
- The most prominent approaches are based on so called background subtraction and KDE which are based on statistical representation of the background
- It is highly desirable these systems to be free from task-specific thresholds and tuning – fully automatic

KDE

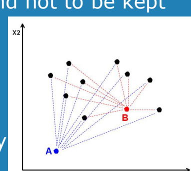
- KDE using Gaussian kernel to estimate the pdf of a pixel:

$$p\left(x(t)\right)=\frac{1}{N}\sum_{i=1}^{N}\frac{1}{\sqrt{2\pi\sigma_j^2}}e^{-\sum_{i=1}^{r}\frac{\left(x_j(t)-x_j(i)\right)^2}{2\sigma_j^2}}$$



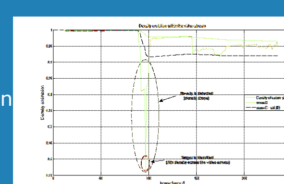
RDE

- The main idea is to approximate the pdf by a *Cauchy type* of kernel instead of Gaussian and recursively calculate it
- This approach allows the image frames to be discarded once processed and not to be kept in memory
- Cauchy function-based potential represents an estimate of the density of a certain data sample based on similarity to all previously seen data samples



Detection using RDE

The main idea is to recursively estimate the similarity to the pixels in that position from *all* previous frames (without memorising them):



$$IF\ \left(P(x(t)) < \underline{P}(t)\right)\ THEN\ \left(x(t)\ \textit{is foreground}\right)$$

Detection using RDE

- By applying this condition to each pixel of the current frame it is possible to identify the pixels that potentially form a novel object
- Memory required is comparable with a single frame (KDE requires N frames) and the approach is faster in orders of magnitude (30 or more times) RT (in ms range per frame)

Detection using RDE

- One way to determine the object for tracking purposes is by using the *spatial mean of all pixels* that has been classified as a foreground in a given image frame

$$h_l = \underset{i=1}{\overset{F}{mean}} \{h_i\} \qquad v_l = \underset{i=1}{\overset{F}{mean}} \{v_i\}$$

- The use of *mean* is prone to noise (due to wind, change of illumination, moves of the leaves of the trees, vibrations etc.)
- This may lead to false positioning which might be misleading for the tracking.

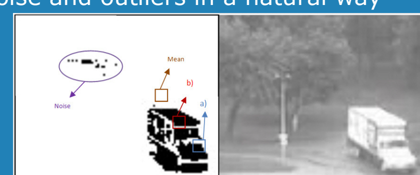
Detection using RDE

- One approach to cope with this problem is to use again the potential (density), but this time in spatial terms inside a frame

$$T = [h_l, v_l]; \quad l = \arg\max_{i=1}^{F}\{P(i)\}$$

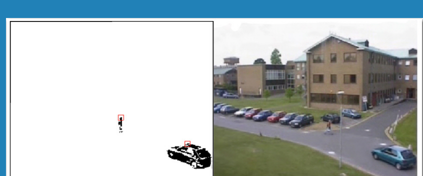
Detection using RDE

- The logic is now inverted - the point with the max density will guarantee a better lock on the target because it ignores the noise and outliers in a natural way



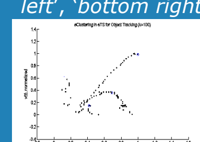
Multiple targets identification by clustering

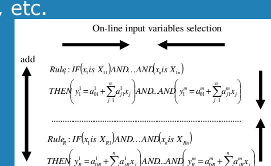
- Using clustering we were able to correctly identify multiple targets



Tracking using eTS

- eTS represents a fuzzy mixture of Kalman filters that are locally active
- The local regions of the data space represent different parts of the image frame, e.g. '*upper left*', '*bottom right*', etc.





Tracking using eTS

- In the tracking problem the aim is to predict the next position of the color blob in the next, *(t+1)th* frame identified by the RDE

$$\hat{T}(t+1) = f\left(T(t)\right)$$

- eTS neuro-fuzzy system has another advantage – it can be represented by linguistically tractable fuzzy rules:

$$Rule_i : IF\ \left(h(t)\ is\ close\ to\ 333\right)\ AND\ \left(v(t)\ is\ close\ to\ 354\right)$$

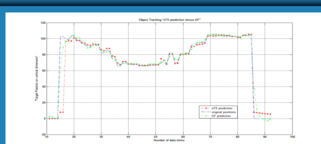
$$THEN \begin{cases} \hat{h}^i(t+1) = 50.37 + 0.8h(t) + 0.05v(t) \\ \hat{v}^i(t+1) = 248.54 - 0.94h(t) + .1.18v(t) \end{cases}$$

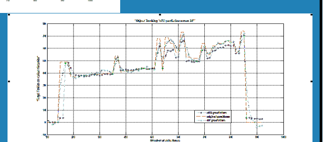
Experimental Results

	Method	window size	Frame size (pixels)	Time per frame (sec)	Memory used Per pixel (bites)	Memory calculation
Video Clip (1)	KDE	20	176×144	15.57	60	O(60)
	RDE	1	176×144	0.43	4	O(4)
Video Clip (2)	KDE	20	320×240	44.56	60	O(60)
	RDE	1	320×240	1.17	4	O(4)

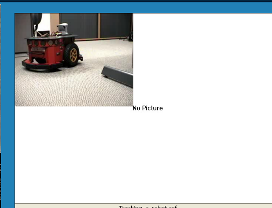
	Method	RMSE	NDEI	VAF (%)
v, pixel	KF	15.58	0.7	50.57
	eTS	13.2	0.56	69.14
h, pixel	KF	23.78	0.66	55.58
	eTS	21.31	0.56	68.56

Experimental Results





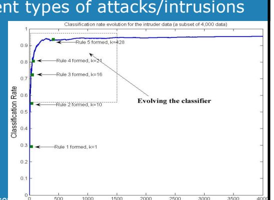
Detect and track RDE + eTS



Cyber security

- Intruder detection algorithms that learn the hackers possibly changing tactics
- Billions of data logs – batch impossible
- Automatically detect different types of attacks/intrusions
  - guessing password
  - port scanning
  - denial-of-service,

  etc.

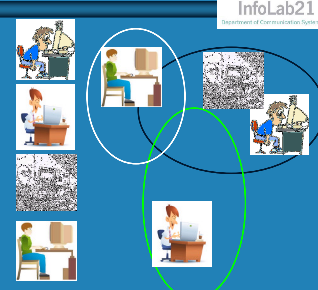


User behaviour clustering

courtesy of Dr. Jose Antonio Iglesias

- Automatic on-line classification of users based on the log info (UNIX commands) they use into not pre-defined groups

SS, postnews, enscript, fg, enscript, cd, *ES*, *SS*, rlogin…



Machine Health Monitoring

Courtesy of Dr. D. Filev, Ford, USA

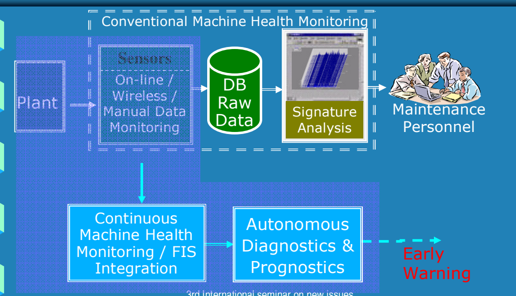
Drive one.

InfoLab21

Nowadays Machine Health Monitoring is a synergy between FIS and Autonomous Diagnostics and Prognostics

Machine Health Monitoring

InfoLab21



Industrial Diagnostics

InfoLab21

- Model-based diagnostics: *reasoning based on the first principle models that declaratively describe a system's structural and behavioral properties*
- Model-based diagnostics: *universal approximators*
  - Predefined sets of symptoms and faults
  - Train (supervised) a universal approximator as a model (NN, fuzzy model, multiple switching model approximator, etc.)

Industrial Diagnostics

InfoLab21

- Unsupervised Diagnostics: Novelty / Anomaly Detection
  - Pattern change
  - Unsupervised learning
  - Inexpensive / integrated equipment (manufacturing)
  - Alternative applications - pattern / signature monitoring

Novelty Detection

Inspired from Process Monitoring

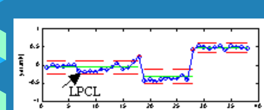
InfoLab21

- Statistical Process Control Charts
  - Statistical process control (SPC) involves using statistical techniques to measure and analyze the variation in processes
- Pattern Recognition Approach
  - Conventional classification methods require enough examples for all classes; problem – limited fault data
- Novelty detection is the process of learning the *normality* of a system by fitting a model to the set of normal examples

Novelty Detection

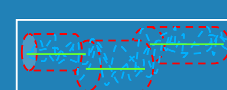
InfoLab21

Scalar condition



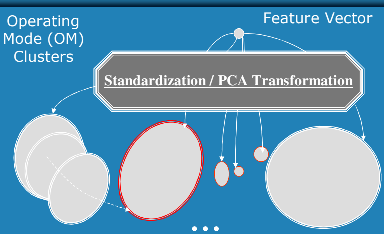
$|y - y_i^*| < 3\,\sigma_{yi}$

Vector condition



$(\underline{y} - \underline{y}_i^*)'\, C_{yi}^{-1}(\underline{y} - \underline{y}_i^*) < \chi^2_{p,\alpha}$

Unsupervised Novelty Detection



Off-line:

Time Domain (kurtosis, root mean square, skewness, crest factor, autoregressive model parameters);

Frequency / Energy (peaks of Fourier transform, power spectrum, frequency band energy, overall energy)

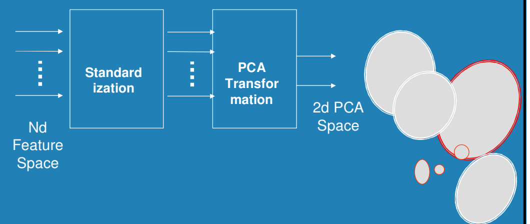
Mixed Domain (wavelet coefficients)

Fault Type I (Incipient): OM cluster centers approaching the boundary of an OM cluster with a low health factor

Fault Type II (Drastic): Rapid generation of new OM clusters with low health factors

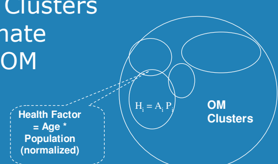
Preprocessing

Feature space transformation and clustering



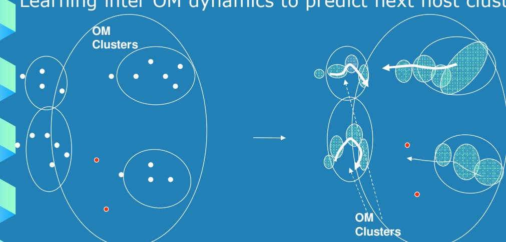
OM Health Factor

Learning Operating Mode (OM) Clusters to Approximate Equipment OM



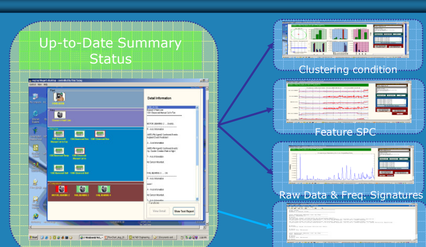
OM dynamics prognostics

Learning inter OM dynamics to predict next host cluster



Evolving Models (eTS) approximate local OM dynamics

Ford Machine Health Monitoring System



Validation: *SKF R&D Facility in Novi, MI, 2005*
Production Pilot: *Ohio Truck Plant, 2005*

Machine Health Prognostics

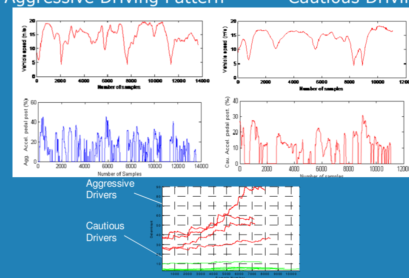
- Machine health prognostics can also be applied to:
  - Identifying a change in the driver's performance style (speed, acceleration, torque request)
  - Estimation of the cognitive load change (control actions – acceleration, braking, steering)

Unsupervised Novelty Detection

- Clustering approach requires significant resources for on-board vehicle applications implementation
- Overall variance "status" is (in some cases) sufficient to characterize a major change
- Recursively estimated determinant of the covariance matrix represents the aggregated total variance

Example: Real Time ...n of Aggressive vs. Cautious Driving

Aggressive Driving Pattern Cautious Driving Pattern



Accelerator Pedal & Derivative Covariance Determinant

Lecture 3 Review

1. Process industries (eSensors)
   a) predicting quality in oil refineries (CEPSA)
   b) modelling polymerisation (The Dow Chemicals, TX)
2. Robotics, SLAM, landmarks
3. Security and video-analytics
4. Automotive industry

Conclusions, Review

In this short course of 3x2 lectures we have introduced:

1) L1: Concept
2) L2: Algorithms
3) L3: Applications

of *Evolving intelligent systems* – a new emerging paradigm on the crossroads of machine learning, adaptive systems and AI