Evolutionary Image Analysis, Signal Processing and Pattern Recognition

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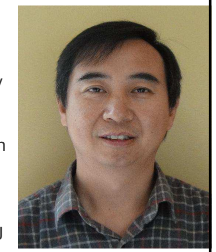
Instructor



Mengjie Zhang is currently Professor of Computer Science at Victoria University of Wellington, where he heads the interdisciplinary Evolutionary Computation Research Group. He is a Associate Dean (Research) in the Faculty of Engineering. His research is focused on evolutionary computation particularly genetic programming and particle swarm optimisation with application areas of computer vision and image processing, job shop Scheduling, and feature selection and dimension reduction for classification. He has published over 300 research papers in refereed international journals and conferences.

He has been serving as an associated editor or editorial board member for six international journals including IEEE TEVC, ECJ (MIT Press) , and GPEM. He has been a major chair for six international conferences, including the Tutorial Chair for GECCO 2014. He is a reviewer for over 20 journals and 80 conferences.

Prof Zhang is the Chair of the IEEE CIS Evolutionary Computation Technical Committee, a vice-chair of the IEEE CIS Task Force on Evolutionary Computer Vision and Image Processing, and the founding chair of the IEEE Computational Intelligence Chapter in New Zealand.

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Instructor

Stefano Cagnoni works at the University of Parma, where he has been Associate Professor since 2004.

Recent research grants include: co-management of a project funded by Italian Railway Network Society (RFI) aimed at developing an automatic inspection system for train pantographs, and a "Marie Curie Initial Training Network" grant, for a four-year research training project in Medical Imaging using Bio-Inspired and Soft Computing.
Editor-in-chief of the "Journal of Artificial Evolution and Applications" from 2007 to 2010. Since 1999, he has been chair of EvoIASP, an event dedicated to evolutionary computation for image analysis and signal processing, now a track of the EvoApplications conference. Since 2005, he has co-chaired MedGEC, workshop on medical applications of evolutionary computation at GECCO. Co-editor of special issues of journals dedicated to Evolutionary Computation for Image Analysis and Signal Processing. Member of the Editorial Board of the journals “Evolutionary Computation” and “Genetic Programming and Evolvable Machines”.

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Outline

- Computer vision and image analysis
- ECV methods:
  - GP
  - PSO
  - LCS
- ECV applications
  - Image analysis
  - Signal processing
  - Pattern recognition – feature selection
- Major ECV events
- References
- Acknowledgement

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Computer Vision

- The “art” of making computers see (and understand what they see)
- Computer vision vs image processing
- Sub-topics:
  - Image acquisition
  - Image enhancement
  - Image segmentation
  - 3D-information recovery/feature extraction
  - Image understanding

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Computer and Human Vision

HUMAN	COMPUTER
Perception	Image acquisition
Selective information extraction	Feature enhancement (signal/image processing)
Grouping by ‘similarity’	Segmentation
Extraction of spatial relationships	3D-information Recovery
Object recognition and semantic interpretation	Image Understanding

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LOW-LEVEL VISION

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Computer and Human Vision

HUMAN	COMPUTER
Perception	Image acquisition
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Grouping by ‘similarity’	Segmentation
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Object recognition and semantic interpretation	Image Understanding

HIGH-LEVEL VISION

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Computational Intelligence (CI)

- ❖Symbolic intelligence vs CI
- ❖Neural Networks
- ❖Evolutionary Computation
  - Evolutionary Algorithms
  - Swarm Intelligence
  - Others
- ❖Fuzzy Systems
- ❖Other

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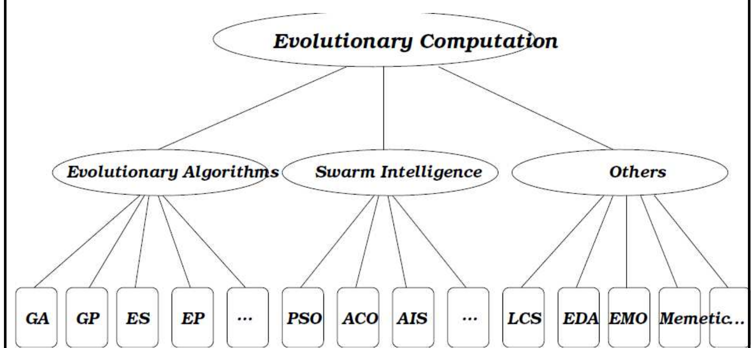
Evolutionary Computation



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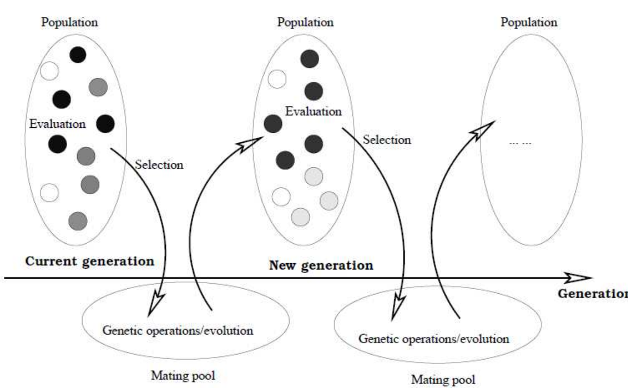
Evolutionary Computation Process



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Application Taxonomy

- ❖ EC techniques
  - GA, GP, ES, EP, PSO, DE, LCS, EMO, EDA, etc.
- ❖ Solution types
  - Optimisation of parameters of specific solutions (using GA, ES, PSO…)
    - Related with a well-defined task or for a whole system
  - Generation of solutions from scratch (GP, …)
    - Performance optimization based on specific objective functions
    - It is difficult to choose a model with reasonable assumptions
- ❖ Role of EC techniques
  - Interactive qualitative comparisons between solutions
  - Generation of emergent collective solutions
    - Achievement of higher-level and complex tasks from collective use of trivial, local, hard-wired behaviours: generation of full EC-based solutions, NOT parameter optimization tasks

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Applications (Stefano Cagnoni)

- Optimization of filter/detector AND algorithm parameters for event detection and image segmentation
- Design of implicitly parallel binary image operators and classifiers
- Qualitative optimization of image processing algorithms
- Object detection, segmentation, tracking

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Applications (Stefano Cagnoni)

- GA-based design of a detector for ECG signals.
- Optimization of a 3D segmentation algorithm for tomographic images based on an elastic contour model.
- SmcGP-based low-level image processing and low-resolution character recognition.
- GP-based design of lookup tables for color processing of MR images.
- Object detection and tracking using PSO
- Details can be seen from GECCO 2008 and 2014 Tutorials by Stefano

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Applications (this tutorial)

- EC techniques: GP, PSO, LCS, EMO
- Image Analysis
  - Object tracking
  - Edge detection
  - Segmentation
  - Motion detection
  - Object/digit recognition
- English stress detection(signal processing)
- Pattern Recognition: feature selection and biomarker detection

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GP for ECV Applications

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Genetic Programming -- Origin

- Genetic algorithms (GAs) with tree-like representation
- Automatic programming: one of the major challenges of computer science --- use a computer to do what needs to be done without telling/knowing the specific steps.
- GP = Automatic programming + GAs
- GP genetically breeding a population of computer programs using principles of Darwinian natural selection and biologically inspired operations

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GP: Representations

- Tree based GP: John Koza
  - Lisp programs
  - Koza:92 vs 1980s: Cramer
  - Most commonly used
- Linear GP: Wolfgang Banzhaf
  - C/C++/Java programs
  - Graph: like NNs but not fully connected and more flexible
- Grammar based GP/Grammatical Evolution: Peter Whigham, Bob McKay, Michael O'Neill
- Cartesian GP: Julian Miller

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GP for Vision Tasks

- Object detection
- Object classification
- Object tracking
- Motion detection
- Edge detection
- Segmentation
- Many domains: medical, military, agriculture, biology, transportation, …

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GP for Object Tracking

- Use GP to track an object in low-quality webcam footage, at a real-time speed.
- Test the GP method on two object tracking problems of varying difficulty.

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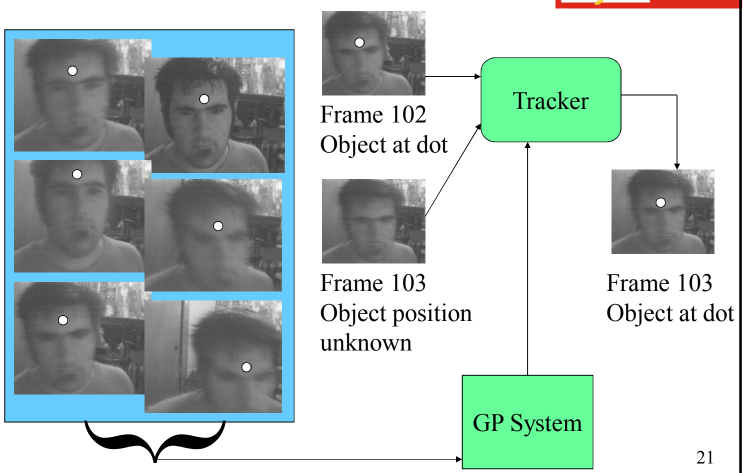
Object Tracking Task



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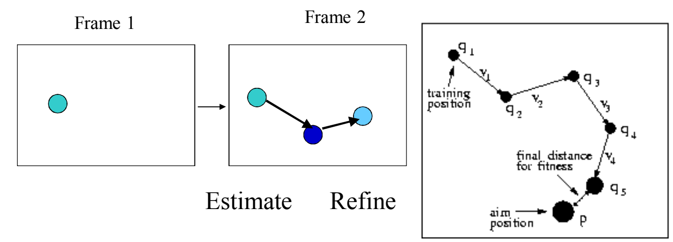
Tracker Programs



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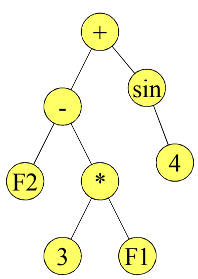
Standard Evolved Programs



(F2 – 3 * F1) + sin(4)

- Evolved programs (or genetic programs)
  - Tree-like expression structure
  - Internal nodes are functions
  - Leaf nodes (terminals) are constants or input (feature) values.
  - Evaluating program produces a single value.

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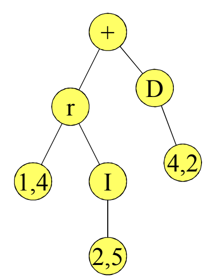
GP Tracker Program



((1,4) rot. by I(2,5)) + D(4,2)

- Non-standard
- Nodes deal with two-valued vectors
  - Not single values
  - Program output is a two-valued vector
- Input features are functions
  - Not terminals
  - Not just elements in a fixed length feature-vector
- Still uses a tree

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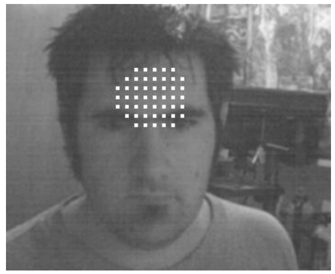
Training

- Specify target object position
- Evaluate tracker program at a set of training points around target producing refined estimates.
- Fitness of program = avg. distance from target



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Data Sets

- We used two short pieces of webcam footage of a person moving around at a fixed distance from the camera.
  - 358 x 288, 15 fps, 256 shade, greyscale
  - Very low quality.
  - Fast movement looks very blurry.
  - Include some tricky movements like moving close to the border, looking up, moving quickly and obscuring face.
- Two tasks
  - Left eye
  - Centre of forehead

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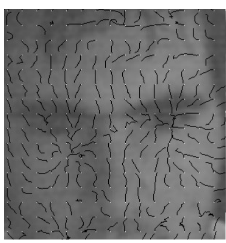
Experiment 1:Tracking the left eye



Trails of tracker convergence

Tracking, every 20th frame

- Tracks well, even when the face was quite blurry due to fast movement.

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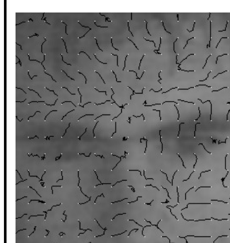
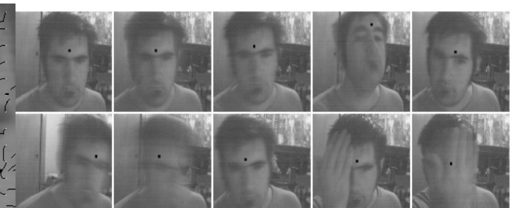
Experiment 2:Tracking the head



Trails of tracker convergence



Tracking, every 20th frame

- Tracks well, even when the face was quite blurry due to fast movement and when the head looks up.

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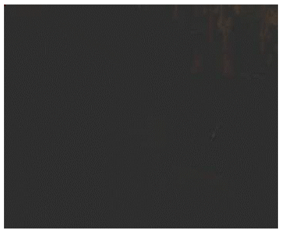
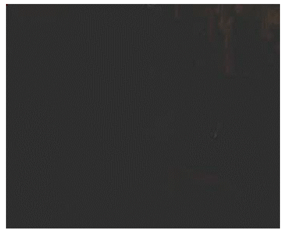
Example Videos





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Summary

- GP programs very successfully tracked the objects in the video-sequences.
- No domain knowledge was necessary
  - programs automatically constructed
  - Just 15 images with object positions located
- Non-standard GP program structure was critical.
  - Vector outputs
  - Feature functions
- Evolution identifies a small number of point features to compute while tracking
  - Efficient.
- Tracks about nine times faster than real-time
  - This is with non-compiled evolved programs
  - Compiled would be faster.

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GP for Image Segmentation

- *A figure-ground segmentation method* is developed using GP to evolve segmentors from the local image information.
- Based on this proposed method, a wide range of features have been investigated as *terminal sets*.

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Construction of GP-based Method using Local Information

Generate a classifier

↓

Use the classifier to sweep the test image, assign a label to sub-images

↓

Use a voting scheme to finalize each pixel's label, generate the output.

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Function Set

Function Set

Function Name	Definition	Type
Add(a_1, a_2)	$a_1 + a_2$	Arithmetic
Sub(a_1, a_2)	$a_1 - a_2$	Arithmetic
Mul(a_1, a_2)	$a_1 * a_2$	Arithmetic
Div(a_1, a_2)	$\begin{cases} a_1/a_2 & \text{if } a_2 != 0 \\ 0 & \text{if } a_2 == 0 \end{cases}$	Arithmetic
IF(a_1, a_2, a_3)	$\begin{cases} a_2 & \text{if } a_1 \text{ is true.} \\ a_3 & \text{if } a_1 \text{ is false.} \end{cases}$	Relation
$<= (a_1, a_2)$	$\begin{cases} true & \text{if } a_1 <= a_2 \\ false & \text{if otherwise} \end{cases}$	Relation
$>= (a_1, a_2)$	$\begin{cases} true & \text{if } a_1 >= a_2 \\ false & \text{if otherwise} \end{cases}$	Relation
$== (a_1, a_2)$	$\begin{cases} true & \text{if } a_1 == a_2 \\ false & \text{if otherwise} \end{cases}$	Relation
Between(a_1, a_2, a_3)	$\begin{cases} true & \text{if } a_2 <= a_1 <= a_3 \\ false & \text{if otherwise} \end{cases}$	Relation

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Terminal Sets

Terminal Set

	Features	Category
Terminal Set 1	Raw Pixel Values	Brightness
Terminal Set 2	Histogram Statistics	Texture
Terminal Set 3	GLCM Statistics (Grey-Level Co-occurrence Matrix)	
Terminal Set 4	LBP (Local Binary Patterns)	
Terminal Set 5	Fourier Power Spectrum	
Terminal Set 6	Gabor Features	
Terminal Set 7	Moments + Gradient Statistics	Shape

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Fitness Function and Parameters

$$f = \frac{Number\ of\ correctly\ classified\ samples}{Number\ of\ total\ training\ samples}$$

Population Size	500	Generation Number	51
Crossover Rate	0.9	Mutation Rate	0.1
Max tree depth for initialization	6	Max tree depth for evolution process	17

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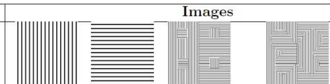
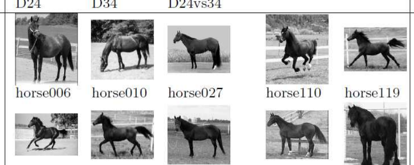
Database	Images	Descriptions
Bitmap	 P14 P24 Rectangular Butterfly	Size: 256*256 Synthetic, binary images
Brodatz	 D24 D34 D24vs34	Size: 320*160 Grayscale images
Weizmann	 horse006 horse010 horse027 horse110 horse119 horse121 horse122 horse159 horse165 horse317	Average Size:248*211 Real images Varing horse positions One object
PASCAL (Name prefix: 2007_00)	 0033 0256 0738 1288 1761 2099 2266 2376	Average Size:500*350 Real images Varing object locations/sizes Multiple objects

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Result Evaluation Measures

Evaluation Measures

- Segmentation Accuracy
  - *Simple; commonly-used.*
  - *The higher the better.*
  - **Problem: insufficient (e.g. a small object in a test image is segmented totally as background, the accuracy can still be high)**
- F1 Measure
  - *Combine precision and recall together.*
  - *Best at 1, worst at 0.*
- Negative Rate Metric (NRM)
  - *Consider mismatches between a prediction and ground truth.*
  - *Best at 0, worst at 1.*

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Results

Results on Bitmap Images

	Ground Truth	Result Examples	Accuracy(%)	F_1	NMR
Intensity			98.81 ± 0.22	0.99	0.20
Intensity			95.96 ± 1.27	0.96	0.12

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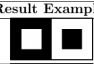
Results on Texture Images

Feature	Result Examples	Accuracy(%)	F_1	NMR
Ground Truth		-	-	-
Intensity		**94.26 ± 2.75**	**0.94**	0.15
Histogram Statistics		93.98 ± 2.30	**0.94**	**0.07**
GLCM Statistics		92.67 ± 1.45	0.92	0.15
LBP		66.82 ± 10.06	0.53	0.35
Fourier Power Spectrum		91.16 ± 0.94	0.90	0.13
Gabor		90.91 ± 0.72	0.90	0.15
Moments + Gradient		92.02 ± 2.11	0.92	0.39

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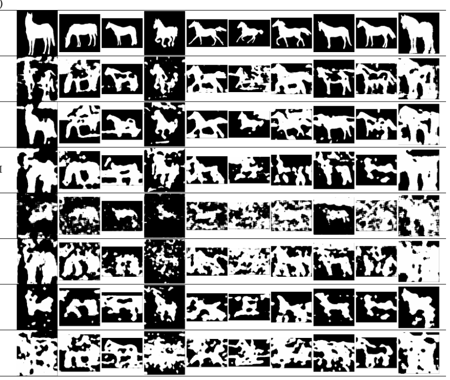
Results

Results on Weizmann Images



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Results

Statistical Results on Weizmann Images

Feature	Accuracy (%)	F_1	NRM
Intensity	74.41 ± 8.37	0.62	0.47
Histogram Statistics	77.37 ± 9.09	**0.84**	0.47
GLCM Statistics	76.74 ± 3.92	0.68	0.47
LBP	66.19 ± 10.95	0.52	0.48
Fourier	68.38 ± 7.38	0.61	0.50
Gabor	**78.29±5.40**	0.66	**0.42**
Moments + Gradient statistics	65.04 ± 10.39	0.58	0.50

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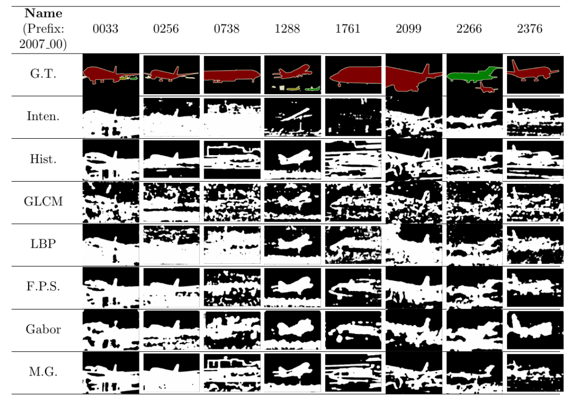
Results

Results on PASCAL Images



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Results

Statistical Results on PASCAL Images

Feature	Accuracy (%)	F_1	NRM
Intensity	71.39 ± 10.63	0.49	0.50
Histogram Statistics	74.56 ± 6.89	0.61	0.50
GLCM Statistics	67.39 ± 9.60	0.49	0.52
LBP	63.75 ± 14.07	0.54	0.50
Fourier	75.10 ± 7.90	0.61	**0.46**
Gabor	**75.60±8.10**	**0.62**	**0.46**
Moments + Gradient statistics	74.53 ± 7.83	0.59	0.48

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Summary

- When segmenting complex images, *higher-level information* (e.g. spectral or statistical information) are necessary.
- The GP-based method using local image information can achieve accurate segmentation *across a wide range of images*.
- Results on images from Weizmann and PASCAL datasets are obviously worse than those on binary or texture images. Need better features
- This local information based method often produces inaccurate boundaries. Need global information

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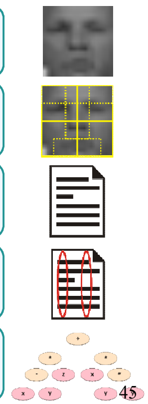
GP for Image Recognition/Classification

The traditional way

Domain-specific pre-extracted features approach

Input	The input is raw image pixel values
Design	The feature areas need to be designed by domain-experts
Feature Extraction	Transform the pixel values of the selected areas to a different domain
Feature Selection	Select a subset out of the extracted features (optional)
Classification	Feed the extracted features (with or without selection) to a GP-based classifier



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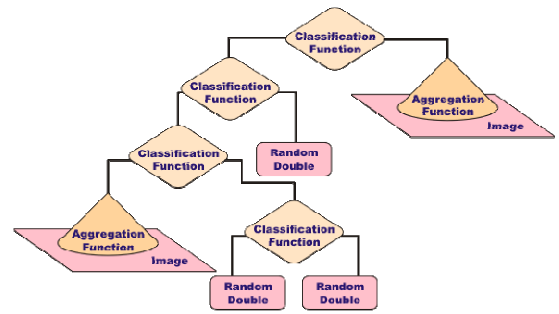
Two-Tier GP Method



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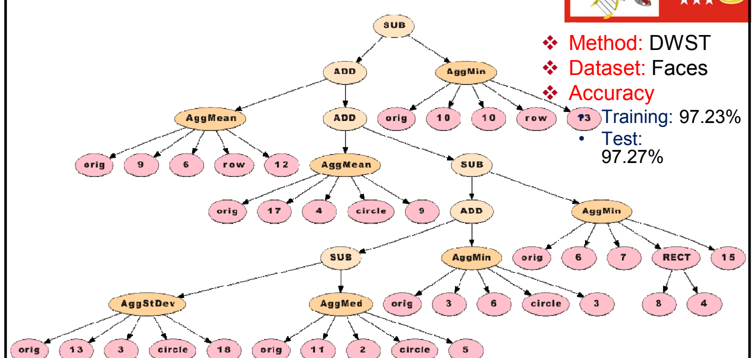
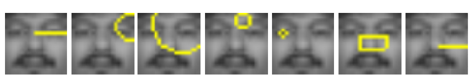
Analysis



- Method: DWST
- Dataset: Faces
- Accuracy
  - Training: 97.23%
  - Test: 97.27%



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GP for Motion Detection: without noise

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Motion Detection: with noise

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Test Detector 1 in raining day

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Test Detector 2

Detector 2 can perform well on videos with additive noise of variance **50**.

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Test Detector 2 in raining day

Moving camera

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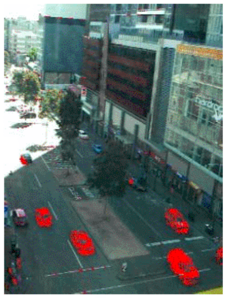
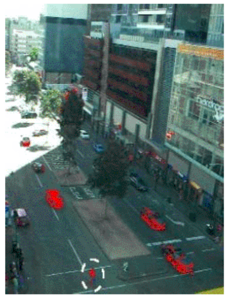
Comparison: Background Modelling -1

All pixels in motion are marked in red, including pedestrians and minor false positives.

Note: the camera position was fixed in this experiment.

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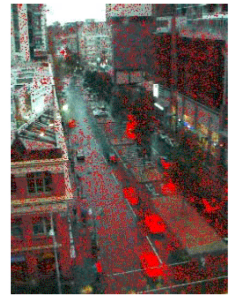
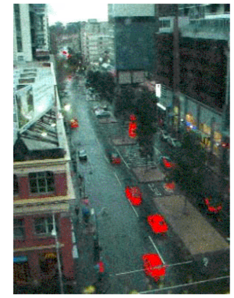
Comparison: Background Modelling -2

Left: model trained on no-noise data performing on raining day. (No camera movement)

Right: model trained on noise data performing on raining day. (No camera movement)

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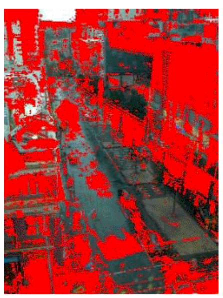
Comparison: Background Modelling-3




Applying background model on unseen data.

Left: unseen raining condition.

Right: changed camera angel (not even a moving camera).

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PSO for Edge Detection

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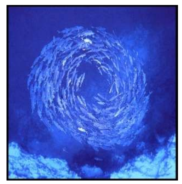
Particle Swarm Optimisation

- PSO as a global optimisation method was proposed by Kennedy and Eberhart in 1995
- It is a simulation of a simplified social model like bird flocking and fish schooling



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Key Concepts in PSO

- Particle: there is a population containing *m* potential solutions (called particles)
- Velocity and Position Equations: the particles move through *n*-dimensional search space according to position and velocity update equations

$$\vec{X}_i(t+1) = \vec{X}_i(t) + \vec{V}_i(t+1)$$

$$\vec{V}_i(t+1) = w\vec{V}_i(t) + C_1 Rand_1(\vec{X}_{pbest_i} - \vec{X}_i(t)) + C_2 Rand_2(\vec{X}_{leader} - \vec{X_i}(t))$$

- Topology: defines how particles are connected to each other as an information sharing or exchanging mechanism

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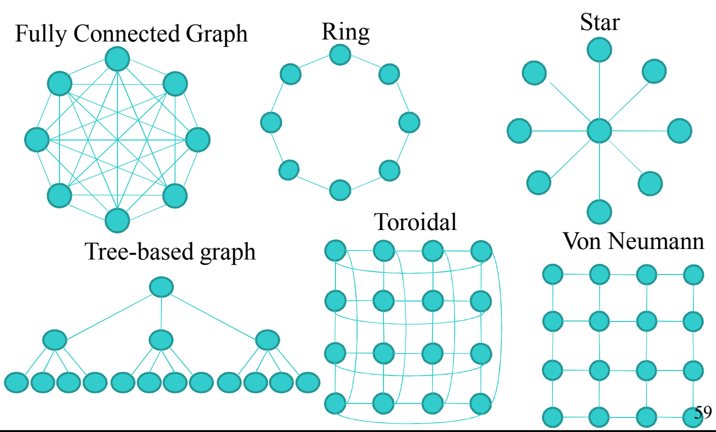
Some of Well-Known Static Topologies



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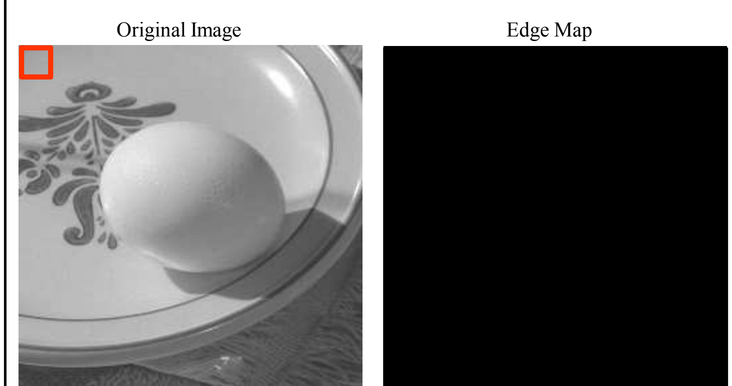
Convolution of Red Rectangle on an Image



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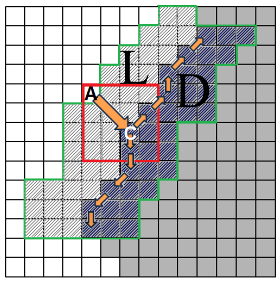
A New Fitness Function

- Maximise distances among an intensity of pixels belonging to two regions separated by a continuous edge and minimise distances within the regions.



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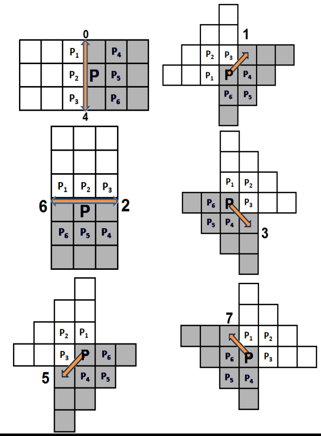
Probability Score of Curve *C*



$$EdgeMag_m(P) = \frac{InterDis_m(P)}{1 + IntraDis_m(P)}$$

$$InterDis_m(P) = min\left(1, |avg_{m_d(P)} - avg_{m_l(P)}|/w_1\right)$$

$$IntraDis_m(P) = \frac{1}{\binom{n}{2}}\left(\sum_{\substack{\forall P_i, P_j \in D \\ i>j}} min\left(1, |I_{P_i} - I_{P_j}|/w_2\right) + \sum_{\substack{\forall P_i, P_j \in L \\ i>j}} min\left(1, |I_{P_i} - I_{P_j}|/w_2\right)\right)$$

$$PScore_m(P) = \frac{1}{1 + e^{-\frac{1}{TH}(EdgeMag_m(P) - TH)}} \times \frac{1}{1 + e^{-2(NMS_d(P) - 4)}}$$

$$NMS_m(P) = |\{P_i | i \in 1..6, EdgeMag_m(P_i) < EdgeMag_m(P)\}|$$

$$U_C = \frac{1}{255 * (max)} \sum_{i=1}^{max} |I_{P_{i+1}} - I_{P_i}|$$

$$PScore(C) = \frac{\sum_{\forall P_i \in C} PScore_{m_i}(P_i)/(max+1)}{1 + U_C}$$

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Curvature Cost of Continuous Edges

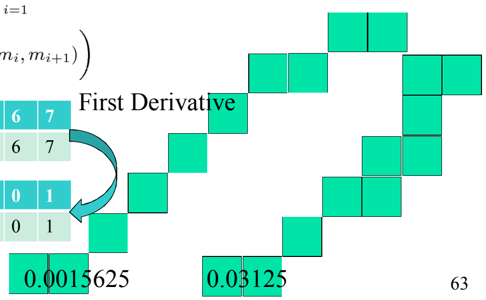
$$CC(m_i, m_{i+1}) = \begin{cases} |m_i - m_{i+1}|/w_3 & , \ |m_i - m_{i+1}| \le 4 \\ (8 - |m_i - m_{i+1}|)/w_3 & , \ otherwise \end{cases}$$

$$CCost(C) = \frac{1}{max - 2}\left(\sum_{i=1}^{max/2-1} CC(m_i, m_{i+1}) + \sum_{i=max/2+1}^{max-1} CC(m_i, m_{i+1})\right)$$

7	6	7	6	6	6	6	6	7
7	5	5	7	5	7	6	6	7

First Derivative

0	1	1	1	0	0	0	0	1
0	2	0	2	2	2	1	0	1



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A New Fitness Function With Two Constraints

$$Fitness(C) = PScore(C) - CCost(C)$$

- Subject to two constraints:
  - The curve *C* never crosses itself.
  - The probability score of the curve *C* must be larger than the predefined threshold *HP*.

$$Cross(C) = 0 \quad and \quad PScore(C) > HP$$

- A simple preservation method is used to handle these constraints in PSO.

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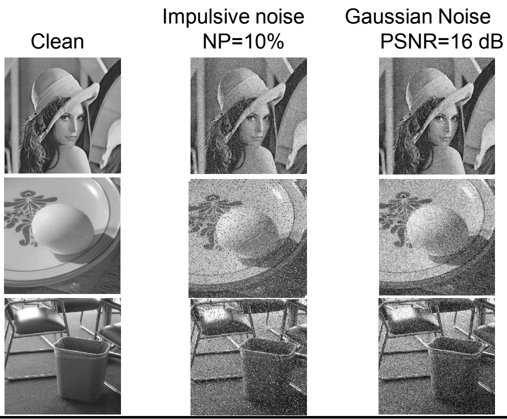
Image Set

(From South Florida University Database)



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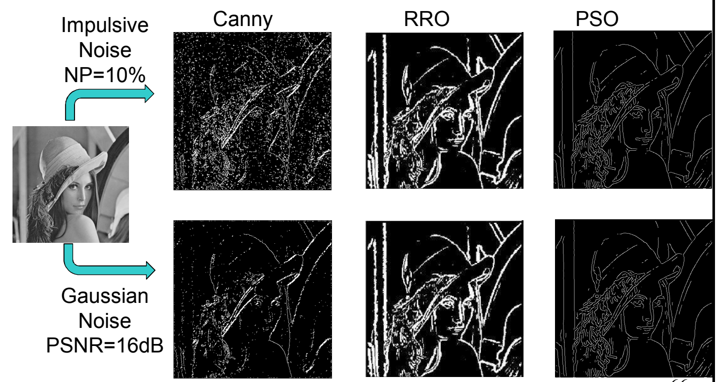
Example 1: PSO vs Canny and RRO



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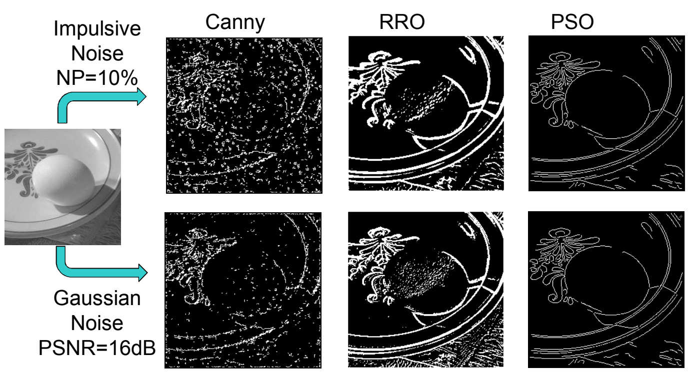
Example 2: PSO vs Canny and RRO



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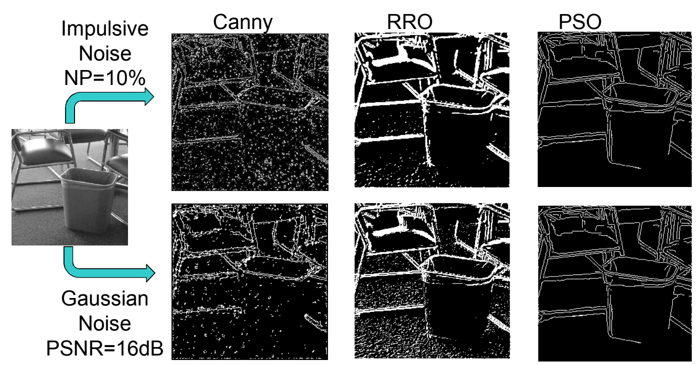
Example 3: PSO vs Canny and RRO



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LCS for Hand-written Digit Recognition

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Learning Classifier Systems

- Machine learning for Robotics:
  - Needs to be **reinforcement**-based and **online**
  - Preferably also **adaptive** and **transparent**
- Learning from visual input is hard:
  - High-dimensionality vs. sparseness of data
- Why Learning Classifier Systems
  - Robust reinforcement learning
  - Limited applications for visual input

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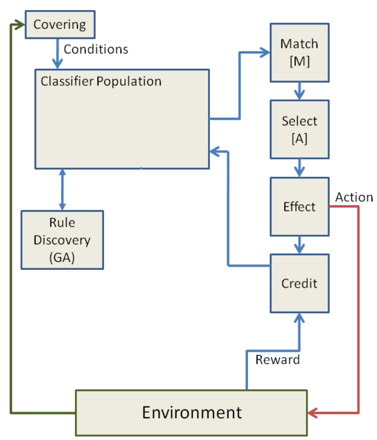
Learning Classifier Systems



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MNIST Digits Dataset

- Well known handwritten digits dataset
- **60 000** training examples, **10** classes
- Examples from **250** subjects
- **28x28** pixel grey-scale (**0..255**) images
- **10 000** evaluation examples (test set, different subjects)

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MNIST results

- Performance:
  - Training set: **92%**
  - Test set: **91%**
  - Increase to **96%** (after improvement)
- Supervised and off-line methods reach 99%
- Encouraging initial results for reinforcement learning

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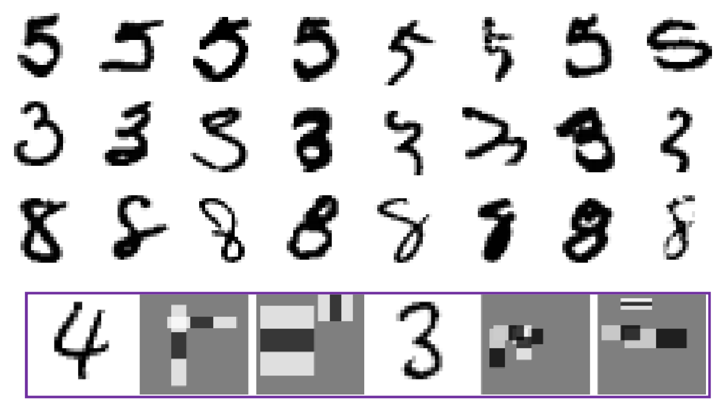
Why not 100% performance?



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Demo

❖Feature Pattern Classifier System (FPCS)

❖Handwritten Digit Classification with LCS

❖ Toktam Ebadi, Ignas Kukenys, Will N. Browne, Mengjie Zhang: Human-Interpretable Feature Pattern Classification System Using Learning Classifier Systems. Evolutionary Computation 22(4): 629-650 (2014)

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Signal Processing

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GP for English Stress Detection

- English becomes more and more important as a communication tool in the world.
- Provide P2P training to ESL students is very expensive. Therefore, software is desirable.
- Correct *rhythmic* stress in ESL students' speech is a key point to make the speech sound like native. Therefore, to accurately detect rhythmic stress in spoken English becomes an important functionality in this kind of software.

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Known Stress Classifiers

- Bayesian classifier
- Support vector machine classifier
- Decision tree classifier
- Neural networks classifier

The best accuracy is around 85%. It is not high enough for a commercial use.

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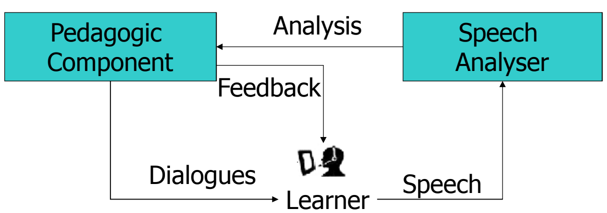
Overview of the whole project



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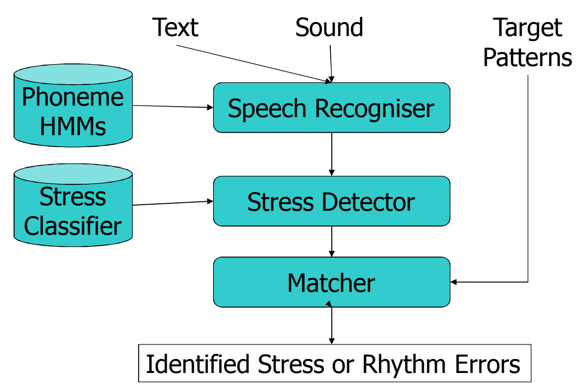
The Speech Analyser



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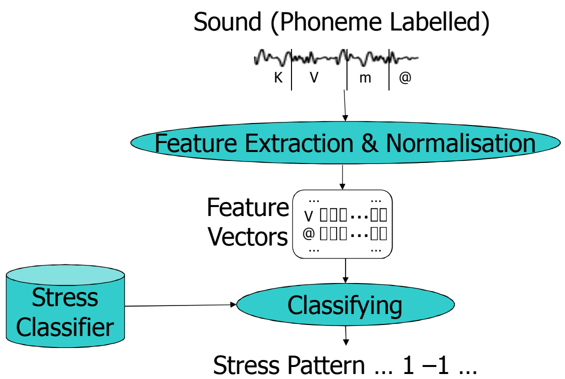
The Stress Detector



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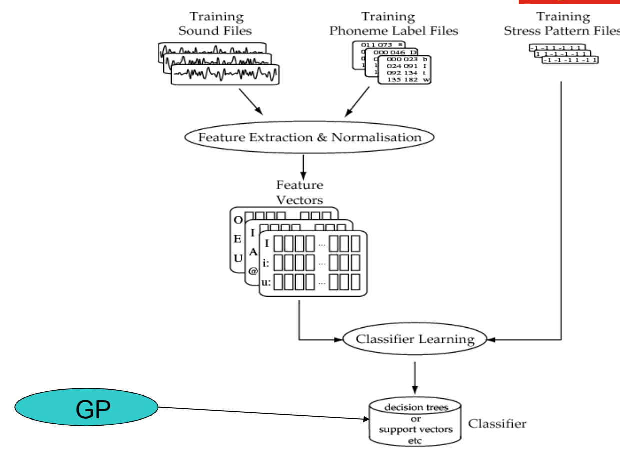
Classifier Learning Procedure



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GP adapted to stress detection

- ❖Feature extraction & normalisation
- ❖GP configuration
  - Terminal sets and the function set
  - Fitness function
  - Genetic parameters
  - Termination criteria

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Feature extraction & normalisation

Rhythmic stress is related to:

- Prosodic features – such as duration, amplitude, pitch, and etc.
- Vowel quality – full vowel and reduced vowel. It is defined by the configuration of the tongue, jaw, and lips.

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Feature extraction & normalisation – Prosodic (cont.)

- Calculation of prosodic features is well known
  - Duration is how long a syllable lasts
  - Amplitude relates to the loudness of the syllable
  - Pitch is the perceptual correlate of the fundamental frequency of the sound signal
- Need several levels of normalisations to reduce variations of differences between speakers, recording situations or utterance context, etc.
- There are 17 prosodic features used in our study

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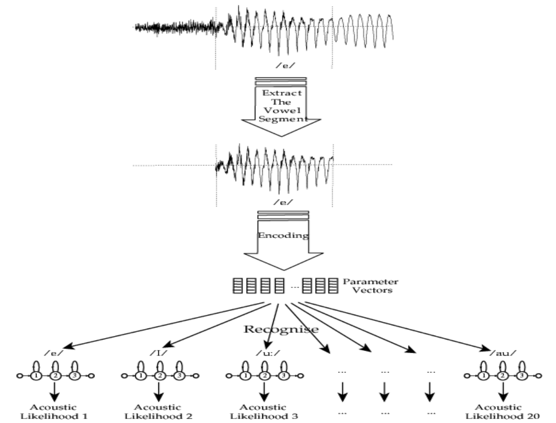
Feature extraction & normalisation – Vowel Quality (cont.)



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Feature extraction & normalisation – Vowel Quality (cont.)

- Find the score of the expected vowel type S_e, the score of the best matching full vowel S_f and the score of the best matching reduced vowel S_r from the above 20 scores.
- Compare S_f and S_r to S_e respectively and measure the difference between the likelihoods and the ratio of the likelihoods.

$$R_d = \begin{cases} -log(S_r - S_e) & \text{if } S_e < S_r \\ 0 & \text{if } S_e = S_r \\ log(S_e - S_r) & \text{if } S_e > S_r \end{cases} \qquad R_r = \log(S_e/S_r) = \log S_e - \log S_r$$

$$F_d = \begin{cases} -\log(S_f - S_e) & \text{if } S_e < S_f \\ 0 & \text{if } S_e = S_f \\ \log(S_e - S_f) & \text{if } S_e > S_f \end{cases} \qquad F_r = \log(S_e/S_f) = \log S_e - \log S_f$$

- Also include a Boolean feature to deal with cases where these 4 features can't be calculated if the vowel segment is so short.

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GP configuration

- A linear-structured GP
- Terminal sets
  - I : 17 prosodic features
  - II : 5 vowel quality features
  - III : combination of sets I and II
- The Function Set

  {abs, sqrt, cos, sin, +, -, *, /, iflt, ifpr, ifnr}

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GP configuration (cont.)

- Fitness function – error rate.
- Genetic parameters
  - Population size: 1024
  - Tournament size: 4
  - Initial program size: 80
  - Max program size: 256

	I	II	III
Crossover rate	71%	57%	47%
Mutation rate	97%	87%	83%

- The learning process stops when:
  - Max number of generations without improvement reaches 200
  - Fitness of the best program is zero on the training data set

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Experiment Design

- Data set: 703 vowels in 60 utterances of ten distinct sentences produced by 6 female speakers – 340 stressed and 363 unstressed
- Scaled feature values in the range [-1,1] are also used.
- Three experiments are conducted on the three terminal sets respectively.
- 10 times 10-fold cross validation for training and testing
- Comparing with
  - DT -- C4.5
  - SVM -- LibSVM (with Radial Basis Function kernel and C = 1)
  - GP: Discipulus

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Detection Accuracy (%)

Terminal Set I (prosodic features)			
	GP	DT	SVM
Unscaled	91.9	80.4	79.7
Scaled	91.6	80.6	83.2
Terminal Set II (vowel quality features)			
	GP	DT	SVM
Unscaled	85.4	79.7	79.1
Scaled	84.6	78.9	80.5
Terminal Set III (combination)			
	GP	DT	SVM
Unscaled	92.0	79.9	81.3
Scaled	92.6	80.1	82.0

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Summary

- Amongst prosodic features, duration has a bigger impact than amplitude and pitch.
- In vowel quality features, features reflecting reduced vowel quality are far more useful than those reflecting full vowel quality.
- GP can be used to construct an automatic rhythmic stress detector.
- GP outperforms DT and SVM on this data set
- GP is more robust at handling irrelevant features and has stronger feature selection ability than DT and SVM on our data set

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EC for Pattern Recognition

- GP for mathematical modelling
- PSO and EMO for Feature Selection

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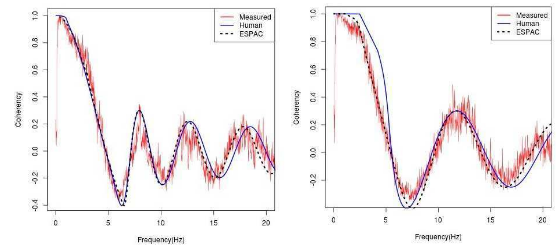
Mathematical Modelling

Assessing Christchurch Earthquake Liquefaction Potential



Human competitive results!

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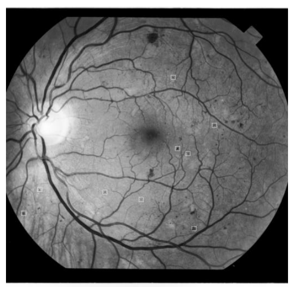
Computer Vision – Satellite and Medical Image Analysis

Satellite image –
Land, water, snow, cloud



Object detection --
Human retina image

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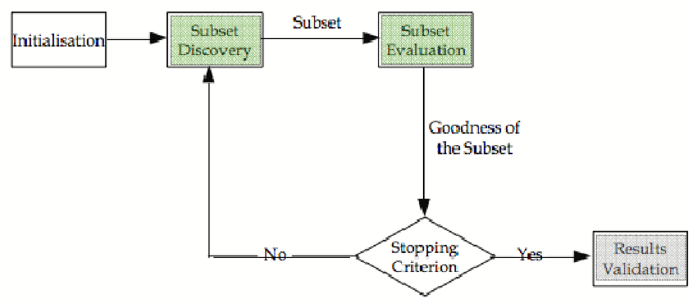
Feature Selection and Biomarker Detection



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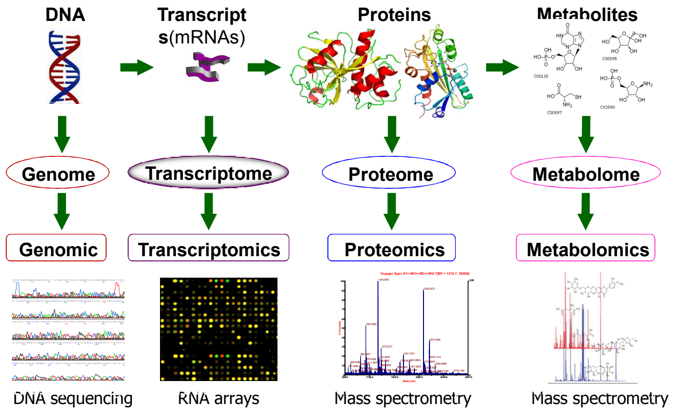
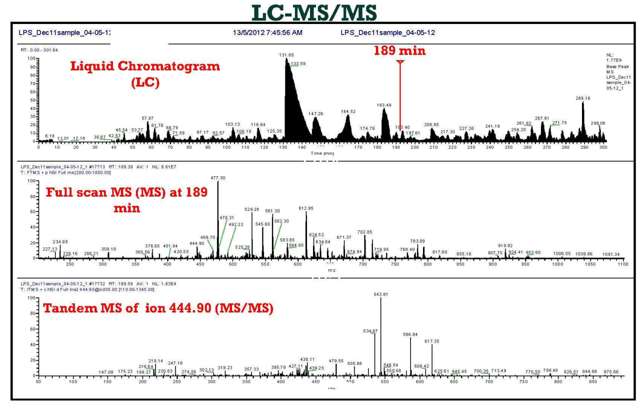
Biology data – LC-MS/MS



Cancer Diagnosis



Why Feature Selection ?

- "Curse of the dimensionality"
  - Large number of features: 100s, 1000s, even millions
- Not all features are useful (relevant)
- Redundant or irrelevant features may reduce the performance (e.g. **classification accuracy**)
- Costly: time, memory, and money

- Feature selection
  - to select a small subset of **relevant** features from the original large set of features in order to maintain or even improve the performance

What can feature selection do ?

- Reduce the dimensionality (No. of features)
- Improve the (classification) performance
- Simplify the learnt model
- Speed up the processing time
- Help visualisation and interpretation
- Reduce the cost, e.g. save memory
- and ?

Multi-objective Problems — challenging

Challenges in Feature Selection

- Large search space: 2^n possible feature subsets
  - 1990: n < 20
  - 1998: n <= 50
  - 2007: n ≈ 100s
  - Now: 1000s, 1 000 000s
- Feature interaction
  - Relevant features may become redundant
  - Weakly relevant or irrelevant features may become highly useful
- Slow processing time, or even not possible

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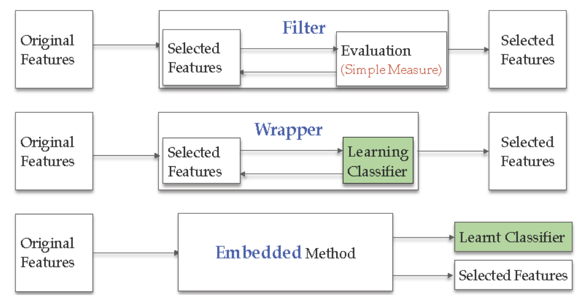
Feature Selection Approaches

- Based on Evaluation ——— learning algorithm
  - Three categories: Filter, Wrapper, Embedded
  - Hybrid (Combined)



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Feature Selection Approaches

- Generally:

	Classification Accuracy	Computational Cost	Generality (different classifiers)
Filter	Low	Low	High
Embedded	Medium	Medium	Medium
Wrapper	High	High	Low

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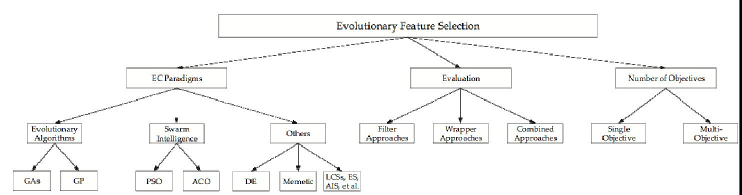
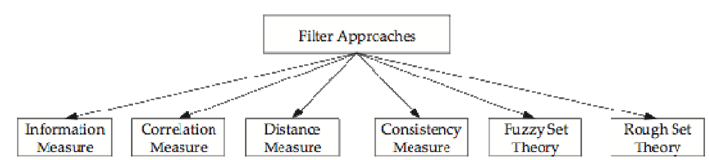
State-of-the-art





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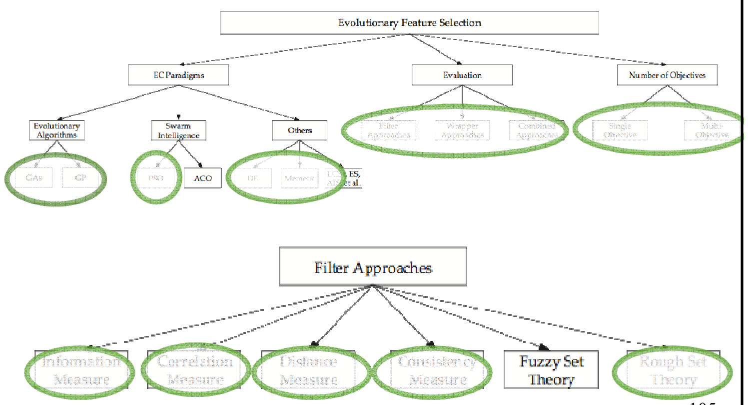
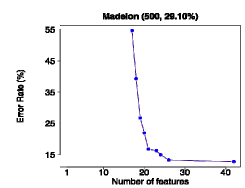
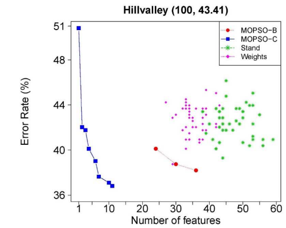
Work from ECRG



Multi-objective PSO for Feature Selection

- Introduce and develop the first multi-objective PSO approach to feature selection
  - Simultaneously minimise the number of features and the error rate





Bing Xue, Mengjie Zhang, Will Browne. "Particle swarm optimization for feature selection in classification: A multi-objective approach, IEEE Transactions on Cybernetics, vol. 43, no. 6, pp. 1656-1671, 2013. **[ARC/ERA Tier A, IF 3.783]**

PSO and Information Theory for Feature Selection

- Information theory in evolutionary feature selection
  - Fast algorithm — mutual information
  - New measures, evaluate multiple features
  - Evolutionary multi-objective filter feature selection

F-MI	0.05	0.05	0.05	0.06	0.07	0.09	0.15	0.18
F-E	2.88	97.7	8.64	27.95	9.85	256.57	2.96	236.42
F-RS	2.07	2485.61	8.21	55.3	14.81	1372.93	0.69	928.25
F-PRS	2.86	2766.29	8.28	38.36	9.95	1827.06	0.68	911.3
W-SVM	24.41	5143.18	53.28	270.64	118.37	2441.21	5.4	10937.87
W-5NN	6.12	9311.59	18.89	264.51	72.72	4095.07	1.68	1936.67
W-DT	5.19	189.43	10.53	43.15	47.87	244.55	3.82	529.7
W-NB	13.46	304.08	15.89	150.37	19.42	377.24	4.13	706.23

Bing Xue, Liam Cervante, Lin Shang, Will Browne, Mengjie Zhang. "A Multi-Objective Particle Swarm Optimisation for Filter Based Feature Selection in Classification Problems". Connection Science. Vol. 24, No. 2-3, pp. 91-116, 2012.

Bing Xue, Liam Cervante, Lin Shang, Will N. Browne, Mengjie Zhang. "Evolutionary Algorithms and Information Theory for Filter Based Feature Selection in Classification". International Journal on Artificial Intelligence Tools. Vol. 22, Issue 04, August 2013. pp. 1350024 -- 1 - 31. DOI: 10.1142/S0218213013500243.

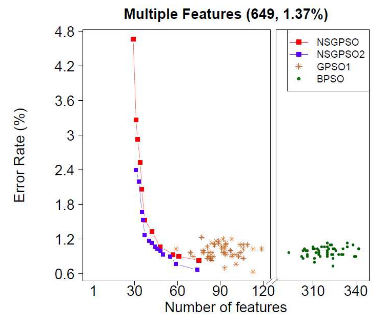
EC and Statistical feature clustering

- Introduce statistical feature clustering to feature selection and develop the first approach
  - reduce the size of the search space
  - #features: from 600 to ~12
  - implicitly consider feature interaction
  - Example:
    - our method achieved accuracy 100%: {10, 7, 3}
    - Single feature ranking: 7, 10, 12, 1, 9, 11, 6, 2, 13, 5, 4, 3

Hoai Bach Nguyen, Bing Xue, Ivy Liu, Peter Andreae, Mengjie Zhang. "Gaussian Transformation based Representation in Particle Swarm Optimisation for Feature Selection". Proceedings of the 18th European Conference on the Applications of Evolutionary Computation (EuroApplications 2015). Lecture Notes in Computer Science. Vol. 9028. Copenhagen, Denmark. 8-10 April 2015. pp. 541-553 (Nominated as Best Paper)

EC and Statistical feature clustering - Multi-Objective

- Feature selection:
  - minimise the number of features
  - minimise the error rate
- In MO, we aim to find the *Pareto front* of non-dominated solutions
- Two new MO methods: NSGPSO, NSGPSO2



Bing Xue, Micthell C. Lane, Ivy Liu, Mengjie Zhang, "Particle Swarm Optimisation for Feature Selection Based on Statistical Clustering", Evolutionary Computation (Journal, MIT Press), *Passed first round review with positive comments* **[ARC/ERA Tier A]**

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EC + Rough Set Theory

- Promote rough set theory for feature selection
  - Others': mainly < 100 features
  - Ours: more than 600 features
- Comprehensive/thorough investigation
  - Over 80,000 runs of experiments (Thanks, ECS Grid)
  - Shows that some existing claims are not correct

Bing Xue, Liam Cervante, Lin Shang, Will Browne and Mengjie Zhang. "Binary PSO and rough set theory for feature selection: a multi-objective filter based approach". International Journal of Computational Intelligence and Applications, Vol. 13, No. 2 (2014). pp. 1450009 -- 1- 34. DOI: 10.1142/S1469026814500096. **[ARC/ERA Tier A]**

Bing Xue, Mengjie Zhang, Will Browne."A Comprehensive Comparison on Feature Selection Approaches to Classification", International Journal of Computational Intelligence and Applications (IJCIA) (*Conditionally Accepted*). 2015 **[ARC/ERA A]**

Bing Xue, Mengjie Zhang, Will Browne, Xin Yao. "A Survey on Evolutionary Computation Approaches to Feature Selection", IEEE Transaction on Evolutionary Computation,*Passed first round review with positive comments.* 2015 **[ARC/ERA Tier A*]**

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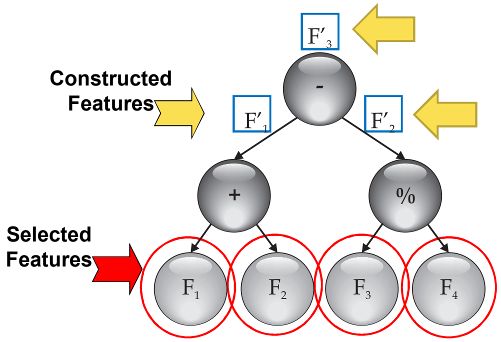
GP for Feature Construction



Soha Ahmed, Mengjie Zhang, Lifeng Peng and Bing Xue."Multiple Feature Construction for Effective Biomarker Identification and Classification using Genetic Programming". Proceedings of 2014 Genetic and Evolutionary Computation Conference (GECCO 2014). ACM Press. Vancouver, BC, Canada. 12-16 July 2014.pp.249--256.

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Biomarker Detection

Apple minus m/z (5 biomarkers)	New Method (5)	Method B (2)
463.0	Yes	No
447.09	Yes	Yes
273.03	Yes	Yes
435.13	Yes	No
227.07	Yes	No

Soha Ahmed, Mengjie Zhang, Lifeng Peng and Bing Xue."Multiple Feature Construction for Effective Biomarker Identification and Classification using Genetic Programming". Proceedings of 2014 Genetic and Evolutionary Computation Conference (GECCO 2014). ACM Press. Vancouver, BC, Canada. 12-16 July 2014.pp.249--256.

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Issues and Challenges

- Scalability Problem
  - thousands, tens of thousands, and even millions
- Computational Cost
- Search Mechanisms
- Measures
- Representation
- Multi-Objective Feature Selection
- Feature Construction
- Number of Instances

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Other Applications

- There have been many ECV applications for the past 15 years
- The work can be seen from;
  - Past EvoIASP workshop proceedings
  - CEC proceedings, special session on ECV
  - GECCO applications, EuroGP proceedings
  - IEEE TEC, IEEE TSMC (Part B) or TCYB, ECJ, PRL letters, …

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Conclusions

- EC techniques play more and more important role in image analysis, signal processing and pattern recognition tasks
- Difficult and Challenging tasks even need more EC.
- Try EC techniques on more CV applications!!

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Upcoming Conferences

- Special Session on Evolutionary Computer Vision, WCCI/CEC 2016: IEEE Congress on Evolutionary Computation
  - Organisers: Mengjie Zhang, Victor Ciesielski, Mario Koeppen,
  - **Paper Submission deadline: 16 Jan 2016**
- Evostar 2015/EvoIASP 2016: Track on Evolutionary Computation in Image Analysis, Signal Processing and Pattern Recognition
  - Track Chairs: Stefano Cagnoni, Mengjie Zhang
  - Time/Venue: Amsterdam
  - **Paper Submission deadline: 10 Nov 2015**
- Special Session on Evolutionary Computation in Feature Selection and Construction, WCCI/CEC 2016: IEEE Congress on Evolutionary Computation
  - Organisers: Bing Xue, Mengjie Zhang,
  - **Paper Submission deadline: 16 Jan 2016**

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Acknowledgement

- Marsden Fund council from the government funding (VUW1209), administrated by the Royal Society of New Zealand.
- Thanks my colleagues and research students particularly Dr Bing Xue, Dr Will Browne, Dr Will Smart and Dr Ignas Kukenys, Dr Toktam Ebadi, Dr Mahdi Setayesh, Dr Huayang Xie, Dr Wenlong Fu, Harith Al-Sahaf, Yuyu Liang, Liam Cervante, Mitch Iane, etc.
- Thanks GECCO2015 organisers

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