Evolutionary Computer Vision

Survey on the State-of-the-Art

Dr. Gustavo Olague

CICESE Research Center

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Evolutionary Computer Vision

- Evolutionary Computer Vision (ECV) is a recent research area devoted to the study of artificial vision through evolutionary and genetic computing approaches.

  1. Computer vision as a scientific discipline is concerned with the theory and technology for building artificial systems that obtain information from images or multi-dimensional data.
  2. Evolutionary computation is a research field of computational intelligence devoted to the study and application of artificial evolution to develop problem solving systems.

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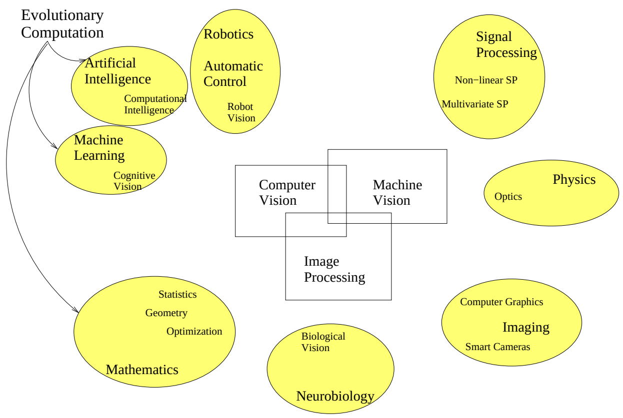
Computer Vision

- The following diagram shows the main areas related to computer vision:



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Computer Vision Applications

1. Industrial
2. Entertainment/Media Industry
3. Environment
4. Human
5. Forensic
6. Medical
7. Military
8. Remote Sensing
9. Scientific
10. Security and Surveillance
11. Sports
12. Others

slide #4

Typical functions found in CV Systems

1. Image Acquisition
2. Pre-processing
3. Feature Extraction
4. Detection Segmentation
5. High-level Processing

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Contents of Tutorial

- Early Visual Processing
  1. Image Transformations and Filters
  2. Feature Extraction Methods
- Intermediate Visual Processing
  1. Systems, Models, Calibration, and Parameter Estimation
  2. Sensor Fusion and Registration
  3. Motion, Tracking and Time Sequence Analysis
- Visual Learning
  1. Object, World, and Scene Representations
  2. Recognition, Planning, and Scene Understanding

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Where to publish

- Conference proceedings
  1. EvoIASP 2008
  2. CEC 2008
  3. ICPR 2008
- Journals
  1. Pattern Recognition
  2. Pattern Recognition Letters
  3. Image and Vision Computing

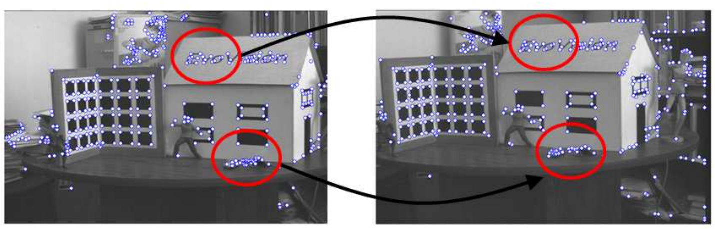
slide #7

Bibliographie: Main Subjects

1. Image Classification [1, 6, 8, 33, 40, 199, 211, 233]
2. Image Segmentation and Clustering [3, 15, 22, 29, 32, 89]
3. Video and Motion Analysis [11, 19, 102, 84, 196]
4. Face Recognition and Modeling [6, 17, 79, 118, 119, 207, 212, 214, 240]
5. Feature Extraction [8, 18, 21, 82, 91, 96, 108, 126, 137, 145, 167, 201]
6. Medical Image [2, 34, 73, 129, 138, 216, 217]
7. Object Recognition [16, 48, 179, 237, 238]
8. Geomatics [9, 27, 156, 224, 83, 125, 23, 24]
9. Sensor Planning and Calibration [146, 39, 55, 93, 147, 30, 35, 151, 50, 53, 74]
10. Visual Learning [28, 86, 76, 107, 144, 241]
11. Matching and Registration [36, 42, 45, 47, 50, 60, 63, 67, 70, 75, 88, 121]
12. Others

slide #8

Synthesis of Interest Point Detectors



- A stereo pair taken at the EvoVisión Laboratory, notice how interest points can be used to compute the correspondence between both images.
- The interest points depicted on both images were obtained with the IPGP2 presented in this work that outperforms past human designs.

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Learning Interest Point Detectors

- Interest point detectors are computer programs that are applied to a set of images with the goal of detecting the same set of features across all images.
- Hypothesis: genetic programming provides a machine learning strategy that could solve the problem of learning interest point detectors.

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Synthesis of Interest Point Detectors

Hand Coded Designs ? VS Genetic Programming Designs

- *Analysis* is understood as the science which treats of the exact relations existing between quantities or magnitudes, and of the methods by which, in accordance with these relations, quantities sought are deducible from other quantities known or supposed; the science of spatial and quantitative relations.
- *Synthesis* is understood as the combination of separate elements of thought into a whole, as of simple into complex conceptions. Thus, synthesis refers to the art or process of making a compound by putting the ingredients together, as contrasted with analysis.
- *Analysis and synthesis*, though commonly treated as two different methods, are, if properly understood, only the two necessary parts of the same method. Each is the relative and correlative of the other.

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Goals for ECV?

- A main aim of genetic programming research is to show that this new machine learning paradigm is able to provide solutions which are human competitive.
- This work shows that a deep analysis of the problem provides the criteria, fitness functions, as well as the definitions of the function and terminal sets to achieve *human competitive results*. We claim that this research is moving forward the state-of-the-art of interest point detection providing not only the probe that previous man made designs have been rediscovered by genetic programming, but also that new interest point detectors have been synthesized.

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Technical Approach

- Koza's *Genetic Programming: On the Programming of Computers by Natural Selection* (1992) provides a detailed description of genetic programming. Here we focus on two aspects:
  1. The fitness measure which evaluates the structures, and
  2. The structures that undergo adaptation.
- All synthesized results have been achieved with a prototype written in *Matlab* and a more efficient system developed with the *VXL* and *LilGP* libraries.

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Repeatability

A point x_1 detected in image I_1 is repeated in image I_i if the corresponding point x_i is detected in image I_i. In the case of planar scenes a relation between points x_1 and x_i can be established with the homography $H_{1,i}$ where:

$$x_i = H_{1,i} x_1 \tag{1}$$

The repeatability rate measures the number of repeated points between both images, with respect to the total number of detected points.

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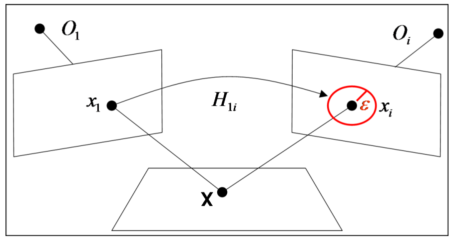
Repeatability



A 3D point X is projected onto points x_1 and x_i on images I_1 and I_i respectively. Point x_1 is said to be repeated by x_i, if a point is detected within a neighborhood of x_i of size ϵ. For planar scenes x_1 and x_i are related by the homography $H_{1,i}$.

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Repeatability

The set of point pairs $\left(x_1^c, x_i^c\right)$ that lie in the common part of both images and correspond within an error of size ϵ is defined by:

$$R_i\left(\epsilon\right) = \left\{\left(x_1^c, x_i^c\right) | dist\left(H_{1,i}x_1^c, x_i^c\right) < \epsilon\right\} \tag{2}$$

Thus the reapeatability rate $r_i\left(\epsilon\right)$ of points extracted from image I_i with respect to points from image I_1, is defined by the following equation:

$$r_i\left(\epsilon\right) = \frac{\left|R_i\left(\epsilon\right)\right|}{min\left(\gamma_1, \gamma_i\right)} \tag{3}$$

where $\gamma_1 = \left|\left\{x_1^c\right\}\right|$ and $\gamma_i = \left|\left\{x_i^c\right\}\right|$ are the total number of points extracted from image I_1 and image I_i respectively.

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Fitness Function

- Our approach uses a fitness assignment that is proportional to its mean repeatability rate $r_J\left(\epsilon\right)$ computed for a set $J = \{I_i\}$ of n training images, where $i = 1...n$. A base image I_i is used to compute the repeatability on all other images in J.
- The GP search could easily get lost in unwanted maxima if appropriate considerations are not taken into account when designing the fitness function.

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Fitness Function

Hence, a *good* detector should extract uniformally distributed points across the image plane. Consequently, three other terms were incorporated in the fitness function and combined in a multiplicative way:

$$f\left(x\right) = r_J\left(\epsilon\right) \cdot \phi_x^\alpha \cdot \phi_y^\beta \cdot N_\%^\delta \tag{4}$$

where the functions,

$$\phi_x = \frac{1}{1 + e^{-a(H_x - c)}} \tag{5}$$

$$\phi_y = \frac{1}{1 + e^{-a(H_y - c)}} \tag{6}$$

are sigmoidal functions used to promote point dispersion along the x and y directions.

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Fitness Function

The terms $H.$ given by:

$$H. = -\sum_{\cdot} P(\cdot) log_2\left[P(\cdot)\right] \tag{7}$$

represent the entropy value of the spatial distribution of detected interest points along each direction. $P(\cdot)$ is approximated by the histogram of interest point localizations. Moreover, because of the logarithmic nature of the entropy function, ϕ_x and ϕ_y are set to promote entropy values lying within a very small range. The final term,

$$N_\% = \frac{requestedpoints}{extractedpoints} \tag{8}$$

is a penalizing factor that reduces the fitness value for detectors that return less than the total number of requested points. Finally, α, β and δ control the amount of influence that each term has on $f\left(x\right)$.

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Function Set

The function set F contains 6 unary functions and 5 binary functions. All functions, input and output, are data matrices with the same size as images in J. The subset of binary and unary functions are:

$$F_{2ary} = \{+, -, |-|, *, /\} \tag{9}$$

$$F_{1ary} = \left\{A^2, \sqrt{A}, log_2, EQ, G(\sigma=1), G(\sigma=2)\right\} \tag{10}$$

Where EQ is the histogram equalization, and $G(\sigma = x)$ are Gaussian filters with blur σ. The complete function set is:

$$F = F_{2ary} \cup F_{1ary} \tag{11}$$

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Terminal Set

Effective IP operator requires information pertaining to the rate of change in image intensity values. Consequently, the terminal set includes first and second order image derivatives. However, we do not claim that this set is necessary nor sufficient and further work will try to determine an optimal set of useful information for interest point detection. Furthermore, the terminal set is image dependent, which means that each image $I_i \in J$ has a corresponding T_i defined by:

$$T_i = \{I_i, L_{i,x}, L_{i,x,x}, L_{i,x,y}, L_{i,y,y}, L_{i,y}, I_{i,\sigma=1}\} \tag{12}$$

Where $L_{i,w} = I_i * G_w(\sigma = 1)$ are image derivatives computed in the w direction using a convolution with Gaussian kernel derivatives, and $I_{i,\sigma=1}$ is the smoothed image computed by a convolution with a Gaussian smoothing function.

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Experimental Results

- All experiments were developed independently in two different systems to show the robustness of the proposed approach. A first prototype developed on Matlab, with the Genetic Programming toolbox GPLAB [a]. These experiments were also developed in C language using the VXL, LILGP, and CImg libraries.

- All image sets were downloaded from the Visual Geometry Group website [b], along with matlab source code for computing the repeatability rate and binary files for extracting Harris interest points. All matlab codes were translated to C language for testing the second system. The scene images were *VanGogh,Monet, Mars, New York, Graph, Mosaic and Leuven. VanGogh, Monet, Mars and New York present changes of rotation, while Graph and Mosaic present changes of illumination. Finally, Leuven presents changes both rotation and illumination changes.*

[a] http://gplab.sourceforge.net/index.html, GPLAB A Genetic Programming Toolbox for MATLAB by Sara Silva

[b] http://www.robots.ox.ac.uk/~vgg/research/

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GP runtime parameters

Parameters	Description and values
Population size	50 - 75 individuals
Generations	50
Initialization	Ramped Half-and-Half
Crossover & Mutation prob.	Crossover prob. $p_c = 0.85$; mutation prob. $p_\mu = 0.15$
Tree depth	Dynamic depth selection
Dynamic max. depth	5 levels
Real max depth	8 levels
Selection	Tournament (size of 4) with lexicographic parsimony preassure
Survival	Keep best survival strategy
Fitness function parameters	$a_x = 7$, $c_x = 5.05$, $a_y = 6$, $c_y = 4.3$ $\alpha = 20$, $\beta = 20$, $\delta = 2$

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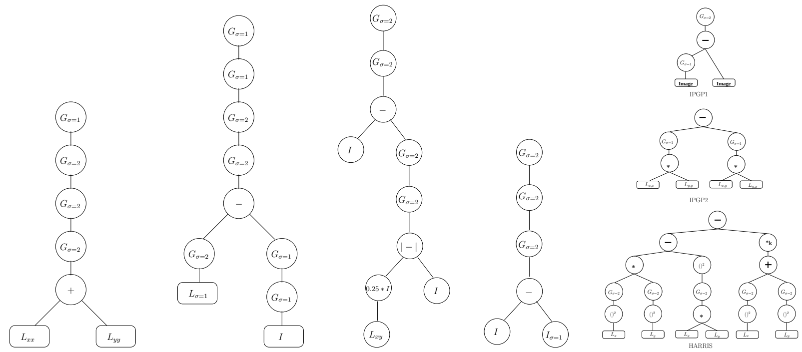
Evolved Operators

Name	Operator
$IPGP1^*$	$G_2 * \|I - G_2 * I\|^2$
$IPGP3$	$G_1 * G_1 * G_1 * G_2 * G_2 * (G_1 * I - I)$
$IPGP4$	$G_2 * G_2 * G_2 * (G_2 * I - I)$
$IPGP5$	$G_1 * G_2 * \|I - G_1 * I\|^2$
$IPGP6$	$G_2 * G_2 * G_1 * \left(\frac{I}{G_2 * I}\right)$
$IPGP7$	$G_2 * (2 \cdot L_{yy} + 2 \cdot L_{xx})$
$IPGP8$	$G_2 * \left[L_{xx} + 2 \cdot G_2(L_{xx} + L_{yy})^2\right]$
$IPGP9$	$G_2 * G_2 * (2 \cdot L_{yy} + 2 \cdot L_{xx} + L_{xy})$
$IPGP10$	$G_2 * (L_{yy} + L_{xx})$
$IPGP11$	$G_1 * \left(\frac{G_1 * I}{(G_1 * G_1 * I)^3}\right)$
$IPGP12$	$\frac{G_2 * I^{\frac{3}{2}}}{(G_1 * I)^{\frac{9}{4}}}$

slide #24

DPIPGP1



DPIPGP1 DPIPGP2 DPIPGP5 DPIPGP6 IPGP1-2 y Harris

slide #25

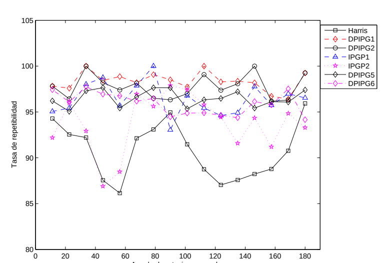
Results (cont.)

Average repeatability rate achieved with the training and testing sets

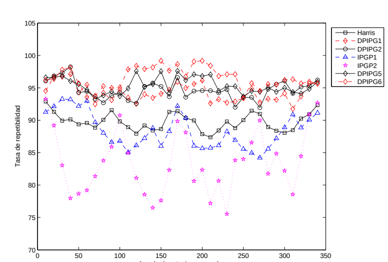
Detector	Average repeatability rate						
	VanGogh	Monet	Mars	New York	Graph	Mosaic	Leuven
IPGP1	96.41	85.17	91.42	88.41	92.04	93.11	69.06
IPGP2	93.74	94.80	86.26	83.47	95.97	93.79	63.18
Harris	90.71	92.96	89.90	89.75	98.00	94.43	70.42
DPIPG1	98.33	86.73	96.00	94.24	94.63	96.51	70.74
DPIPG2	97.75	89.40	95.53	94.64	93.67	96.45	71.22
DPIPG5	96.49	86.69	96.00	95.37	93.76	95.98	76.21
DPIPG6	95.90	82.72	95.85	96.57	95.03	95.82	76.08

slide #26

Results (cont.)



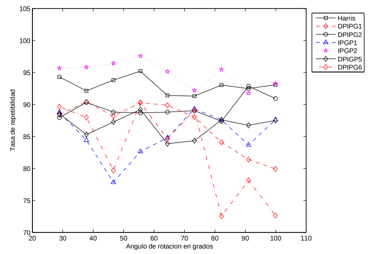
VanGogh



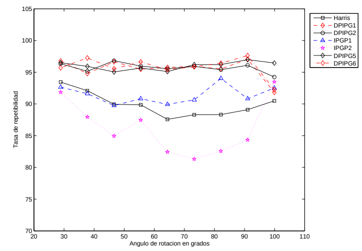
New York

slide #27

Results (cont.)



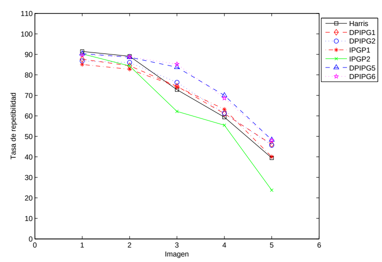
Monet



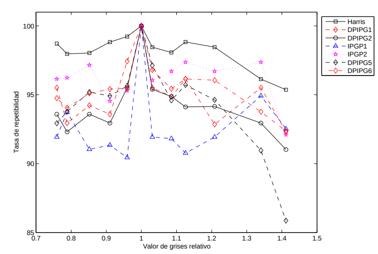
Mars

slide #28

Results (cont.)



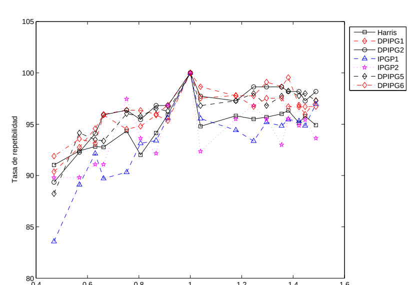
Leuven



Graph

slide #29

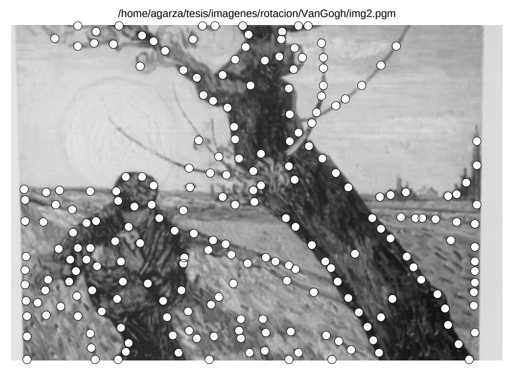
Results (cont.)



Mosaic

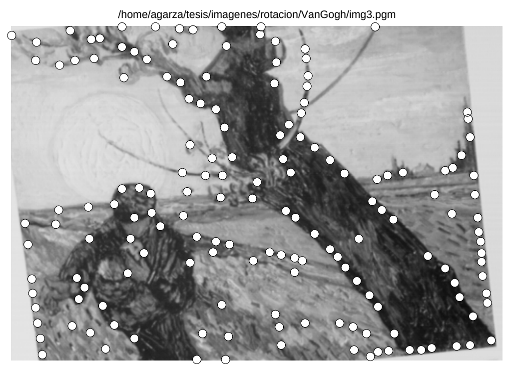
slide #30

DPIPG1 VanGogh sequence



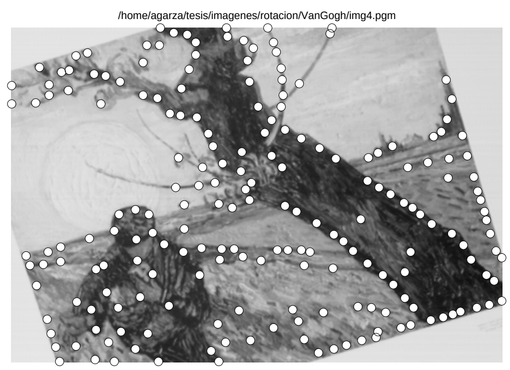
slide #31

DPIPG1 VanGogh sequence



slide #32

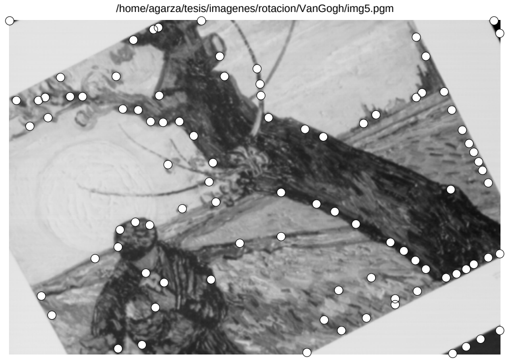
DPIPG1 VanGogh sequence



slide #33

DPIPG1 VanGogh sequence

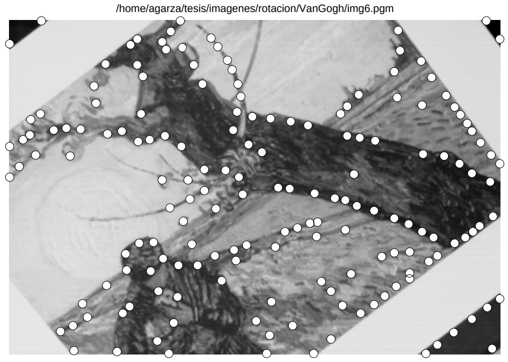
/home/agarza/tesis/imagenes/rotacion/VanGogh/img5.pgm



slide #34

DPIPG1 VanGogh sequence

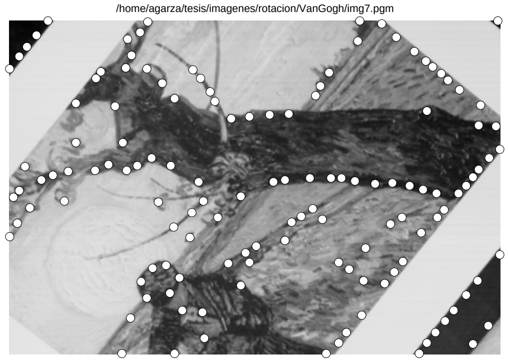
/home/agarza/tesis/imagenes/rotacion/VanGogh/img6.pgm



slide #35

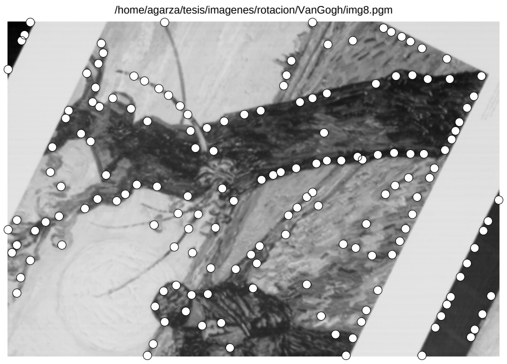
DPIPG1 VanGogh sequence

/home/agarza/tesis/imagenes/rotacion/VanGogh/img7.pgm



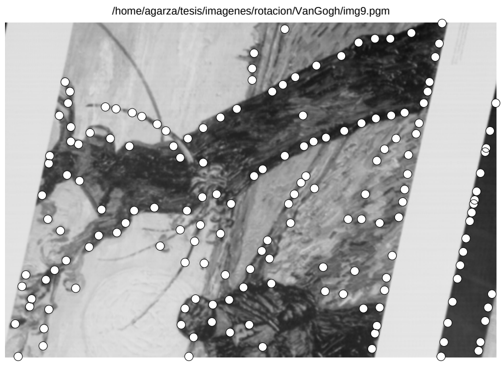
slide #36

DPIPG1 VanGogh sequence



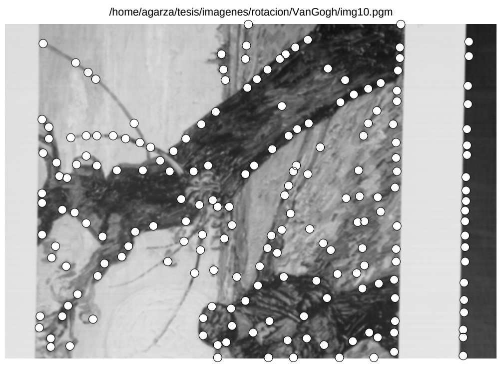
slide #37

DPIPG1 VanGogh sequence



slide #38

DPIPG1 VanGogh sequence



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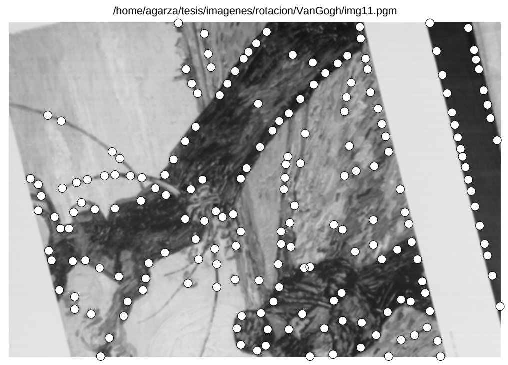
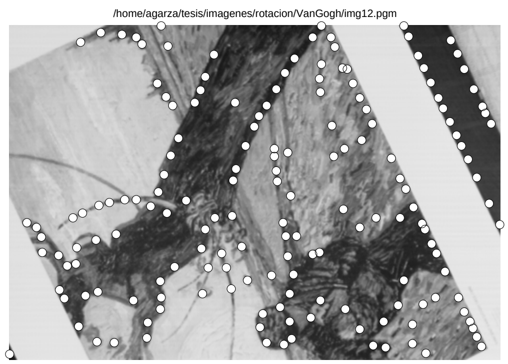
DPIPG1 VanGogh sequence



slide #40

DPIPG1 VanGogh sequence



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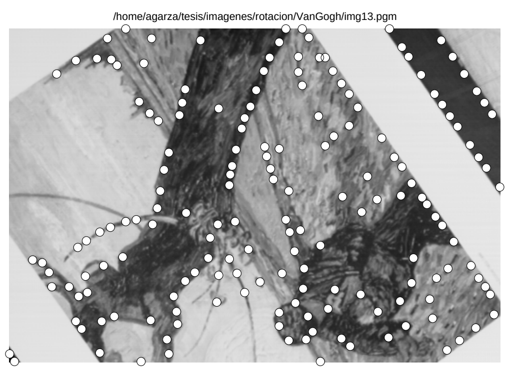
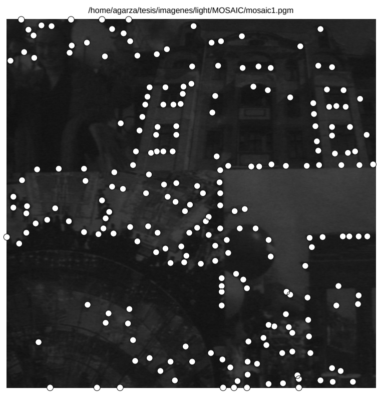
DPIPG1 VanGogh sequence



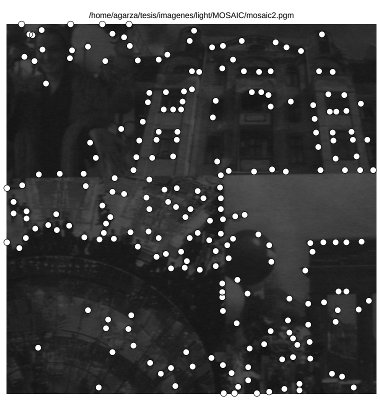
slide #42

DPIPG1 Mosaic sequence



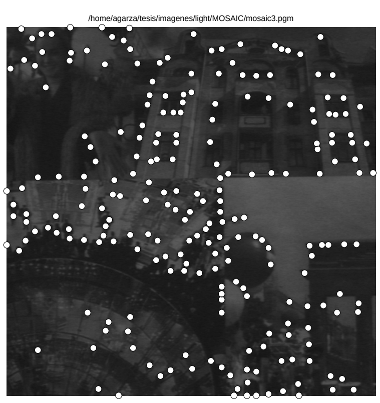
slide #43

DPIPG1 Mosaic sequence



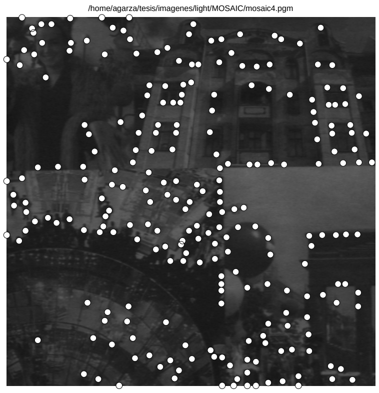
slide #44

DPIPG1 Mosaic sequence



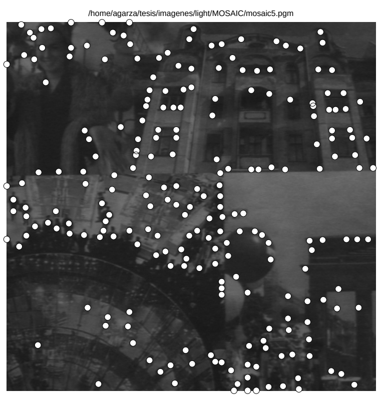
slide #45

DPIPG1 Mosaic sequence



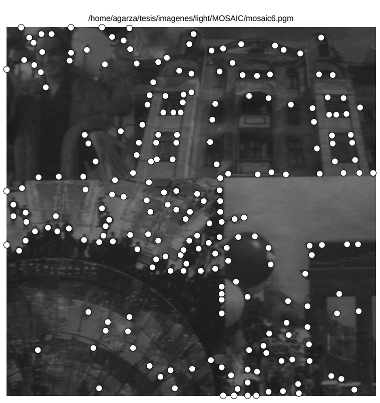
slide #46

DPIPG1 Mosaic sequence



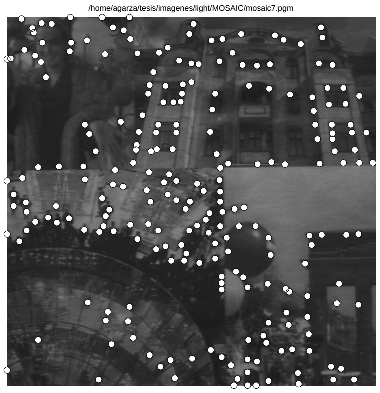
slide #47

DPIPG1 Mosaic sequence



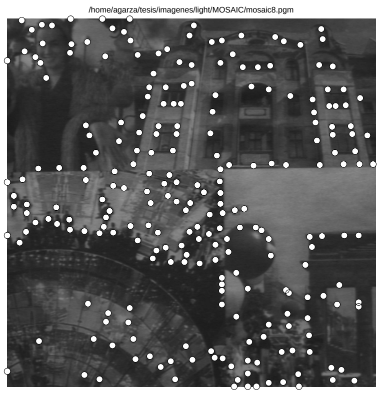
slide #48

DPIPG1 Mosaic sequence



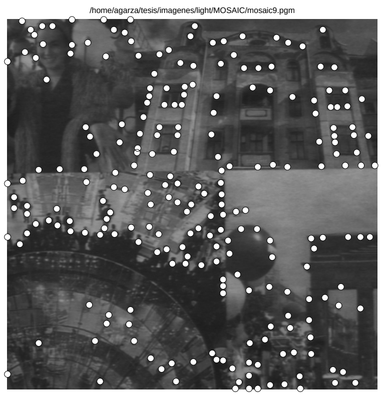
slide #49

DPIPG1 Mosaic sequence



slide #50

DPIPG1 Mosaic sequence



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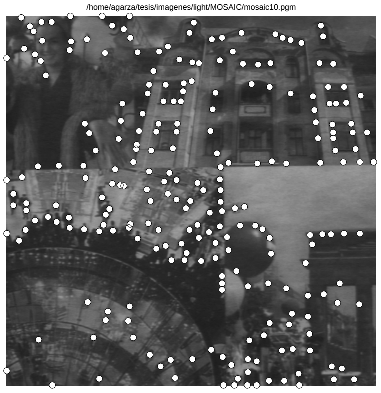
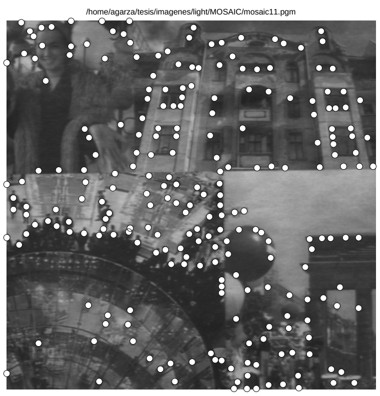
DPIPG1 Mosaic sequence



slide #52

DPIPG1 Mosaic sequence



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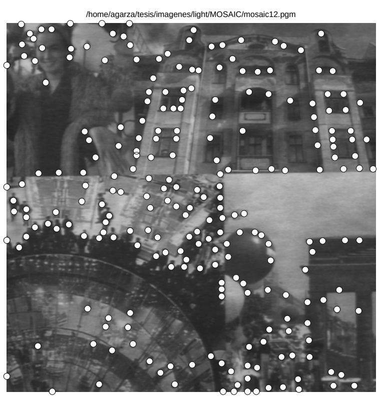
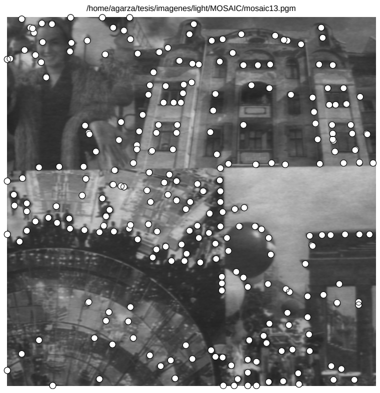
DPIPG1 Mosaic sequence



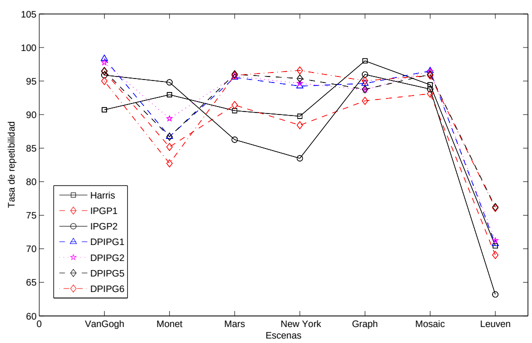
slide #54

DPIPG1 Mosaic sequence



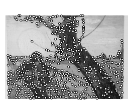
slide #55

Results achieved by 7 detectors

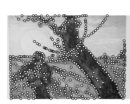


slide #56

Sample Image VanGogh



Harris



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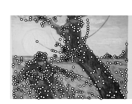
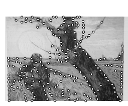


IPGP2



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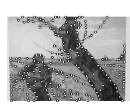

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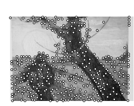

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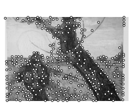
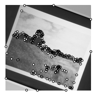
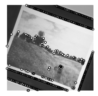


DPIPG6

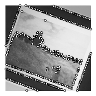
slide #57

Sample Image Monet


Harris


IPGP1


IPGP2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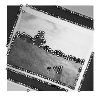
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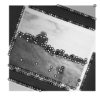
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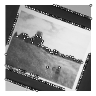
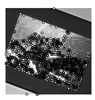
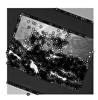

DPIPG6

slide #58

Sample Image Mars


Harris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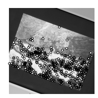
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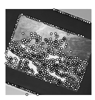
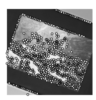

DPIPG1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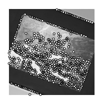
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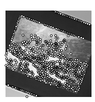
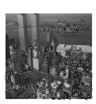
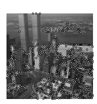
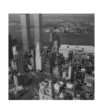

DPIPG6

slide #59

Sample Image New York


Harris


IPGP1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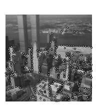
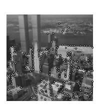

DPIPG1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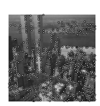
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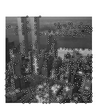

DPIPG6

slide #60

Sample Image Graph


Harris

IPGP1

IPGP2

DPIPG1

DPIPG2

DPIPG5

DPIPG6

slide #61

Sample Image Mosaic


Harris

IPGP1

IPGP2

DPIPG1

DPIPG2

DPIPG5

DPIPG6

slide #62

Sample Image Leuven


Harris

IPGP1

IPGP2

DPIPG1

DPIPG2

DPIPG5

DPIPG6

slide #63

The Honeybee Search Algorithm

- *Introduction* This talk introduces a novel analogy with the way honeybee colonies function in order to solve the problem of sparse and quasi dense reconstruction.
- *Analogy* A new adaptive behavior strategy is presented based on the "divide and conquer" strategy used by the honeybee colony to solve search problems.
- *Application* A new framework is proposed in which the 3D points communicate between them to achieve an improved sparse reconstruction which could be used reliable in further visual computing tasks. The general ideas that explain the honeybee behavior are translated into a computational algorithm following the evolutionary computing paradigm.
- *Results* Experiments demonstrate the importance of the proposed communication system to reduce dramatically the number of outliers.

slide #64

Introduction

- *Why Honeybee Colonies?* Real honeybee colonies are capable of a number of outstanding insect capacities that are coded in the dance language, which is considered the most complex symbolic system decoded, to date, in the animal world [a].
- In this work, a *cooperative coevolutionary approach* is applied based on the individual insect capacities and their communication system. Our work mimics this complex behavioral strategy using the principles of cooperative cooevolution of the *Parisian evolutionary computational approach* [b].

[a] E. Crist. "Can an Insect Speak? The Case of the Honeybee Dance Language". *Social Studies of Science*. SSS and Sage Publications. 34(1), pp. 7-43. 2004.

[b] E. Dunn, G. Olague, and E. Lutton. "Parisian Camera Placement for Vision Metrology". Pattern Recognition Letters, Vol. 27, Issue 11, pages 1209-1219. 2006.

slide #65

Parisian Evolution: Cooperative Coevolution with Honeybees

- *The Parisian approach*, differs from typical approaches to evolutionary computation in the sense that a *single individual* in the population represents *only a part of the solution* [a]. In this paradigm an *aggregation of multiple individuals* should be considered in order to obtain a solution to the problem being studied.
- *The motivation* of such approach is to make an *efficient use* of the genetic search process. First, the algorithm *discards less computational effort* at the end of execution, while considering more than a single best individual as output. Second, the *computational expense* of the fitness function evaluation is considerably reduced for a single individual.

[a] P. Collet, E. Lutton, F. Raynal, M. Schoenauer, 1999. "Individual GP: an alternative viewpoint for the resolution of complex problems", In: Banzhaf et al. (Eds.), Genetic and Evolutionary Computation Conf. GECCO99.

slide #66

Parisian Evolution

- In traditional cooperative coevolution the individuals are divided in species that are genetically isolated. The only feedback is through a share domain model which produce a cooperative relationship.
- Contrary to this way of setting the framework for cooperative coevolution the Parisian approach uses the idea of *individual evolution* to promote the exchange of genetic material based on the *local* and *global* fitness evaluations.
- We decide to implement the idea of *separate populations* in the honeybee search algorithm in order to achieve population interaction and coadaptation.

slide #67

Parisian Evolution

- *Partial Encoding.* The genetic representation is achieved through a number of single individuals that encode a *partial solution.*
- Therefore an individual *aggregation* step is necessary in order to create a complete problem solution. This process of aggregation could be explicit or implicit according to the problem being studied. This concept provides to the Parisian approach the strength to decompose the problem by determining automatically an appropriate number of subcomponents and the role that each subcomponent will play.
- *The Environment.* The design of the system should provide an environment where the *different partial solutions* could interact and coadapt in order to allow the emergence of better aggregate solutions.

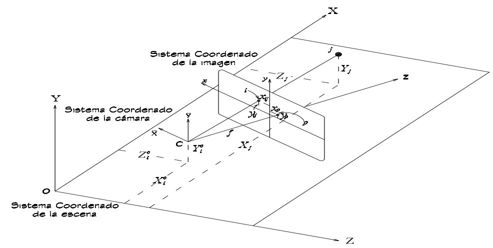
slide #68

Parisian Evolution

- *Local and Global Fitness.* A meaningful merit function must be designed for each partial solution. The evolutionary engine requires a scheme for combining local and global fitness values. This could be explicit or implicit.
- *Population Diversity Preservation.* In contrast to traditional computational intelligence approaches where *diversity* needs to be preserved only during enough time to perform a reasonable exploration of the search space; an individual cooperative coevolutionary approach requires that *all subcomponents* should be present in the final solution.
- *diversity preservation techniques* need to be implemented. In evolutionary algorithms three different techniques could be applied: 1) heuristic modification of genetic operators, 2) fitness function penalization for crowded individuals, and 3) incorporation of some higher level algorithmic structure to generate and manage sub-populations. In this work, we apply the fitness sharing scheme (Goldberg and Richardson, 1987).

slide #69

Imaging and Camera Geometry

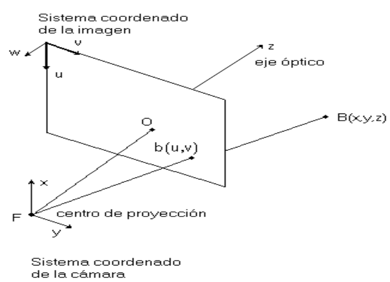


- *Perspective projection* This can be written as a linear mapping between homogeneous coordinates. The equation is only up to scale factor, where $\lambda = Z/f$.

$$\lambda \begin{pmatrix} x \\ y \\ f \end{pmatrix} = \begin{pmatrix} X \\ Y \\ Z \end{pmatrix}. \tag{13}$$

slide #70

Camera Geometric Model

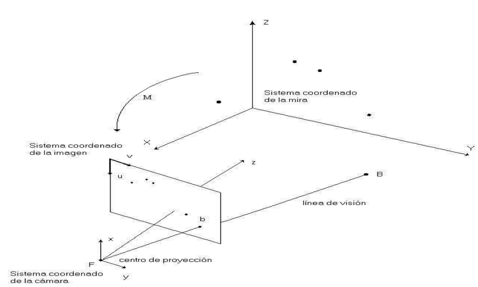


- *Internal camera parameters* Where the units of k_u and k_v are in [pixels/length].

$$\mathbf{K} = \begin{pmatrix} -k_u & 0 & 0 & u_0 \\ 0 & k_v & 0 & v_0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{14}$$

slide #71

Camera geometric model

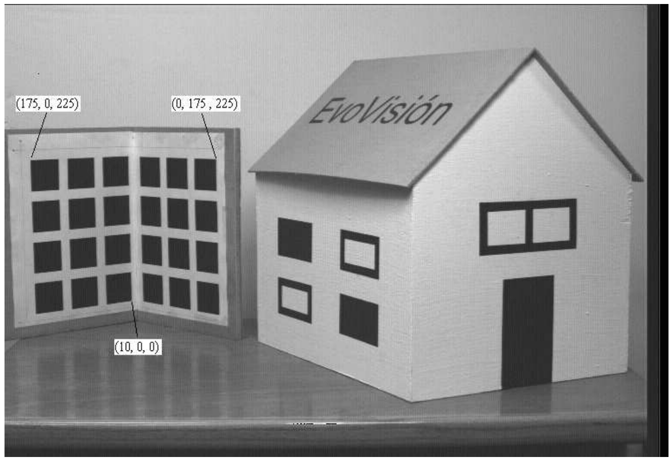


- *External camera parameters* Euclidean transformation between world and camera coordinates.

$$\mathbf{A} = \begin{pmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0} & 1 \end{pmatrix}. \tag{15}$$

slide #72

Euclidean coordinate system.



slide #73

Internal Parameters

Foto	α_u	α_v	u_0	v_0
1	-181.860	206.802	272.685	134.143
2	-182.435	207.513	272.573	134.107
3	-186.876	212.852	272.816	134.170
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
18	-184.466	209.814	272.961	134.538
19	-183.284	208.471	273.185	134.633
20	-175.497	199.044	273.522	134.869
Media	-184.099	209.444	272.700	134.404
Desv.Est.	5.199	6.248	0.389	0.229

slide #74

External Parameters

Foto	$\mathbf{R}_x$	$\mathbf{R}_y$	$\mathbf{R}_z$	t_x	t_y	t_z
1	-89.308°	-46.487°	-89.796°	-125.225	12.506	351.920
2	-89.431°	-46.476°	-88.068°	-125.471	12.510	352.621
3	-89.204°	-46.556°	-87.892°	-124.950	12.369	359.286
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
18	-89.293°	-46.598°	-87.956°	-124.770	11.996	355.612
19	-89.302°	-46.665°	-87.947°	-124.438	11.818	353.956
20	-89.319°	-46.604°	-87.961°	-123.961	11.632	342.635
Media	-89.329°	-46.550°	-88.076°	-125.204	12.123	355.592
Desv.Est.	0.059°	0.064°	0.408°	0.600	0.287	6.848

slide #75

Two View Geometry

- Cameras $\mathbf{P}$ and $\mathbf{P}'$ such that

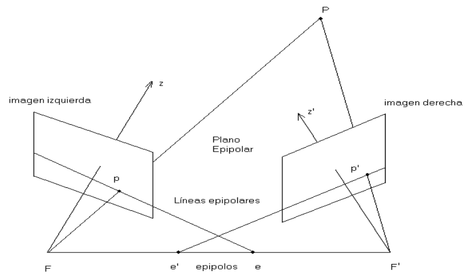
$$\mathbf{x} = \mathbf{P}\mathbf{X} \quad \mathbf{x}' = \mathbf{P}'\mathbf{X}$$

- Baseline between the cameras is non zero.
- *Main Questions*

1. Given an image point in the first image, where is the corresponding point in the second image?
2. What is the relative position of the cameras?
3. What is the 3D geometry of the scene?

slide #76

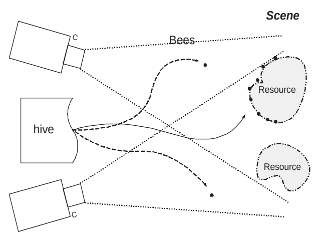
Epipolar Geometry



- *Correspondence Geometry* Given the image of a point in one view, what can we say about its position in another?
- A point in one image "generates" a line in the other image.
- This line is known as an *epipolar* line, and the geometry which gives rise to it is known as epipolar geometry.

slide #77

The Honeybee Search Process



- The honeybee algorithm is based on the idea, first proposed in the fly algorithm, of evolving a population of 3D points in order to concentrate those points on the object surface of the scene.

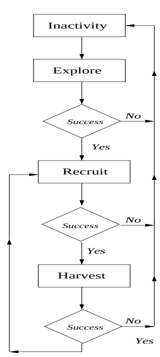
slide #78

The Fly Algorithm

- *The Parisian approach*, in the work of Louchet (2001), was applied to the evolution of a population of 3D points, called flies, whose positions were concentrated on the object surface of the scene. The main drawback of that first attempt was the lack of applying the concepts of *population interaction and coadaptation*, as well as the identification of *local and global* fitness evaluations. Indeed, a high number of *outliers* were produced with their technique due to the overlook of these aspects. Moreover, the omission of these concepts produce a shortcoming of the paradigm to provide those 3D points with *intelligent capabilities.*

slide #79

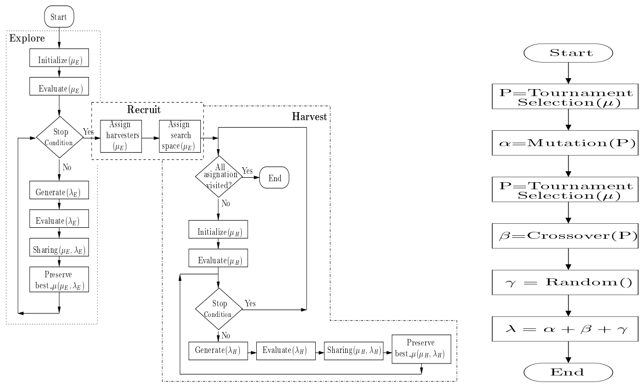
Honeybee Search



- The honeybee search process is composed of three main activities: exploration, recruitment and harvest.

slide #80

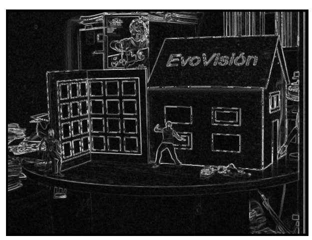
Honeybee Algorithm



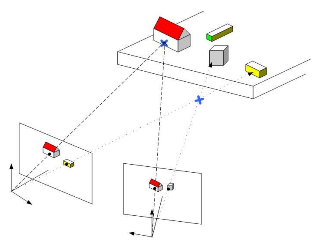
- Flowchart describing the honeybee search algorithm.

slide #81

Honeybee Algorithm



a) Sobel



b) Cross-correlation

- The fitness function of the honeybees' explorers is composed of two main criteria: 1) The contour information obtained with the sobel operator, and 2) The correlation between both images to estimate if the bee is posed on a surface.

slide #82

Evaluating the Fitness Function

- *The Exploration Stage* starts creating a random population μ_E of 3D points called explorers, which are then transformed into a new population λ_E using the mutation, crossover and random steps. This stage attempts to simulate the natural process in which the bees explore asynchronously the space in search of the food source. The evaluation is obtained with the following criteria:

$$\mathcal{F}_E = g(p_{Izq}, p_{Der}) \times f(p_{Izq}, p_{Der}), \tag{16}$$

$$g(p_{Izq}, p_{Der}) = \|\nabla(p_{Izq})\| \times \|\nabla(p_{Der})\| \tag{17}$$

$$f(p_I, p_D) =$$

$$\frac{\sum_{i=-n}^{n} \sum_{j=-n}^{n} (I(x_I + i, y_I + j) - \overline{I(x_I, y_I)}.(I(x_D + i, y_D + j) - \overline{I(x_D, y_D)}}{\sqrt{\sum\sum(I(x_I + i, y_I + j) - \overline{I(x_I, y_I)})^2 . \sum\sum(I(x_D + i, y_D + j) - \overline{I(x_D, y_D)})^2}}$$

slide #83

Fitness Sharing

- *The Exploration Stage* The selection of the best explorers is made with a tournament selection after being evaluated together with the old population. We apply a sharing step in order to balance the distribution of the explorers in the Euclidean world. We repeat this stage until a given number of generations $n = 30$.

slide #84

Recruitment Stage

- Each explorer *recruits* a number of foragers proportionally to its fitness function. The size of the search space is proportional to the distance between the pair of cameras (hive) and the current 3D point (explorer). Obviously the explorers that are closer to the hive should have a bigger search space, compared with the explorers that are farther away. We start with a fixed size ζ to the nearest visited place near the hive. Then, as long as the bees are farther away from this initial bee; the search space starts to be reduced using as information the distance on the images in order to have an evaluation about the depth in which the points are located as follows:.

$$d_i = \sqrt{(x_l - x_r)^2 + (y_l - y_r)^2} \quad .$$

slide #85

Search Space Reduction

Now, we can proceed to reduce the search space with the following relationship:

$$\begin{aligned} f &= 0.5 \times (1-u) + u \quad , \\ \zeta_i' &= \zeta_i \times f \quad . \end{aligned} \tag{18}$$

Where $u = d_i/d_{max}$ represents the degree of desirability that a place holds according to the distance. The value of f lies in the interval $[0.5, 1]$, where 0.5 is related to the highest distance, while 1 is related to the closest 3D point.

slide #86

The Harvest Stage

- The next stage is to harvest the source patch for each explorer using an algorithm similar to the exploration stage. The first cycle is dedicated to visit each place that was selected by the explorer. In this way, the foragers that have been selected by the explorer start a new search process around the point where the explorer is located in order to exploit this location. Hence, the *exploration and exploitation* steps are achieved by the *explorers and foragers* respectively. As we can observe each group of foragers exploits sequentially all places. Note that the number of foragers that have been assigned to each explorer is variable according to the fitness function.

$$p_i = fitness_i / \sum_{j=1}^{N} fitness_j \quad .$$

slide #87

Cooccurrence Matrix

Thus, the number of foragers assigned to each explorer is computed using the following factor

$$r_i = p_i * \lambda \quad , \tag{19}$$

where λ is the total size of the population. Here, the fitness function computation uses besides the ZNCC the homogeneity of the texture without gradient computation. The homogeneity is computed using the *Gray Level Cooccurrence Matrix* because it has been proved reliable in image classification and segmentation for content based image retrieval (Haralick, 1979).

$$homog = \sum_i^n \sum_j^n \frac{M(i,j)}{1 + |i-j|}$$

slide #88

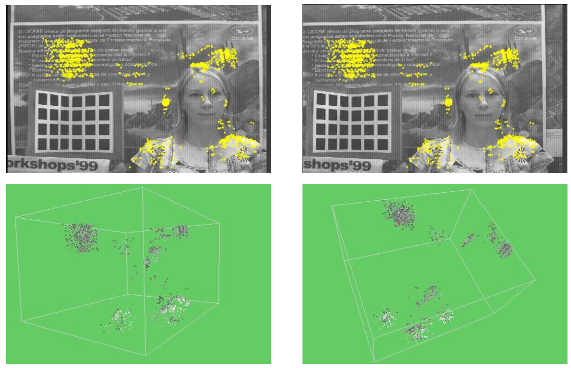
Experimental Results

Parameters of the algorithm that were used in order to compare the mutation operators.

Polynomial Mutation		Normal Mutation	
Population:			
μ_E	100	μ_E	100
λ_E	200	λ_E	200
μ_R	1000	μ_R	1000
λ_R	2000	λ_R	2000
Mutation:			
η_m	25	σ_X	2
		σ_Y	2
		σ_Z	2
Crossover (SBX):			
η_c	2	η_c	2
Sharing:			
σ_{rep}	25	σ_{rep}	25

slide #89

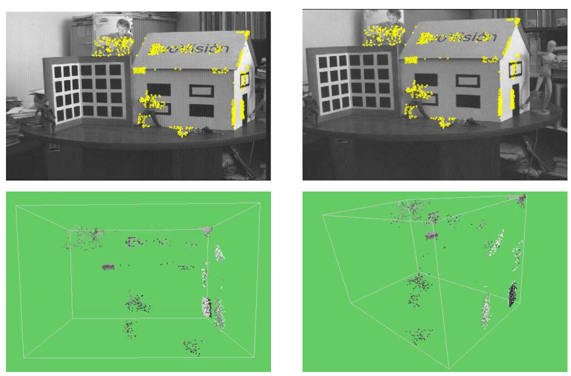
Experimental Results



- Results of applying the honeybee search algorithm to obtain a sparse reconstruction.

slide #90

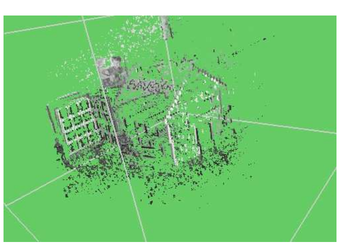
Experimental Results



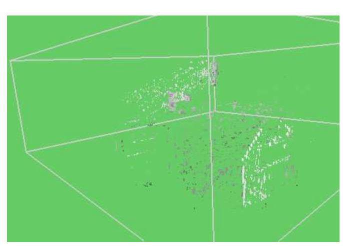
- Results of applying the honeybee search algorithm to obtain a sparse reconstruction.

slide #91

Experimental Results



a) 60000 points.

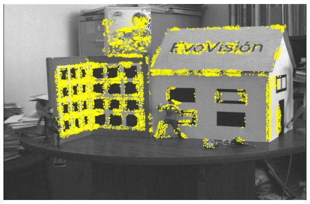


b) 12000 points.

- These images show the 3D reconstruction using the method of triangulation.

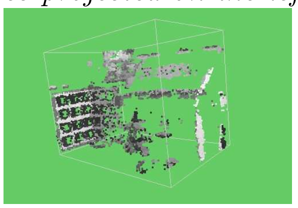
slide #92

Experimental Results

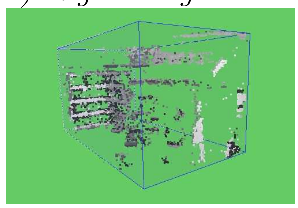


a) Bees projected on the left image.

b) Right image.



c) 16000 bees.

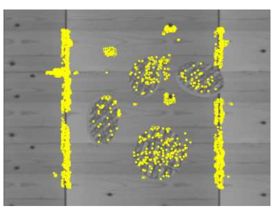


d) 8000 bees.

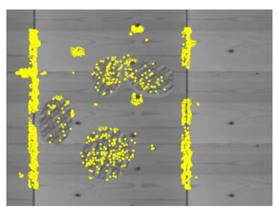
- These images show the results after applying the honeybee search algorithm to a real stereo pair to obtain a quasi-dense reconstruction.

slide #93

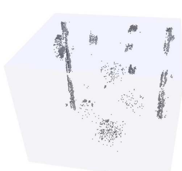
Experimental Results



a) Bees projected on the left image.



b) Right image.



c) VRML.

d) 4000 bees.

- These images show the results after applying the honeybee search algorithm to a real stereo pair to obtain a quasi-dense reconstruction.

slide #94

Conclusions

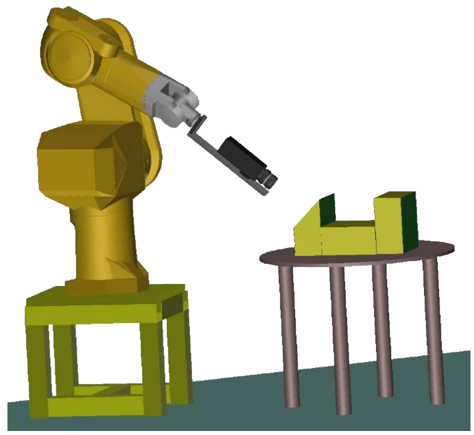
- *The advantage* of using the honeybee search algorithm is the *robustness against outliers*. We can appreciate in the *VRML* images that all 3D points are grouped coherently with the goal of reconstructing compact patches. This is due to the intelligent process described in this paper in which some artificial honeybees (explorers) guide the search process to obtain an improved sparse and quasi-dense reconstruction.

- *This work has shown* the benefit of using an intelligent approach in which the total number of points needed to obtain a significant model of the scene is smaller for the honeybee search algorithm compared to the triangulation approach. The explorers guide the foragers using texture and correlation information during the whole process.

- *Similar to the natural process* the goal is achieved using a communication system that we have adapted to the classical evolutionary algorithm. It is suitable to think that the honeybee search algorithm could be applied in other contexts.

slide #95

Autonomous Measurement System



slide #96

Some Initial Questions

- Where should we placed the cameras in order to obtain the minimal 3D error?
- From this question several subproblems arise:
  1. How can we develop a good criterion to judge our configuration?
  2. What conditions are needed for our system to work?
  3. Which are the interrelated aspects involved in the development of the system?
  4. What would be a good method to optimize the placement of the cameras?

slide #97

Photogrammetric Network Design

- Camera calibration is understood as the process of determining the interior orientation parameters. Beside the camera constant and the location of the principal point this may also include the parameters of lens distortion. This is a well established procedure (standard) in photogrammetry and computer vision.
- Bundle adjustment is recognized as a critical factor in exploiting the mensuration potential of photogrammetry and is almost exclusively used in applications requiring high-accuracy.
  1. In our previous work (Olague and Mohr, 2002)the projective model was used to derive an analysis of the uncertainty that is useful in the determination of a camera configuration.
  2. The projective and collinearity based approaches have been used recently (Olague and Dunn, 2007) to achieve a practical photogrammetric network design.

slide #98

Error Propagation in Computer Vision

- The key to simulate networks of complex objects and testing the solution in the real world with a standard laptop is a much faster analytical method based on Taylor series used to estimate the 3D measurement accuracy:

$$f(\mathbf{p}) = f(E[\mathbf{p}]) + \frac{\partial f(E[\mathbf{p}])}{\partial \mathbf{p}}(\mathbf{p} - E[\mathbf{p}]) + \Theta(\mathbf{p}) \ . \tag{20}$$

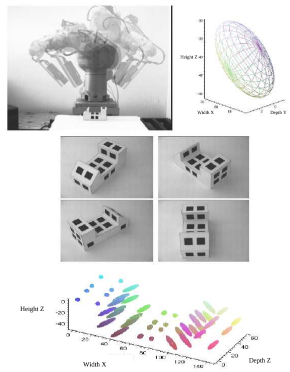
  The analytical approach takes account that the 3D measurement point $\mathbf{P}_j$ is related to the input data $\mathbf{p}_{ij}$ by an analytical function f (non-linear). This relationship is approximated by a linear one through a first order expansion.

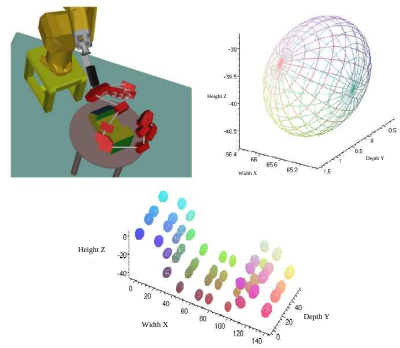
- After ignoring the second order terms, it is easy to compute the mean value of the output meaurements and consequently the covariance of the measurements

$$\Lambda P = \frac{\partial f(E[\mathbf{p}])}{\partial \mathbf{p}} E[(p - E[\mathbf{p}])(\mathbf{p} - E[\mathbf{p}])^T](\frac{\partial f(E[\mathbf{p}])}{\partial \mathbf{p}})^T \ ,$$

slide #99

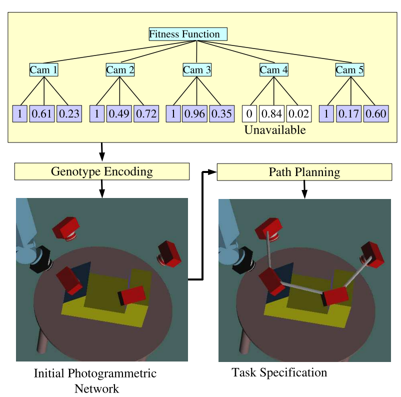
Experimental Results





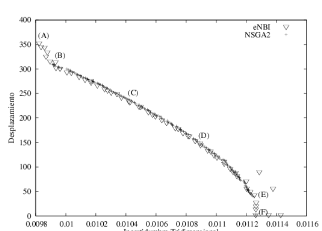
slide #100

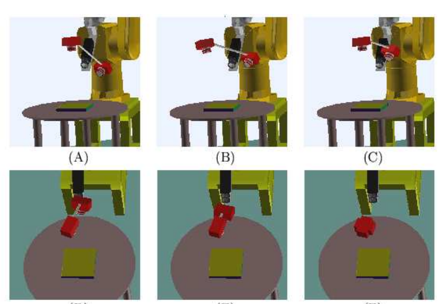
Genetic Representation



slide #101

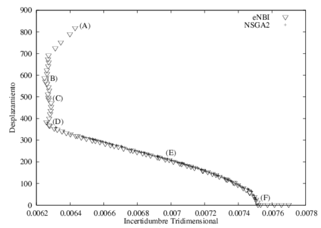
Experimental Results

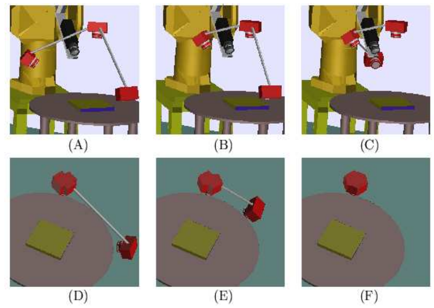




slide #102

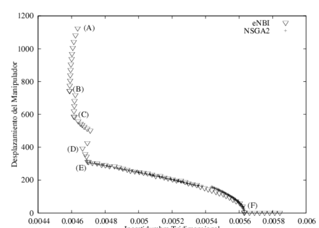
Experimental Results

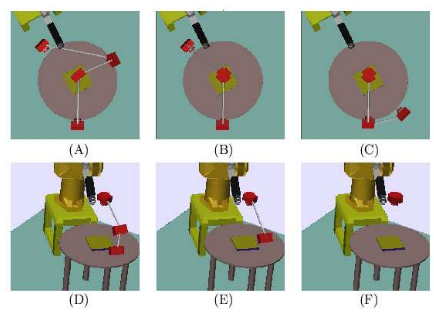




slide #103

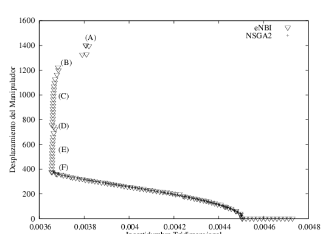
Experimental Results

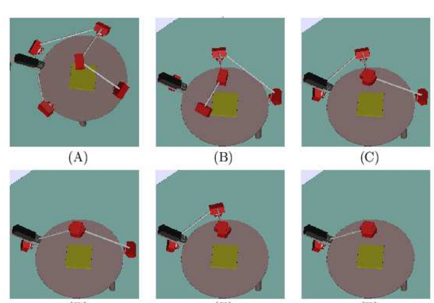




slide #104

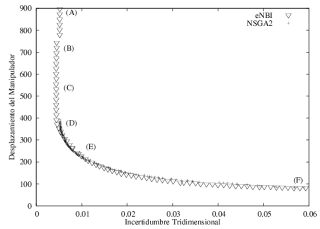
Experimental Results

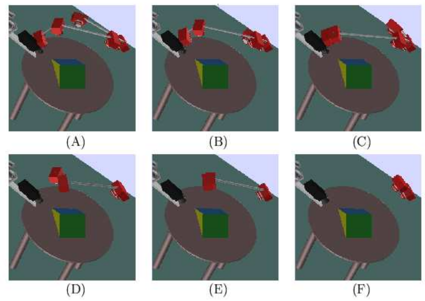




slide #105

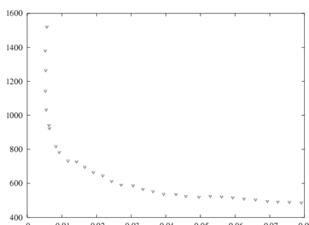
Experimental Results

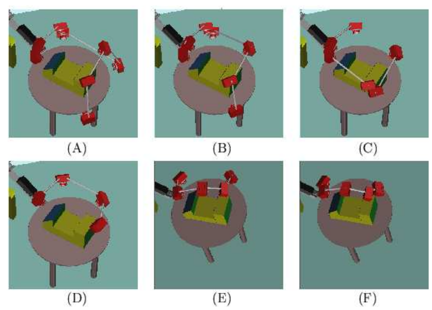




slide #106

Experimental Results





slide #107

Evolutionary Visual Learning

- Texture Linear Genetic Programming for Multi-Class Object Recognition

1. Recognition is a classical problem in computer vision whose task is that of determining whether or not the image data contains some specific object, feature, or activity.
2. This task can normally be solved robustly by a human, but is still not satisfactory solved by a computer for the general case: arbitrary objects in arbitrary situations.

slide #108

Evolutionary Visual Learning

- Texture Linear Genetic Programming for Multi-Class Object Recognition

1. Our LGP approach solves simultaneously the region selection and feature extraction tasks, that are applicable to common image recognition problems.
2. The method searches for optimal regions of interest, using texture information as its feature space and classification accuracy as the fitness function.
3. Texture is analyzed based on the gray level cooccurrence matrix and classification is carried out with a SVM committee.
4. Results show effective performance compared with previous results using a standard image database.

slide #109

Multi-Class Object Recognition

- Recognition of a particular object and recognition of a class of objects.

1. Imagine the problem of identifying our own car. The object that we are looking for is obviously a car with unique attributes which correspond to the car that belong us. On the other hand, the problem of recognizing a class of objects is more general, for example that of identifying cars as a class of objects.

2. In this work, the task is to use the information from a training dataset in order to create an internal model of the idea of car, that will be used in activities such as detection and classification of objects into cars or no-cars. This problem could be further extended into the problem of face recognition, background extraction, or even more complicated like facial expression recognition.

slide #110

Object Recognition

The task of object recognition is that of determining if an object belongs to one or more classes in a collection or sequence of images.

- Given an image I, a database of k objects, and one representation R_j for each object j in the image database; the object recognition could be expressed as follows:

$$Q = arg\, min\, c(R_j, I) \qquad j \,\epsilon\, 1, .., k \quad ,$$

where $c(R_j, I)$ is a function which provides the compatibility or consistency for representing the object j in the image I.

slide #111

Object Recognition

A simpler definition proposed by Russell and Norving (1995) could be expressed as follows:

1. *Given a set of images that contains one or more objects selected from a collection of objects $O_1, O_2, ..., O_n$ known* a priori*, and*

2. *Given an image of the scene taken from an unknown position and orientation;*

Answer the following question:

1. *Which objects $O_1, O_2, ..., O_n$ are presented in the scene?*

2. *In such a way that, for each object, it is possible to determine the position and orientation of the observer.*

slide #112

Images for the class "building"

(a) Set of training images

slide #113

Images for the class "building"

(b) Set of testing images

slide #114

Images for the class "faces"

(c) Set of training images

slide #115

Images for the class "faces"

(d) Set of testing images

Images for the class "cars"

(e) Set of training images

Images for the class "cars"

(f) Set of testing images

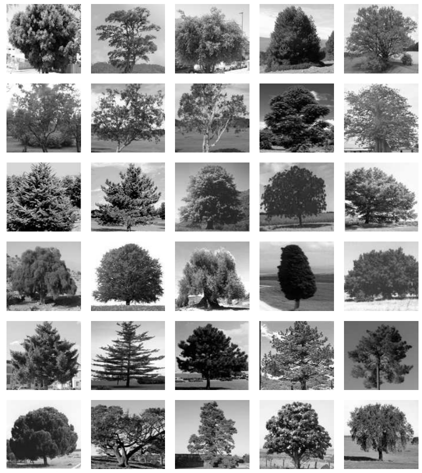
slide #118

Images for the class "trees"

(g) Set of training images

slide #119

Images for the class "trees"



(h) Set of testing images

slide #120

Images for the class "cows"

(i) Set of training images

slide #121

Images for the class "cows"

(j) Set of testing images

slide #122

Evolutionary Learning

- The general methodology that is proposed in this work considers the identification of Regions of Interests (ROIs) and the selection of the set of features of interest (texture descriptors). Two tasks are solved simultaneously.
  1. The first task consists in identifying a set of suitable regions where feature extraction is to be performed.
  2. The second task consists in selecting the parameters that define the GLCM, as well as the set of descriptors that should be computed. This second task could be further extended with other image operators.
- The output of these two tasks is taken as input by a SVM committee that gives the experimental accuracy of a multiclass problem using the selected features and ROIs.

slide #123

Linear Genetic Programming

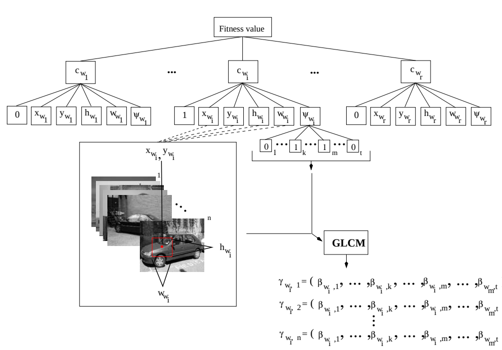


figure 1: *LGP uses a tree structure similar to the Multicellular Genetic Algorithm (Olague, 2002).*

slide #124

Evolutionary Learning

- The LGP searches for the best set Ω of ROIs for all images and optimizes the feature extraction procedure by tuning the GLCM parameter set

$$\pi_{\omega_i} \ \forall \omega_i \in \Omega$$

through the selection of the best subset

$$\{\beta_{\omega_i,1}, ..., \beta_{\omega_i,2t}\}$$

of mean and variance descriptor values from the set of all possible descriptors Ψ , to form a feature vector $\vec{\gamma}_i = (\beta_{\omega_i,1}, ..., \beta_{\omega_i,2t})$ for each $\omega_i \in \Omega$.

slide #125

ROI Selection

1. r structural variables $\{c_1....c_r\}$, represented by a single bit each. Each one controls the activation of one ROI definition block. These variables control which ROI will be used in the feature extraction process.
2. r ROI definition blocks $\omega_1....\omega_r$. Each block ω_i, contains four parametric variables $\omega_i = \{x_{\omega_i}, y_{\omega_i}, h_{\omega_i}, w_{\omega_i}\}$, where the variables define the ROIs center $(x_{\omega_i}, y_{\omega_i})$, height (h_{ω_i}) and width (w_{ω_i}). Basically, each ω_i establishes the position and dimension for a particular ROI.

slide #126

Feature Extraction

1. A parameter set π_{ω_i} is coded $\forall \omega_i \in \Omega$, using three parametric variables. Each $\pi_{\omega_i} = \{R_{\omega_i}, d_{\omega_i}, \theta_{\omega_i}\}$ describes the size of the region R, distance d and direction θ parameters of the GLCM computed at each ω_i. Note that R is a GLCM parameter, not to be confused with the ROI definition block ω_i.
2. Eleven decision variables coded using a single bit to activate or deactivate a descriptor $\beta_{\omega_i,j} \in \Psi$ at a given ROI. These decision variables determine the size of the feature vector $\vec{\gamma}_{\omega_i}$, extracted at each ROI in order to search for the best combination of GLCM descriptors. In this representation, each $\beta_{\omega_i,j}$ represents the mean and variance values of the jth descriptor computed at ROI ω_i. This part of the chromosome could be further enhanced with new image operators.

slide #127

Classification and Fitness Evaluation

- Since the recognition problem aims to classify every extracted region ω_i, we implement a SVM committee that uses a voting scheme for classification. The SVM committee Φ, is formed by the set of all trained SVMs $\{\phi_i\}$, one for each ω_i.
- The SVM Committee uses voting to determine the class of the corresponding image.
- In this way, the fitness function is computed with the *Accuracy*, which is the average accuracy of all SVMs in Φ for a given individual. In other words,

$$Accuracy = \frac{1}{|\Phi|}\sum_x Acc_{\phi_x},$$

summed $\forall \phi_x \in \Phi$, where Acc_{ϕ_x} is the accuracy of the ϕ_j SVM.

slide #128

SVM Parameters

- *Kernel Type:* A *Radial Basis Function* (RBF) kernel was used, given by:

$$k(x, x_i) = exp(-\frac{\|x - x_i\|^2}{2\sigma^2}) \quad (21)$$

The RBF shows a greater performance rate for classifying non linear problems than other types of kernels.

- *Training Set:* The training set used was extracted from a whole set of different images, see Section **??**.
- *Cross Validation:* In order to compute the accuracy of each SVM, we perform k-fold cross validation, with k=6. In general, the accuracy computed with crossvalidation will out perform any other type of validation approach (Goutte, 1997). In k-fold cross validation the data is divided into k subsets of (approximately) equal size. The SVM was trained k times, each time leaving out one of the subsets from training, but using only the omitted subset to compute the classifiers accuracy.

slide #129

CALTECH Image Database

- The image database (CALTECH, 2005) contains 240 images from which 120 images contain several objects and the other 120 correspond to the same images that have been segmented manually.
- The experiments consider such database to test the accuracy of the proposed methodology using a standard database, as well as a set of images downloaded from the web.
- These images contain objects with different lighting conditions, in different positions, and with several viewpoints. The database could be considered as one representing a challenging multi-class object recognition problem.
- The experiments confirm that evolution have found always the simplest solution using only one ROI.

slide #130

Individual 92.22%

This individual performs very well with a high average accuracy for training that achieves 92.22%, while the testing is quite good with 73%. This difference is due to the new characteristics of the images downloaded from the web. The LGP selects only one big region located in the lower part of the image because most of the cars are in this part of the images.

	Building	*Faces*	*Cars*
Building	**68%**	20%	12%
Faces	18%	**78%**	4%
Cars	14%	14%	**72%**

table 1: Confusion matrix obtained for the testing set: 73%.

slide #131

Individual 88.88%

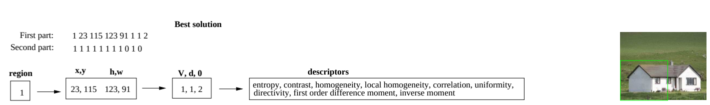
Another solution corresponding to an individual with an average accuracy for training of 88.88% was selected to show the level of classification. Its average during testing was as high as 80% because the set of testing images is composed only by the more similar images with respect to the training stage. Similar to the previous case the best individual selects the lower part of the images due to its characteristics.

	Building	*Faces*	*Cars*
Building	**85%**	11%	4%
Faces	6%	**80%**	14%
Cars	12%	12%	**76%**

table 2: Confusion matrix obtained for the testing set: 80%.

slide #132

Experimental Results



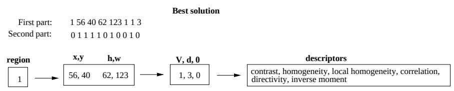
(a) Best individual with an Accuracy of 92.22%

(b) ROI found by the LGP system

figure 2: *Best individual found by the LGP approach using three classes.*

slide #133

Experimental Results



(a) Best individual with an Accuracy of 88.88%

(b) ROI found by the LGP system

figure 3: *Best individual found by the LGP approach using three classes.*

slide #134

Experiment using Five Classes

Due to the encouraging results obtained in our previous experiment, we decide to increase the number of classes. We keep the first three classes of the previous experiment (building, faces, and cars), and two more classes (trees and cows) were added to this second experiment. Therefore, the second experiment to test the multi-class object recognition system considers a total of five classes. The parameters of the LGP were keeped to 85% crossover, 15% mutation, 80 generations, and 80 individuals. Next, the best solution is described:

slide #135

Individual 83.33%

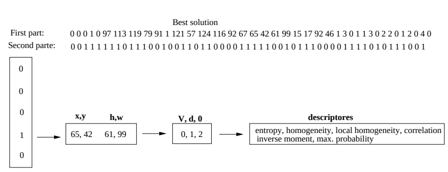
In this experiment, the best individual achieves a training score of 83.33% of classification accuracy. Its average during testing was as high as 77%. In this case, the location of the region of interest is placed over the higher part of the images because the trees are located in general towards this part of the images and because it also covers most parts of the other object classes.

	Building	*Faces*	*Cars*	*Trees*	*Cows*
Building	**74%**	8%	1%	8%	9%
Faces	6%	**80%**	4%	2%	8%
Cars	26%	0%	**68%**	0%	6%
Trees	7%	0%	3%	**87%**	3%
Cows	4%	4%	4%	12%	**76%**

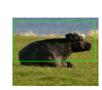
table 3: Confusion matrix obtained for the testing set: 77%.

slide #136

Experimental Results



(a) Best individual with an Accuracy of 77%



(b) ROI found by the LGP system

figure 4: *Best individual found by the LGP approach using five classes.*

slide #137

Comparison with Other Approaches

The advantage of using a standard database is that it is possible to compare with previous results. For example, in (Winn et al., 2005) the authors proposed a method that classifies a region according to the proportion of several visual words. The visual words and the proportion of each object are learned from a set of training images segmented by hand. Two methods were used to evaluate the classification: nearest neighbor and Gaussian model. On the average (Winn et al., 2005) achieved 93% of classification accuracy using the segmented images; while on average the same method achieves 76% after selecting the regions by hand. This last result is comparable to our result. Several aspects could be mentioned:

- The approach proposed in this paper does not use segmented images.
- The ROI was automatically selected by the LGP.
- The images used in the testing stage does not belong to the original database (CALTECH, 2005), these images with a bigger difference were obtained from the web.

slide #138

Comparison with Other Approaches

	Win *et al.*			LGP-SVM	
	NN $k = 2000$	NN $k = 216$	Gaussian	Objects (3) 88.88%	Objects (5) 83.33%
Feature selection	Hand	Hand	Hand	Automatic	Automatic
Accuracy	76.3%	78.5%	77.4%	80.0%	77.0%

table 4: Recognition Accuracy

slide #139

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