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On Computational Intelligence Tools for Vision Based Navigation of Mobile Robots

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PhD Thesis dissertation
University of the Basque Country

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Outline

- Introduction.
- Lattice Computing for localization and mapping.
- Localization from 3D imaging.
- Multi-robot visual control.
- Conclusions.

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General motivations

- To explore the use of innovative Computational Intelligence techniques for vision based localization and mapping for mobile robots.
  - Based on Lattice Computing, in the form of several applications of Lattice Associative Memories (LAM).
  - Based on Hybrid Systems combining Competitive Neural Networks and Evolution Strategies.
- Realize a proof-of-concept physical experience on the vision based control of a Linked Multi-Component Robotic System (MCRS)

Objectives

- Test the capacity of LAMs for landmark view storing and recognition through retrieval in a real robot implementation.
- Test the usefulness of the convex coordinates extracted with LAMs as feature vectors for view classification in a robotic mapping context.
- Test the usefulness of the endmembers induced with LAMs as landmarks in an SLAM context, developing the adequate tools for its on-line use.

Objectives

- Develop an hybrid approach to the use of 3D data provided by innovative 3D ToF cameras for ego-motion estimation.
- Demonstrate a physical realization of vision based control for a multi-robot linked system in the form of a hose transportation system.

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Motivations

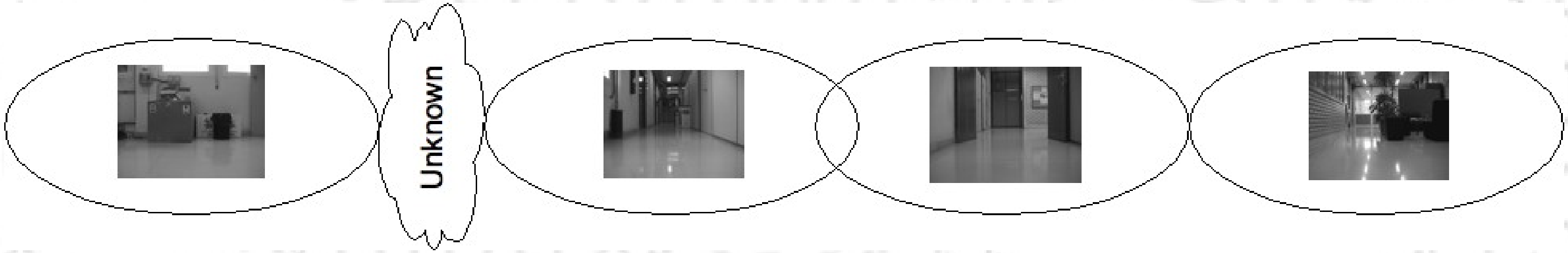
- Lattice Theory has been identified as a central concept for a whole family of methods and applications in Computational Intelligence.
- Application of the group's background knowledge.
- Part of group's ongoing work:
  - Hyper-spectral imaging.
  - Medical Imaging (fMRI).
  - Robotic mapping.

Approaches

- Lattice Heteroassociative Memories (LHAM) for visual mapping and localization.
- LAMs for feature extraction in landmark recognition.
- LAMs for unsupervised landmark selection for SLAM.

LHAM for visual mapping and localization

- Continuation of a previous work.
  - Use LHAM for the storing and retrieval of views as landmarks.
- Implementation in a real robotic platform.
  - Build topological, non-exhaustive maps.
  - Real-time operation.



LHAM for visual mapping and localization

Pioneer robotic platform.

LHAM for visual mapping and localization

- Real-time, real-robot issues:
  - Computational cost:
    - Binary images: Dark and bright spots used as anchors.
  - LHAM size limitation:
    - Multi-memory map: each position stored in one different LHAM.
  - Robustness:
    - Dual LHAM memories for image storing.

LHAM for visual mapping and localization

- Mapping and localization as separate processes.
  - Map was built in a learning walk.
- Real time experiment successful.

Approaches

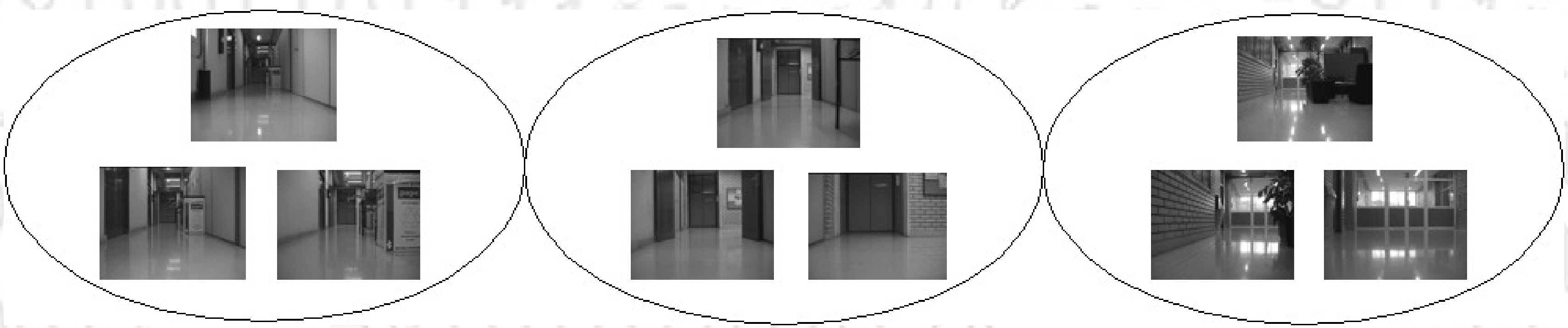
- Lattice Heteroassociative Memories (LHAM) for visual mapping and localization.
- LAMs for feature extraction in landmark recognition.
- LAMs for unsupervised landmark selection for SLAM.

LAMs for feature extraction in landmark recognition

- Use the *convex coordinates* as image feature vector for landmark recognition.
- The convex coordinates are computed through the *spectral unmixing* from the vertices of the convex region which covers the data.
- Vertices are induced as a *Lattice Independent* set.
  - LAM-based Endmember Induction Heuristic Algorithm (EIHA).
  - From the columns of the LAM.

LAMs for feature extraction in landmark recognition

- Induction of the endmembers from the data sample.
- Feature extraction: convex coordinates.
- Landmarks selected by hand.
  - Each landmark identifies a “region” composed of several images.
- Image classification: classes correspond to the landmark regions.



LAMs for feature extraction in landmark recognition

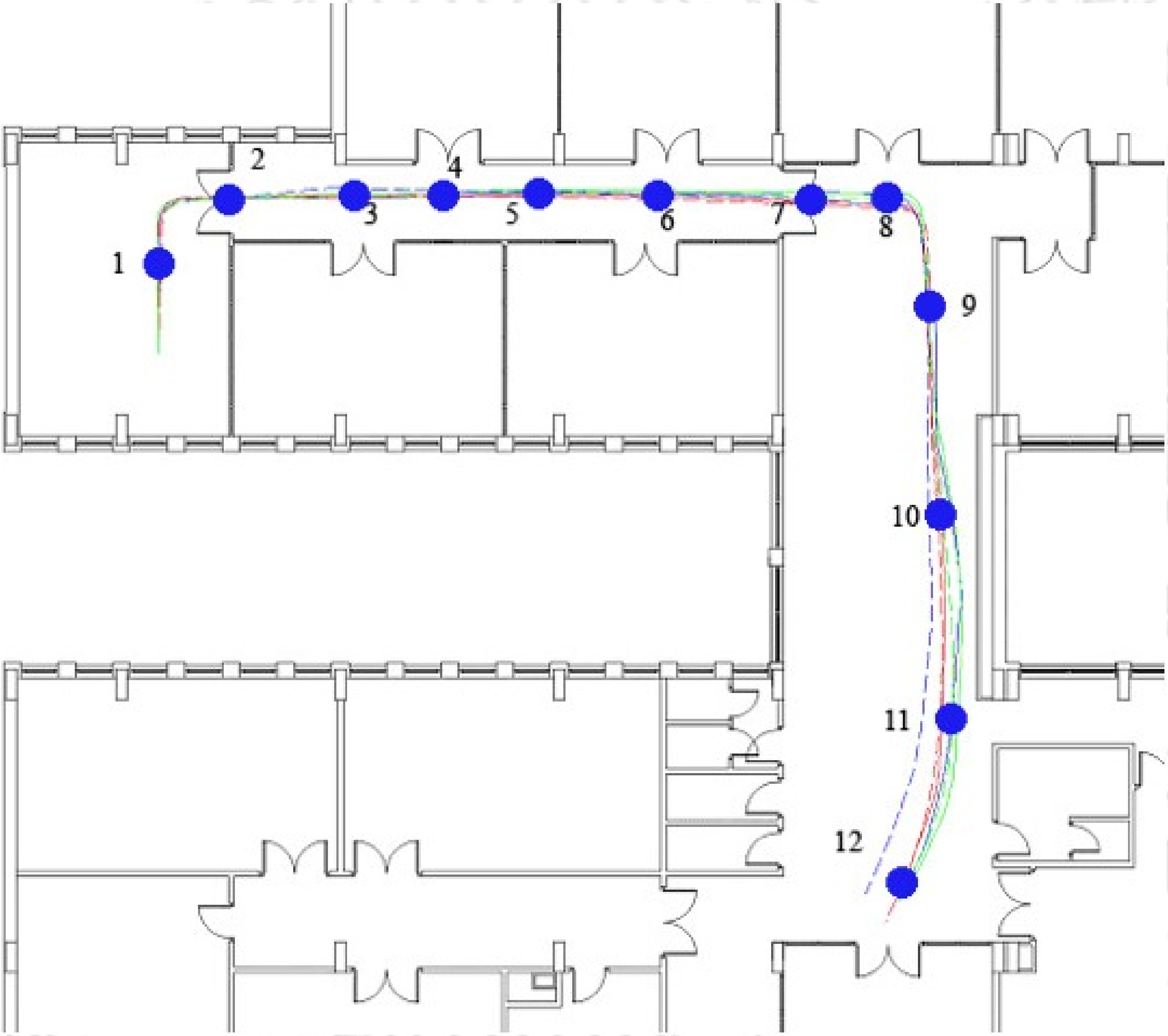
- Localization:
  - Images are classified on the regions.
  - Feature vectors: convex coordinates obtained by an unmixing process from the training set's endmembers.
  - k-NN classifier.

LAMs for feature extraction in landmark recognition

Experimental validation:

- Pre-recorded data sets:
  - 6 walks over the same path.
  - 1st used as training set.
- Landmarks selected as places of practical relevancy.
- Odometry used for validation.

LAMs for feature extraction in landmark recognition



LAMs for feature extraction in landmark recognition

#end	Train	Pass 1	Pass 2	Pass 3	Pass 4	Pass 5	Av.
13	0.94	0.81	0.76	0.72	0.73	0.67	0.772
14	0.94	0.85	0.77	0.69	0.78	0.71	0.79
13	0.94	0.84	0.75	0.70	0.75	0.74	0.787
14	0.94	0.83	0.71	0.63	0.73	0.67	0.752
12	0.94	0.85	0.79	0.69	0.78	0.72	0.795
12	0.93	0.80	0.70	0.67	0.69	0.70	0.748
12	0.94	0.83	0.71	0.59	0.70	0.66	0.738
12	0.93	0.82	0.76	0.69	0.74	0.66	0.767
14	0.94	0.79	0.73	0.64	0.70	0.63	0.738
12	0.92	0.79	0.70	0.63	0.65	0.60	0.715
Av.	0.936	0.821	0.738	0.665	0.725	0.676	0.76

PCA 10	0.96	0.86	0.78	0.66	0.76	0.73	0.792

Landmark recognition success rate based on the convex coordinates representation of the navigation images for several runs of the EIHA with $\alpha = 5$ and using 3-NN.

LAMs for feature extraction in landmark recognition

#end	Train	Pass 1	Pass 2	Pass 3	Pass 4	Pass 5	Av.
5	0.96	0.79	0.74	0.64	0.71	0.61	0.742
10	0.96	0.80	0.76	0.61	0.80	0.72	0.775
15	0.96	0.80	0.74	0.66	0.79	0.69	0.773
20	0.96	0.80	0.76	0.65	0.81	0.67	0.775
25	0.96	0.78	0.72	0.62	0.74	0.68	0.75
30	0.96	0.81	0.73	0.60	0.75	0.69	0.757
Av.	0.96	0.797	0.742	0.63	0.767	0.677	0.762

PCA 10	0.96	0.86	0.78	0.66	0.76	0.73	0.792
PCA 30	0.96	0.87	0.77	0.64	0.78	0.78	0.8

Landmark recognition success rate based on the convex coordinates representation of the navigation images for several numbers of endmembers extracted from the LAM columns and using 3-NN.

Approaches

- Lattice Heteroassociative Memories (LHAM) for visual mapping and localization.
- LAMs for feature extraction in landmark recognition.
- LAMs for unsupervised landmark selection for SLAM.

LAMs for unsupervised landmark selection for SLAM

Could be the induced endmembers used as suitable landmarks?

LAMs for unsupervised landmark selection for SLAM

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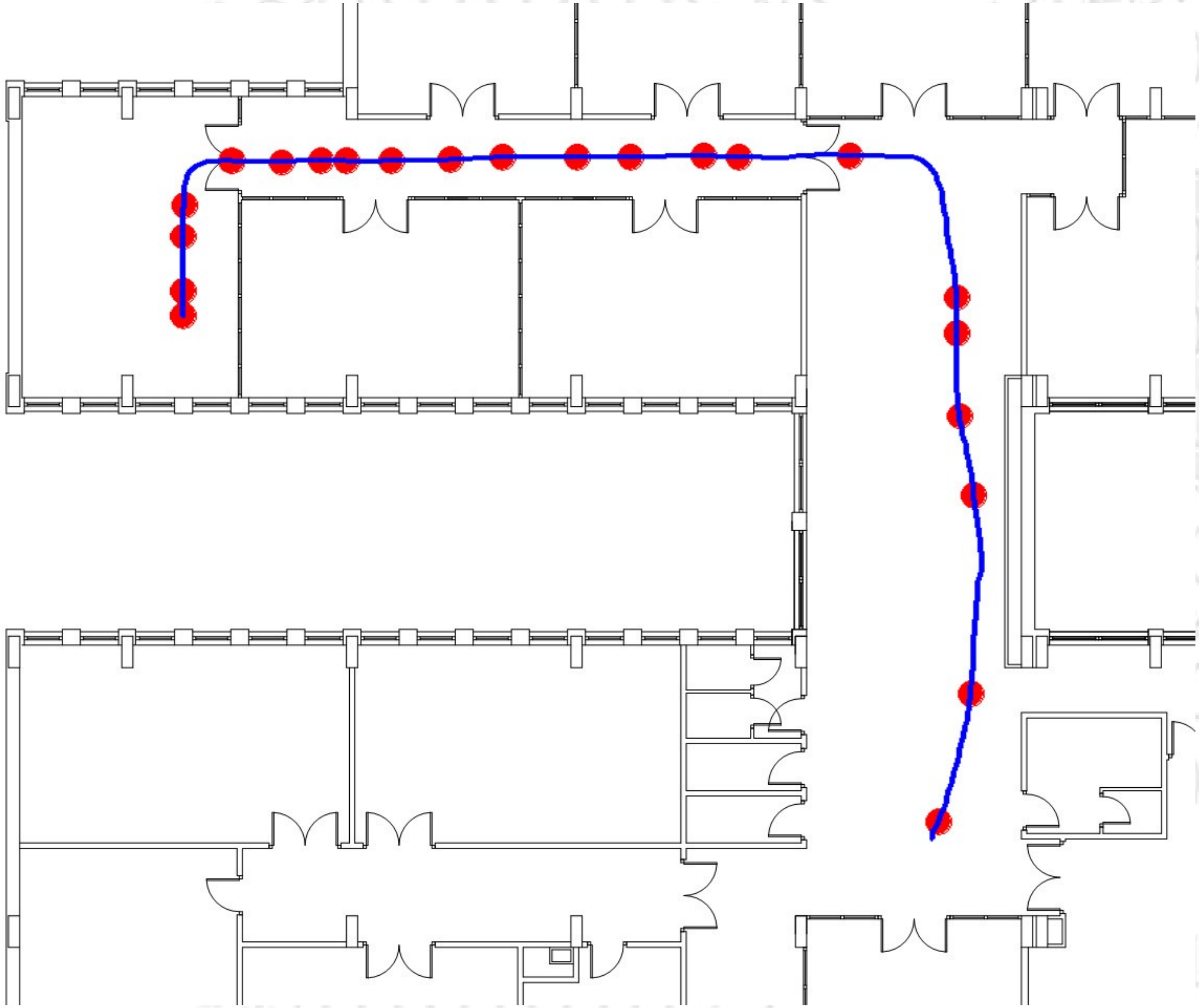
- Induced endmembers:
  - They correspond with physical positions.
  - They seem to be well distributed along the path.
  - They would be good recognition anchors.

LAMs for unsupervised landmark selection for SLAM

- Full dataset not available from the start:
  - EIHA must be modified to operate on-line.
  - Convex coordinates can not be used as feature vectors because endmembers change along the process.
    - Some other dimensionality reduction method required: DCT.

LAMs for unsupervised landmark selection for SLAM



LAMs for unsupervised landmark selection for SLAM

	Train	W1	W2	W3	W4	W 5	Av.
Path 1	0.83	0.75	0.76	0.60	0.69	0.64	0.742
Path 2	0.84	0.68	0.74	0.76	0.59	0.67	0.775
Path 3	0.80	0.66	0.48	0.76	0.71	0.65	0.773
Path 4	0.80	0.49	0.39	0.76	0.41	0.67	0.775
Path 5	0.81	0.72	0.69	0.77	0.63	0.57	0.75

Landmark recognition success rate based on the DCT low frequencies.

Chapter conclusions

- Confirmed the theoretical and simulation results of previous works about using LHAM for map storing.
- Convex coordinates of the data points based on the endmembers induced by the EIHA algorithm can be used as features for landmark recognition, with similar performance to PCA.
- Unsupervisedly induced endmembers are suitable as landmarks.

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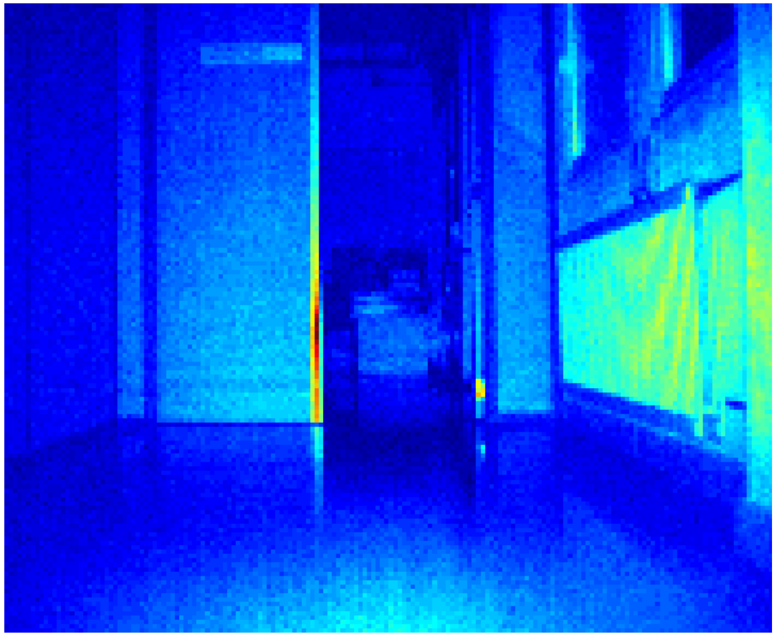
Motivations

- Use of new ToF 3D cameras.
- Application of Computational Intelligence approaches to robot localization using this 3D data.
  - Hybrid neuro-evolutionary system.
- Task: ego-motion estimation.

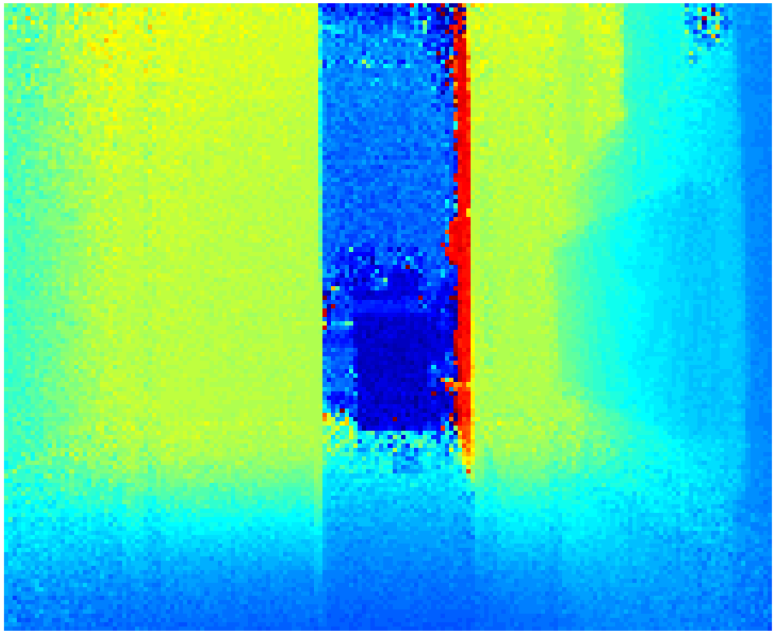
Neuro-evolutionary system

1) Preprocessing step.
2) Competitive Neural Network module.
3) Evolution Strategy module.

Sensor data

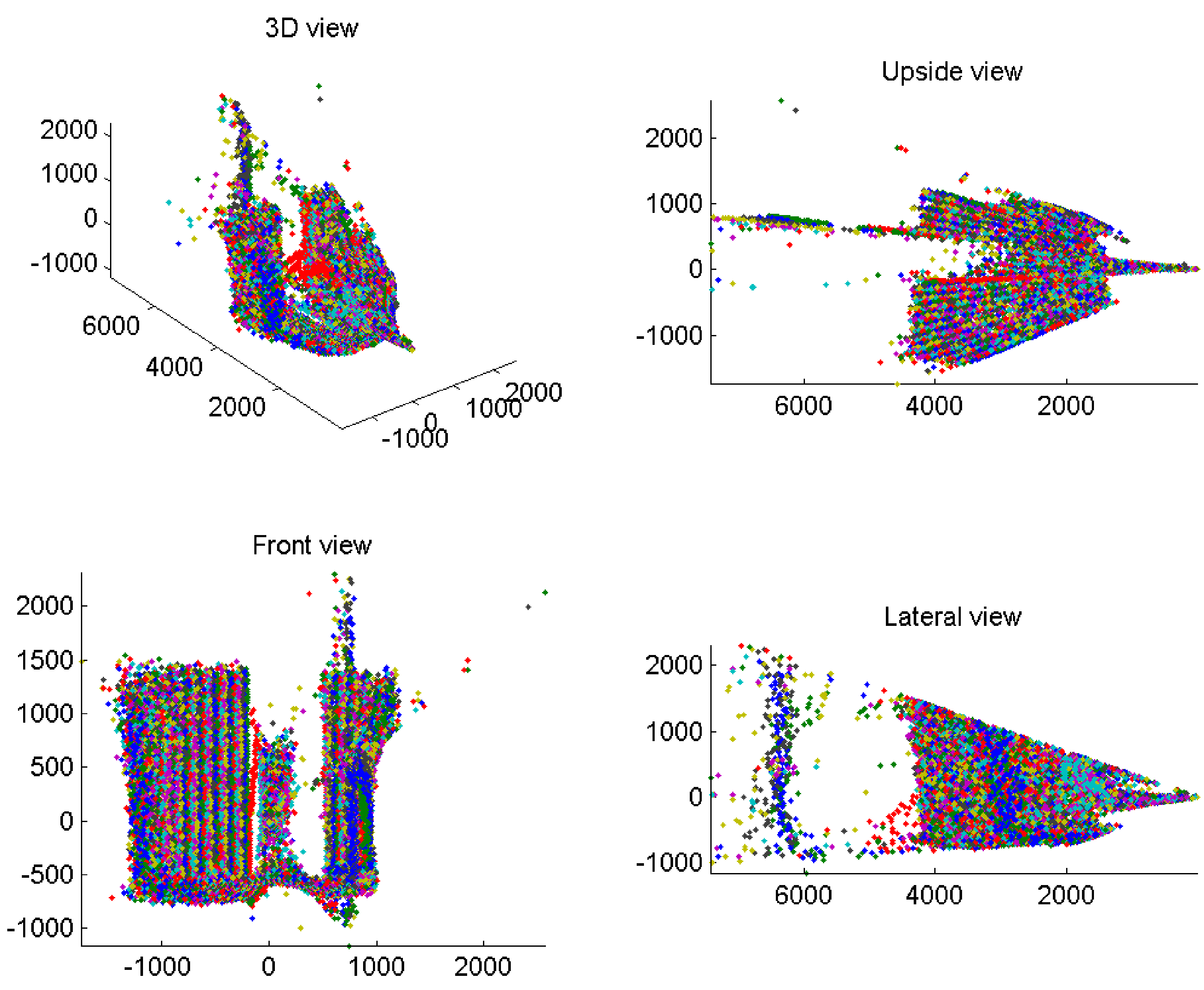


Amplitude Image



Distance Image

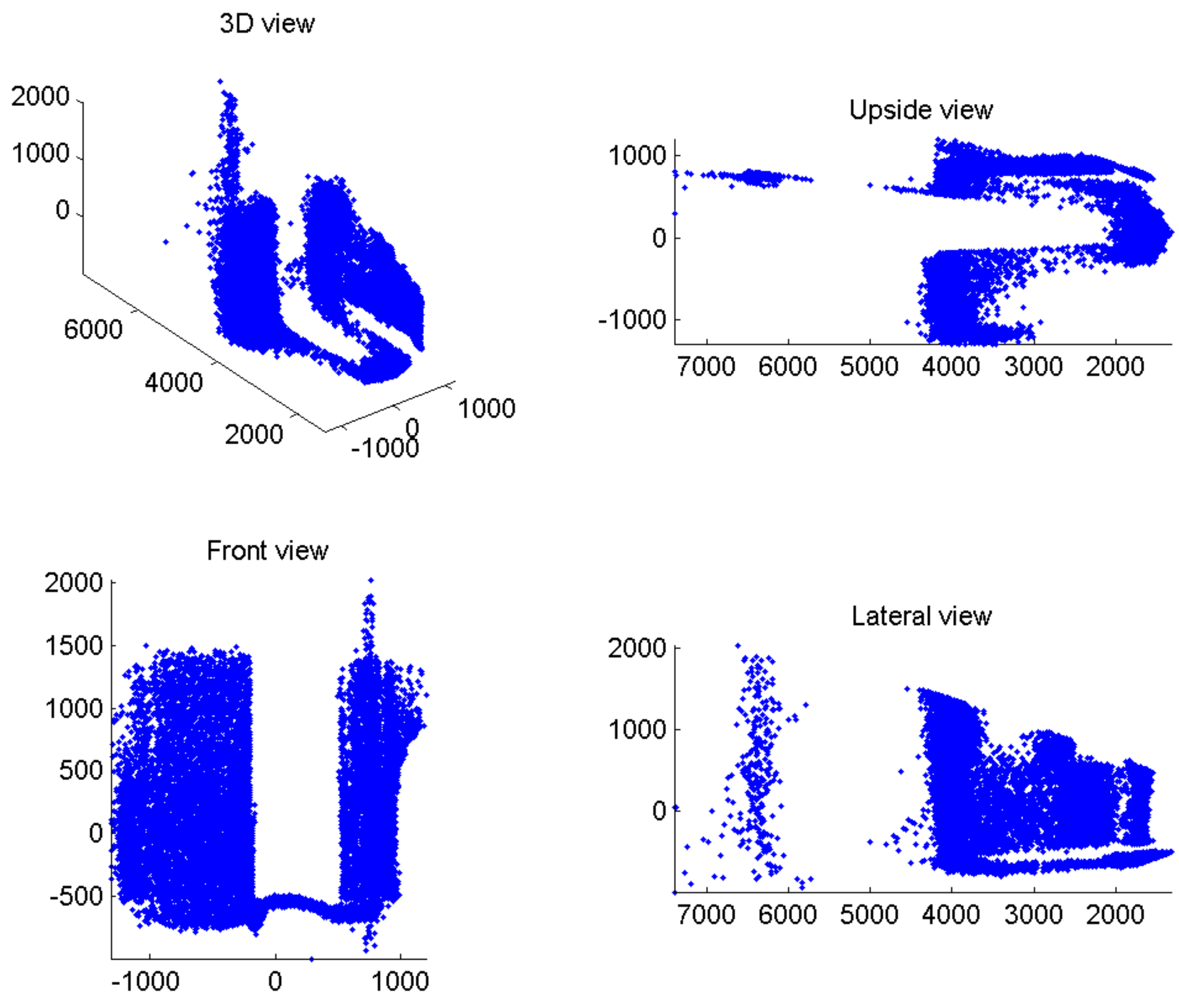
Sensor data


3D view
2000
1000
0
-1000
6000
4000
2000
-1000
0
1000
2000
Upside view
2000
1000
0
-1000
6000
4000
2000
Front view
2000
1500
1000
500
0
-500
-1000
-1000
0
1000
2000
Lateral view
2000
1000
0
-1000
6000
4000
2000

Localization from 3D imaging

Preprocessing

- Filtering: Reliability coeficient $R_i = I_i \times D_i$

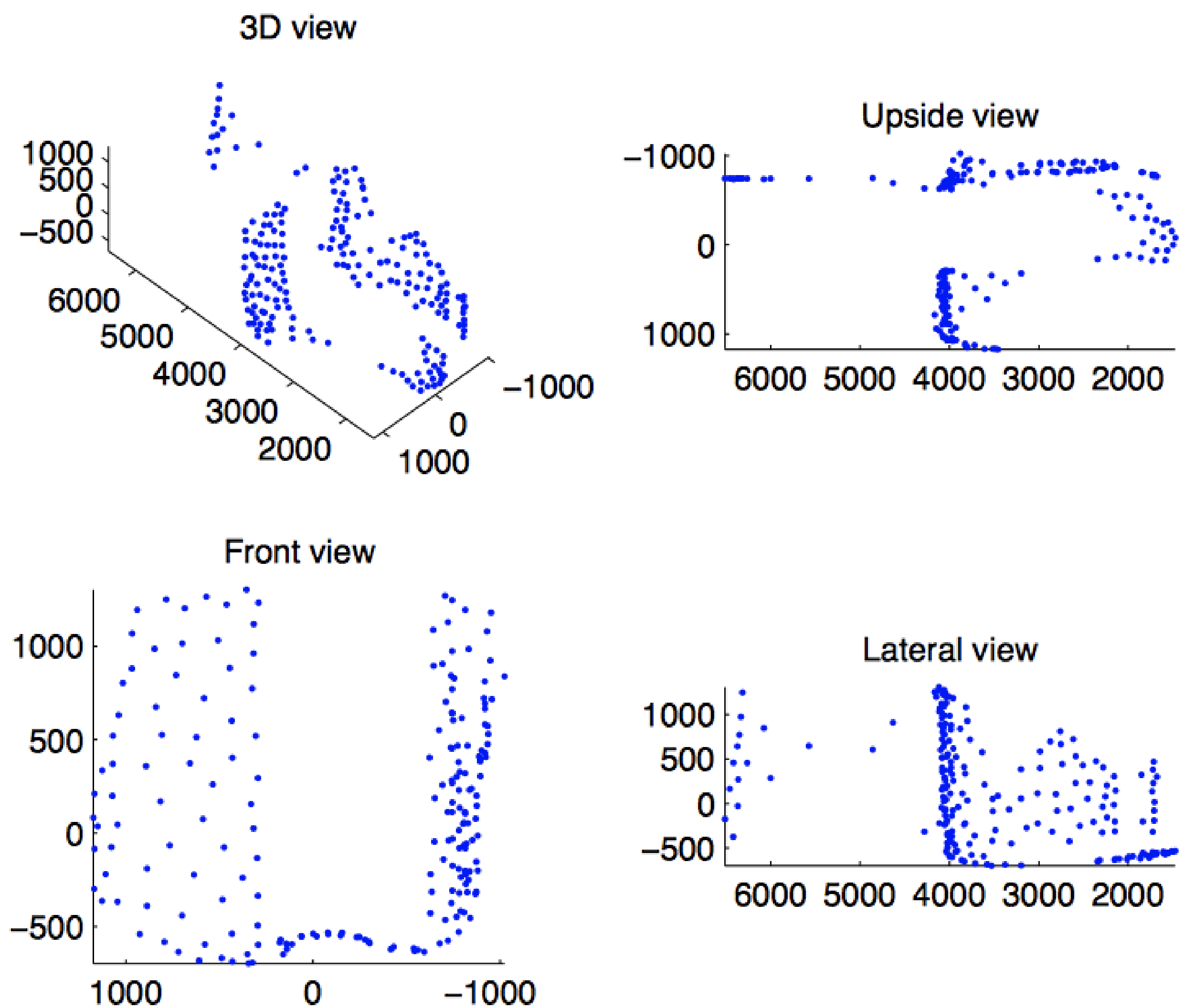


Competitive Neural Network module

- Neural Gas network used to fit a codebook *S* to the point cloud:
  - Keeps the spatial shape of the cloud.
  - Reduces the data amount to a fixed, manageable size.

Localization from 3D imaging

Competitive Neural Network module



Evolution Strategy module

- Objective: compute the displacement between positions P_t and P_{t+1} as the transformation between S_t and S_{t+1}.
- ($\mu/\rho+\lambda$) Evolution Strategy.

Evolution Strategy module

- Evolves an estimation $\hat{T}_{t+1}$ of the transformation matrix.

$$T_{t+1} = \begin{bmatrix} \cos(\Delta\theta_{t+1}) & -\sin(\Delta\theta_{t+1}) & \Delta x_{t+1} \\ \sin(\Delta\theta_{t+1}) & \cos(\Delta\theta_{t+1}) & \Delta y_{t+1} \\ 0 & 0 & 1 \end{bmatrix}$$

$$S_{t+1} \approx T_{t+1} \times S_t$$

- Position estimation:

$$\hat{P}_{t+1} = \hat{T}_{t+1} \times \hat{T}_t \times \ldots \times \hat{T}_1 \times P_0$$

Evolution Strategy module

Given the previous position estimation.

The robot moves to a new physical position P_{t+1}.

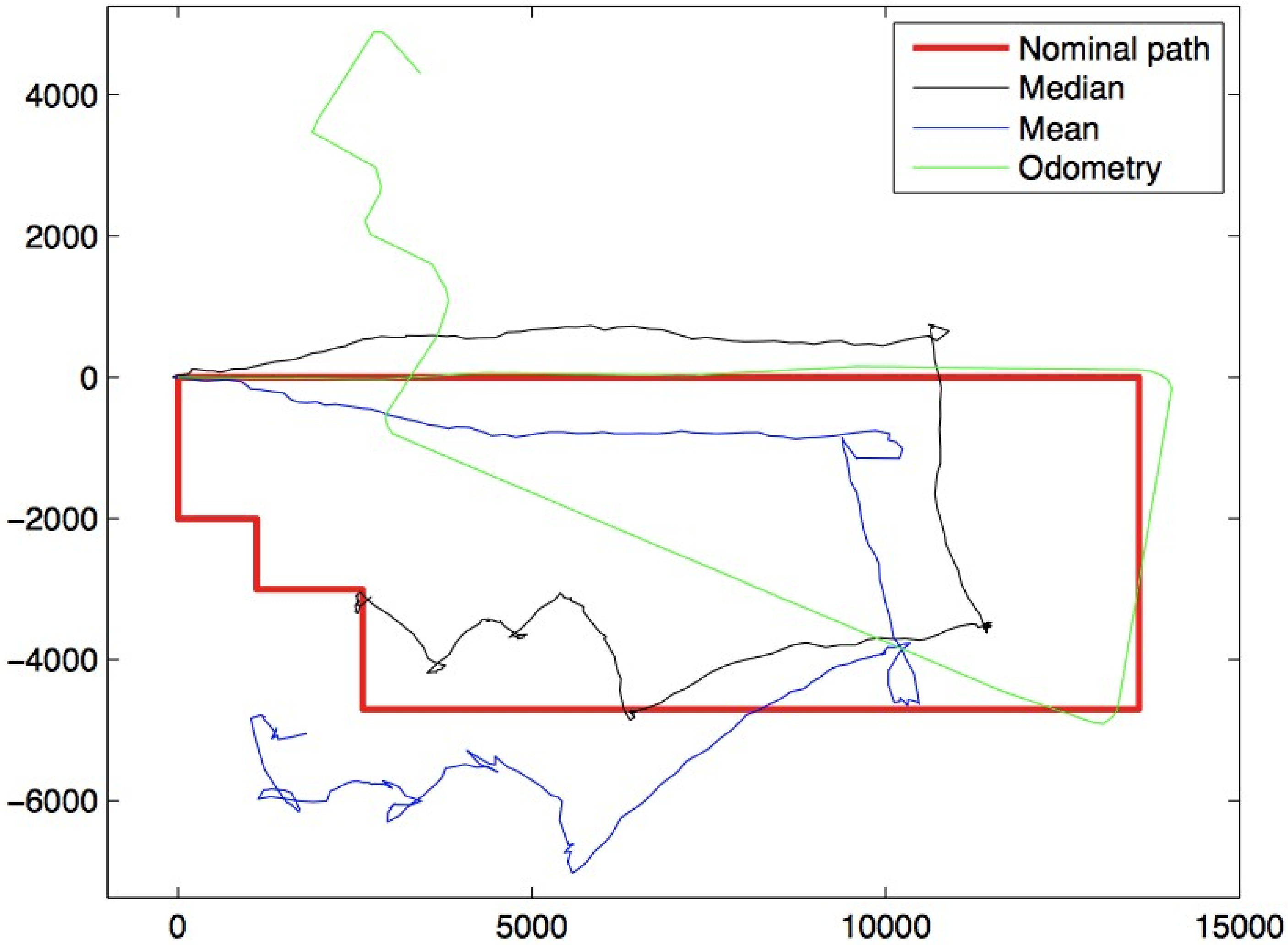
1. Take measurements from the camera.
2. Filter the cloud of 3D points.
3. Obtain S_{t+1} fitting the Neural Gas network to the cloud of filtered 3D points.
4. Generate an initial population H_0.
5. Iterate until stopping condition:
   - 5.1. Select a parent population from previous population.
   - 5.2. Stop if convergence conditions are matched. Continue otherwise.
   - 5.3. Generate the offsprings by recombination and mutation.
   - 5.4. For each offspring:
     - 5.4.1.Build the transformation matrix and compute the prediction of S_{t+1}.
     - 5.4.2.Calculate fitness as the matching distance between observed and predicted codebook.
   - 5.5. Build population H_k as the union of parent and offspring populations.
6. Build the estimation of the transformation matrix from the best hypotesis in the last population.

7.Compute position estimation at time $t+1$.

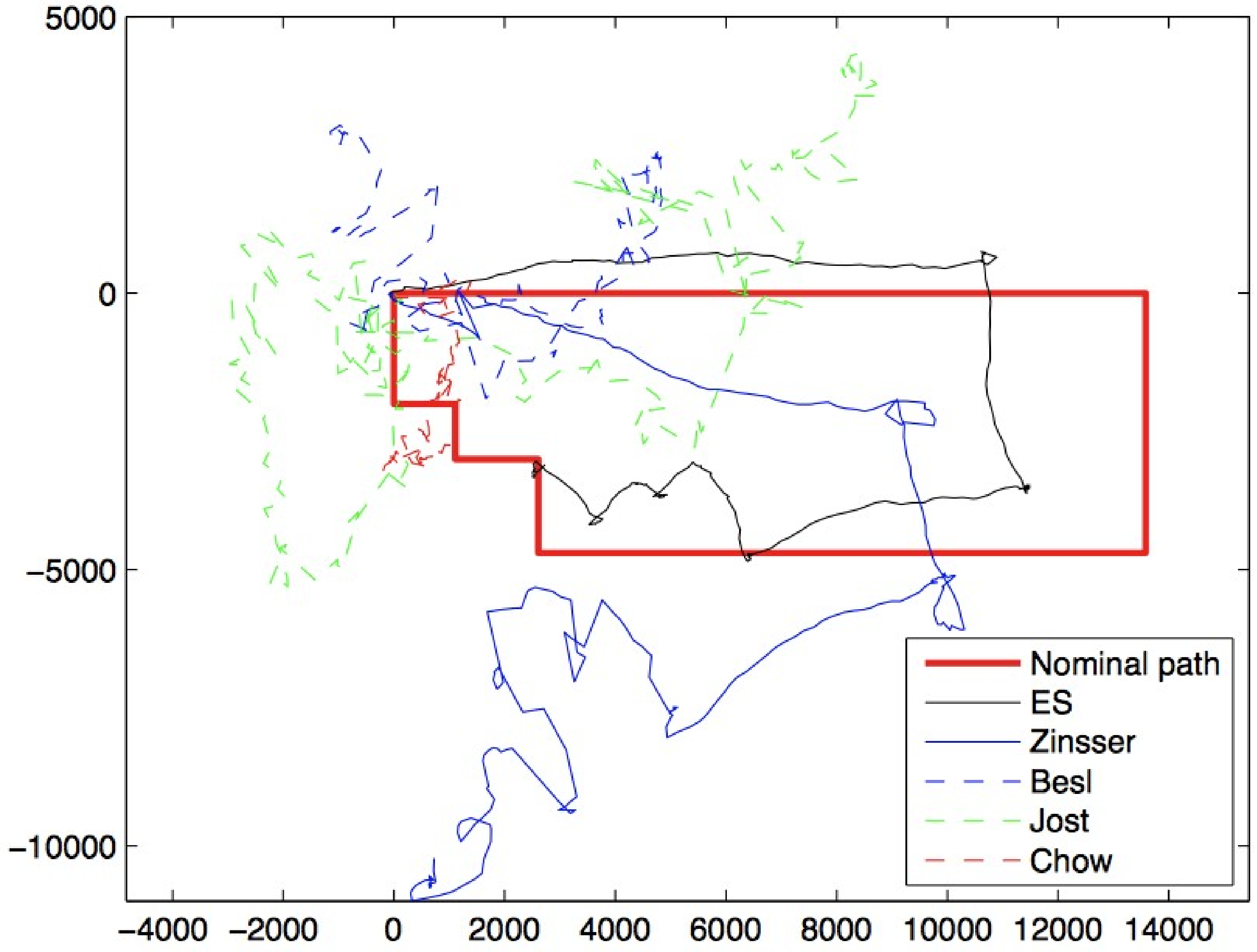
Experimental validation

- Recorded 3D datasets.
- Big, empty room.
- Reconstruct the path followed by the robot.

Experimental validation



Experimental validation



Experimental validation

Algorithm	Mean error	Acc. error	Final error
Odometry	2585	695602	5255
ES	2952	794266	3881
Zinsser	12711	3419386	10291
Besl	9300	2501695	3017
Chow	6893	1854391	2999
Jost	8738	2350702	8478

Experimental validation

Algorithm	100 Codevectors	400 Codevectors
Besl	84	394
Chow	5224	14936
ES	9564	N/A
ES kd-trees	277	964
Jost	63	257
Zinsser	50	389

Chapter conclusions

- Path reconstruction comparable to or even improving the one provided by odometry.
- Comparisons with state of the art registration algorithms:
  - Overall slower.
  - Faster than other evolutionary approaches.
  - Better path reconstruction.
- Drawbacks identified:
  - Slightly overlapping frames.
  - Aperture problem.

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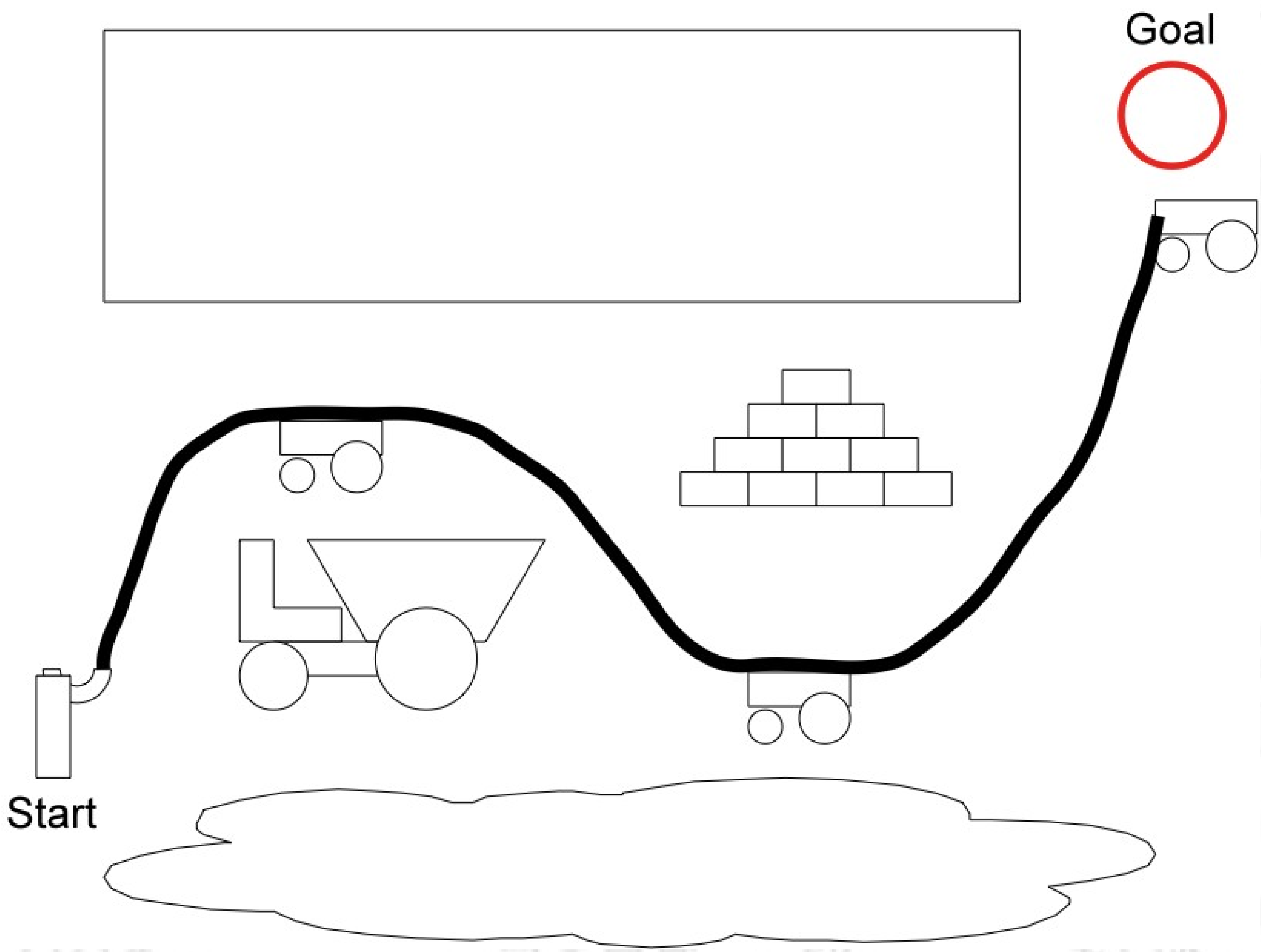
Motivations

- Identify and test the special features of Linked Multi-component Robotic Systems.
  - Realization of a proof-of-concept of a paradigmatic case: a multi-robot hose transportation system.
- Part of a new direction of research efforts.
- Open a wide new field of research.

Multi-robot hose transportation



Basic task

To perform the transportation of the hose in a straight line in an environment without obstacles from an initial arbitrary configuration of hose and robots.

Basic task

- Non-trivial problem:
  - Several robot's control.
  - Keep robot's formation.
  - Keep hose's shape.
  - Robot's physical embodiment limitations.
- Building block for more sophisticated tasks.

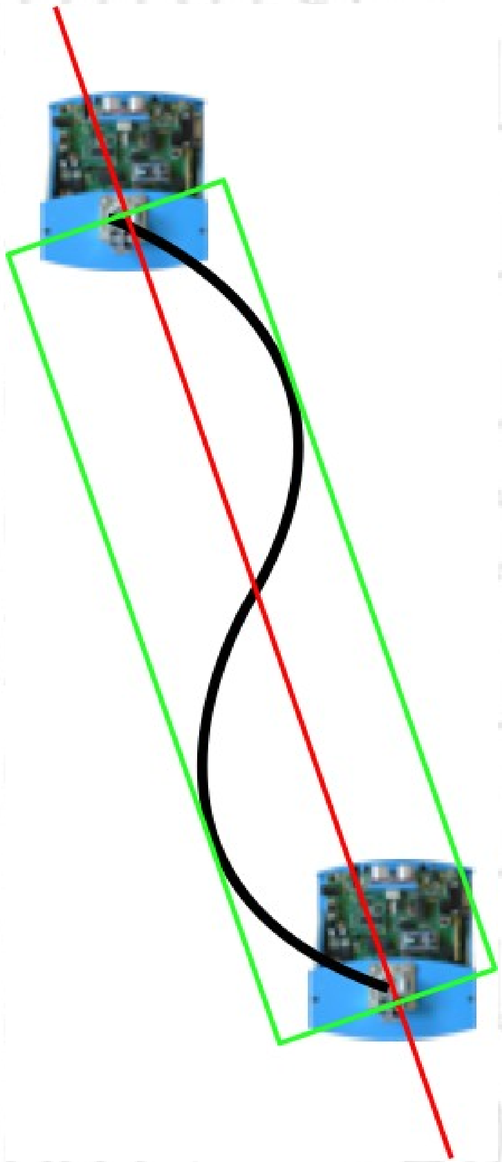
Perception

- Perceive the robot's position and hose state.
- Centralised perception.
- Controlled environment:
  - Bright colored background.
  - Blue colored robots.
  - Dark colored hose.
- Output:
  - Regions containing the robots: $\boldsymbol{R} = \{R_1, \ldots, R_n\}$.
  - Hose's segments: $\boldsymbol{S} = \{S_1, \ldots, S_{n-1}\}$.

Control heuristic

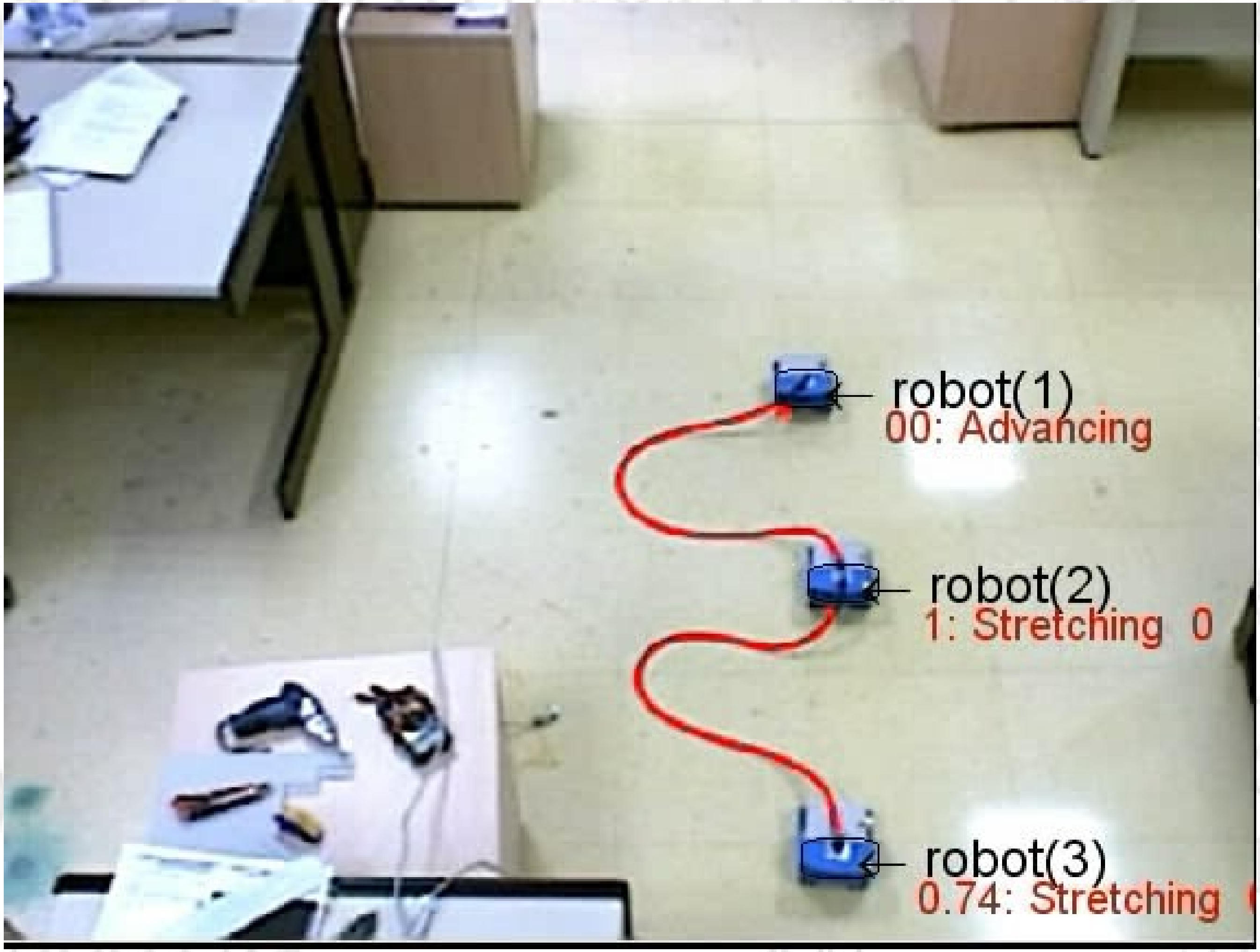
- Centralised control.
  - Each robot's commands computed independently.
- “Follow the leader” strategy.
- Control commands dependent of:
  - Leader's orientation.
  - In front hose segment's state.

Control heuristic



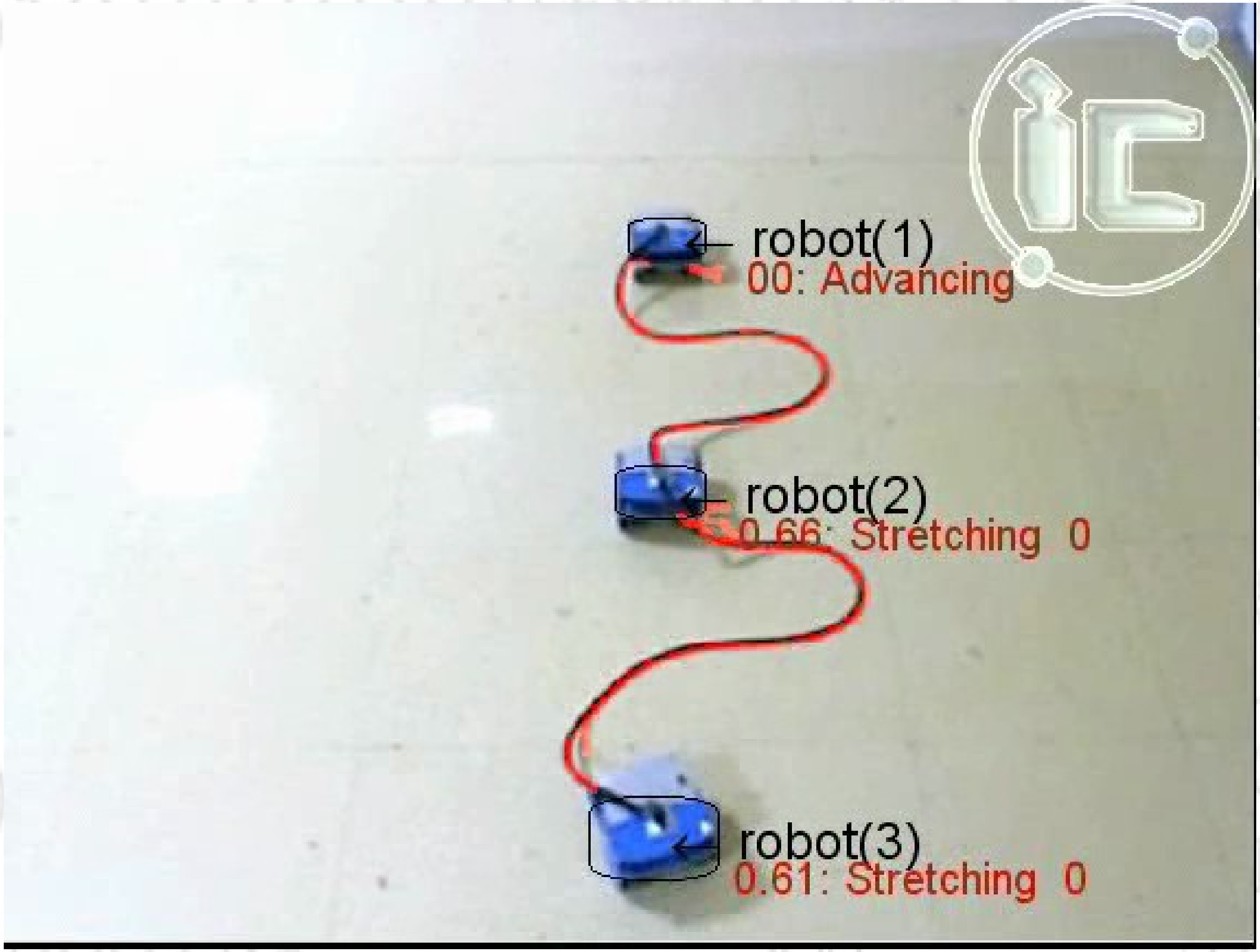
- Hose curvature *c*.
- Three states:
  - *c* too low: Rear robot takes *fast* speed.
  - *c* too high: Rear robot *stops*.
  - *c* between limits: Keep *cruise* speed.

Experiment


robot(1)
00: Advancing
robot(2)
1: Stretching 0
robot(3)
0.74: Stretching

Multi-robot visual control

Experiment



Chapter conclusions

- Successful implementation of the basic task of a Linked MCRS for hose transportation.
- First step to more complex tasks.
- Differences with Distributed MCRS:
  - Hose can be an obstacle for the robots.
  - Hose can drag the robots.
  - Hose imposes restrictions to the robot's movements.
  - Hose is an additional element whose state must be measured.

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Overall conclusions

Computational Intelligence provides innovative tools which can be applied with success to classical problems in vision based mobile robotics.

- Lattice Computing used for landmark storing, recognition and selection.
- Hybrid neuro-evolutionary systems for localization.
- Vision based multi-robot control.

Thank you for your attention.

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