Robots for GW detection and GW detection infrastructure monitoring and operation

Fabio Bonsignorio[1,2,3,4,5,6,7]

RoboCom++ Embodied Intelligence in Natural and Artificial Agents WG Leader[1]
SPARC TG Benchmarking and Competitions[2]
IEEE RAS TC-PEBRAS[3]
Member SPARC Board of Directors[4]
G2Net MC Stakeholders Relations, WG2 Robotics Task Leader, [5]

Heron Robots[6]
And The BioRobotics Institute, SSSA[7]
… ☺

Abstract of the talk

It is possible that multisensory fusion tecjniques applied by means of networks of mobile robotics platforms equipped with seismometers and other sensors may facilitate the understanding and filtering of NN (<30 Hz), acoustic and other noise. We will outline some preliminary ideas.

We will also more broadly discuss possible application of robots, and of the 'robotics mind-set', in the field.

Outline of the talk

- Robotics ‘waves’
- Newtonian Noise (a naïve view)
- Multisensory Fusion in Robotics
- Preliminary Ideas for noise characterization and mitigation in GW detection
- Possible application of robots, and of the 'robotics mind-set’ for GW detection
- Bolder Approaches

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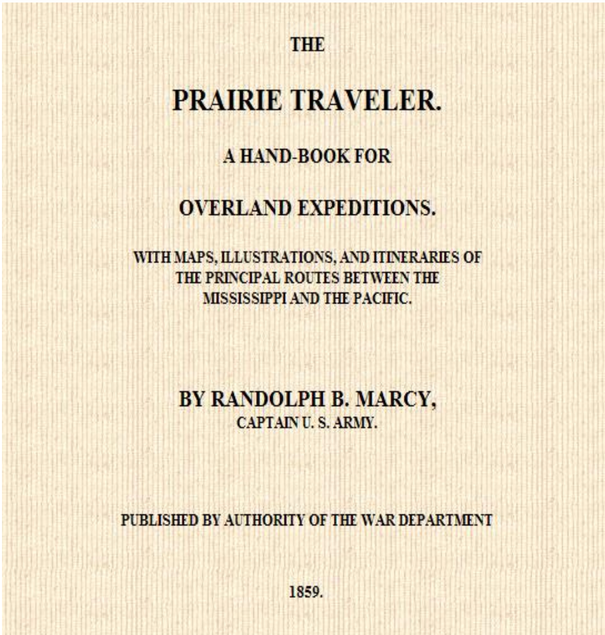
‘Caveat’


THE

PRAIRIE TRAVELER.

A HAND-BOOK FOR

OVERLAND EXPEDITIONS.

WITH MAPS, ILLUSTRATIONS, AND ITINERARIES OF
THE PRINCIPAL ROUTES BETWEEN THE
MISSISSIPPI AND THE PACIFIC.

BY RANDOLPH B. MARCY,
CAPTAIN U. S. ARMY.

PUBLISHED BY AUTHORITY OF THE WAR DEPARTMENT

1859.

ROUTES TO CALIFORNIA AND OREGON

'EMIGRANTS or others desiring to make the overland journey to the Pacific should bear in mind that there are several different routes which may be traveled with wagons, each having its advocates in persons directly or indirectly interested in attracting the tide of emigration and travel over them.

Information concerning these routes coming from strangers living or owning property near them, from agents of steam-boats or railways, or from other persons connected with transportation companies, should be received with great caution, and never without corroborating evidence from disinterested sources'

From 'The Prairie Traveler', R. B. Marcy, Captain, U.S.A, 1859

Older and newer attempts

Juanelo Torriano alias Gianello della Torre, (XVI century) a craftsman from Cremona, built for Emperor Charles V a mechanical young lady who was able to walk and play music by picking the strings of a real lute.

Hiroshi Ishiguro, early XXI century

Director of the Intelligent Robotics Laboratory, part of the Department of Adaptive Machine Systems at Osaka University, Japan

The second wave

Data are very important, but they are not all in a digital economy. ACTIONS, MOBILITY and STRENGTH are also needed! **Robotics**: a great opportunity to **innovate, connect** and **transform. Robotics is technology and business, but it is also creativity and fun!**

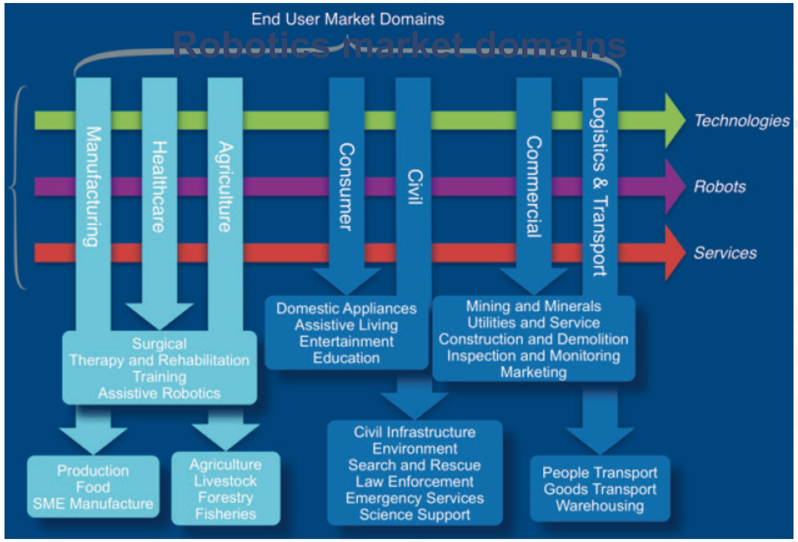
"[...] The size of the robotics market is projected to grow substantially to 2020s. This is a global market and Europe's traditional competitors are fully engaged in exploiting it. Europe has a 32% share of the industrial market. Growth in this market alone is estimated at 8%-9% per annum. Predictions of up to 25% annual growth are made for the service sector where Europe holds a 63% share of the non-military market. […]"

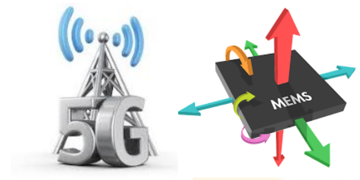
"[…] From today's €22bn worldwide revenues, robotics industries are set to achieve annual sales of between €50bn and €62bn by 2020. […]"

Robotics is one of the 12 disruptive technologies identified by McKinsey

The second wave: Robotics: a great opportunity to innovate, connect and transform

- The web and IoT pull new robotic applications
- Robotics expands the boundaries of the Web and of IoT
- The Web is an ‘infrastructure’ of future robotics





ICT enabling components and technologies, e.g., MEMS, 4G, 5G

- Robotics integrates enabling ICT components
- Robotics will drive the development of new ICT components
- Robotics pulls the development of next generation communication networks

Robots and Jobs

- Creating **new jobs** in robotics
- Creating new industrial opportunities (and **jobs**)
- Taking advantage of robotics and automation to enable GDP growth

The second wave: the success stories

DARPA (American Defense Advanced Research Projects Agency) challenges have demonstrated how current robots are becoming **more accurate**, **fast** and **dexterous in structured and unstructured environments.**

Not everything worked as expected!

The second wave: the current approach shows some limitations

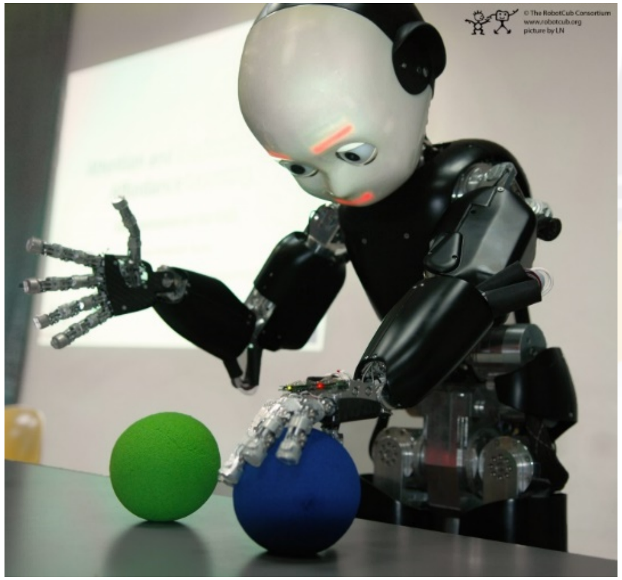
On the other hand the debriefing of DARPA DRC shows clearly that humanoid robots are **still far from the required level of capabilities in fact many metrics**, **such as time-to-completion, are highly application or task specific.**

According to H.Yanco a minimum of 9 people were needed to teleoperate latest DRC's robots!!!

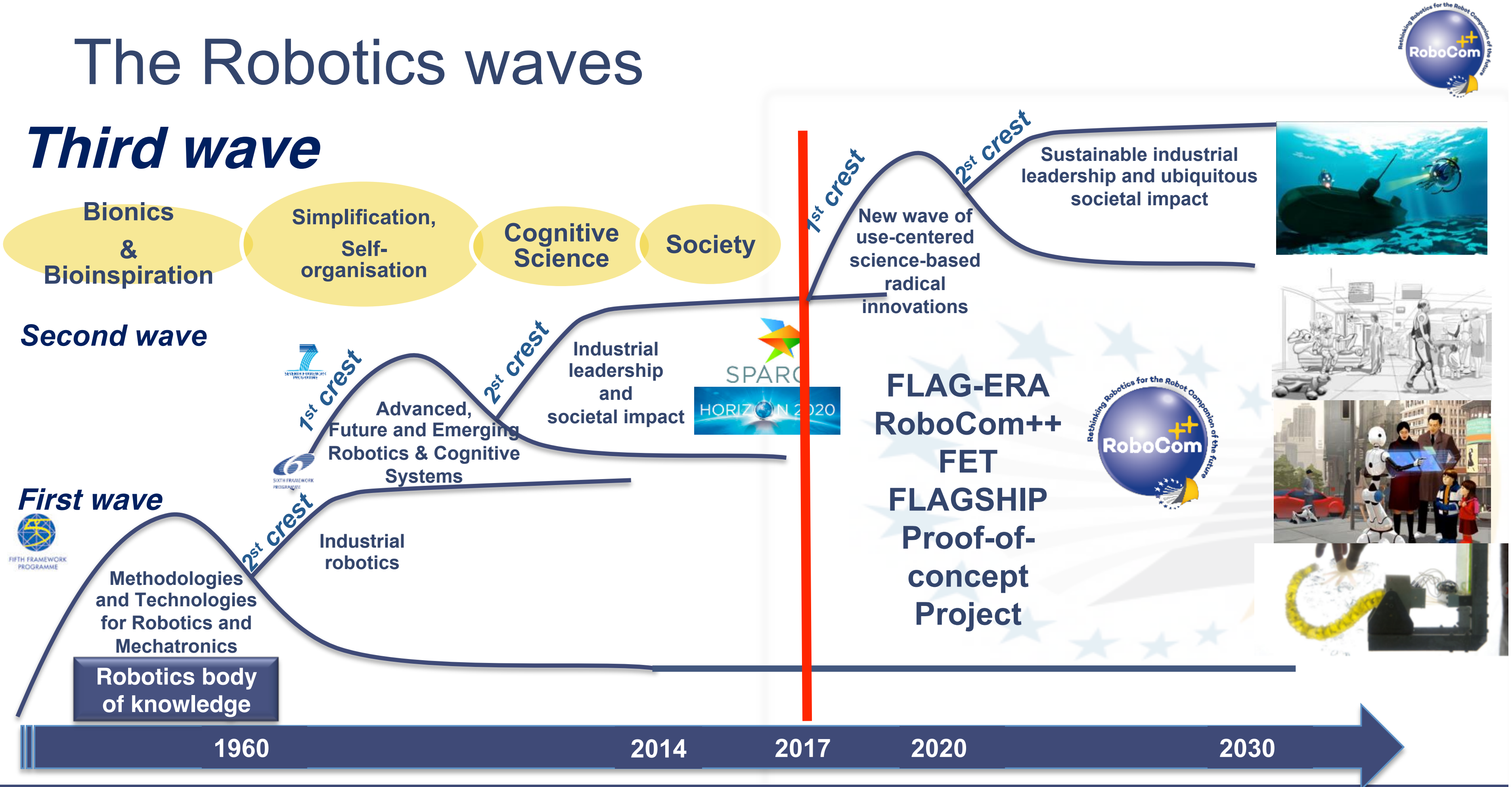
Pursuing new frontiers:
The robotics bottleneck

Today, more functionality means:

- **more** complexity, energy, computation, cost
- less controllability, efficiency, robustness, safety

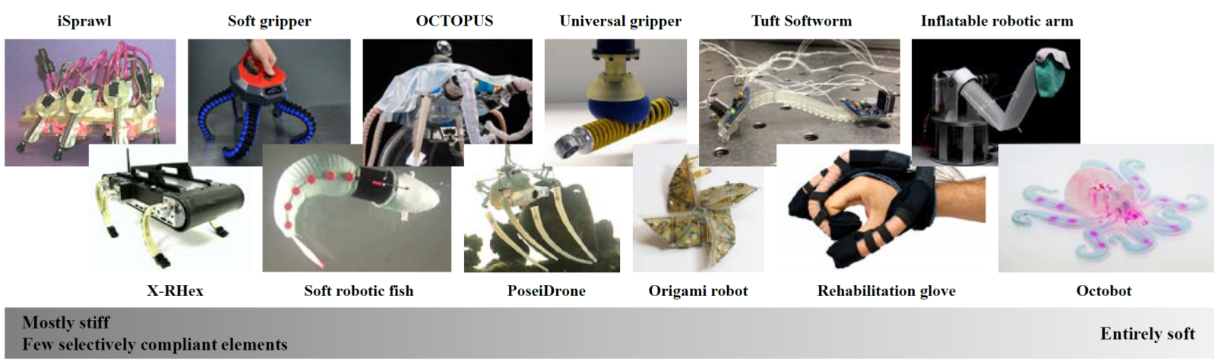


The Robotics waves



SCIENCE ROBOTICS

The marvellous progress of Robotics and AI…'Look Ma, No Hands' syndrome?



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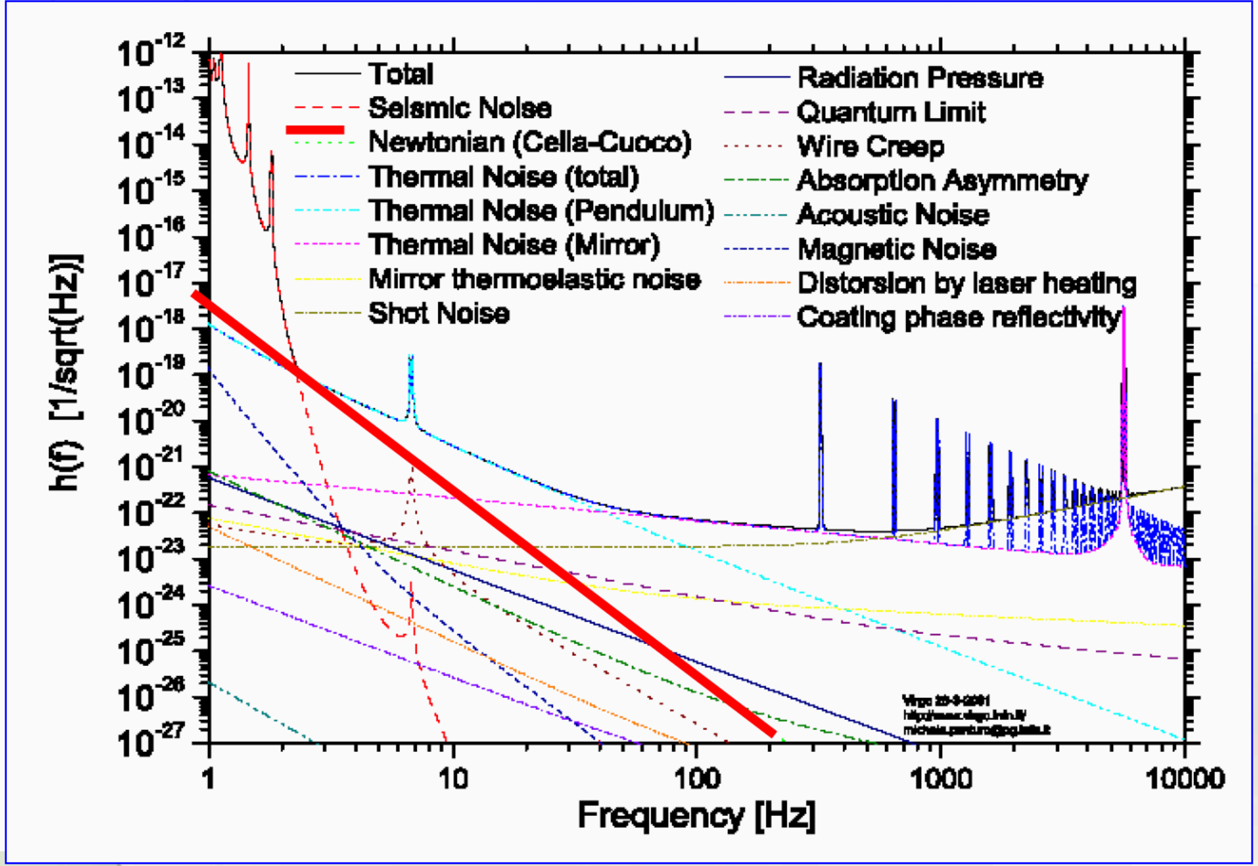
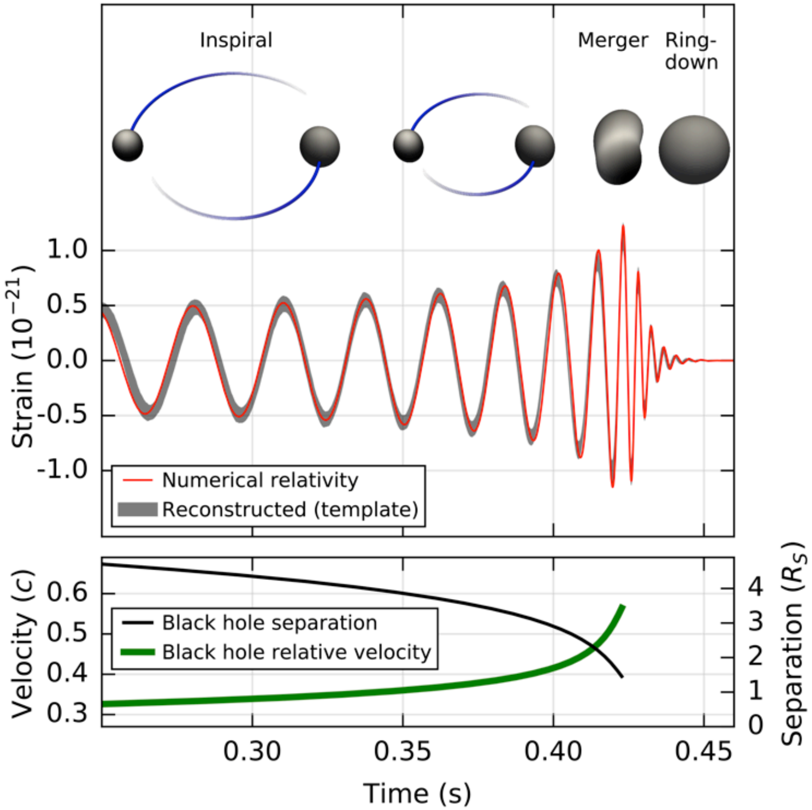
- Off the Record Considerations (possibly weird)

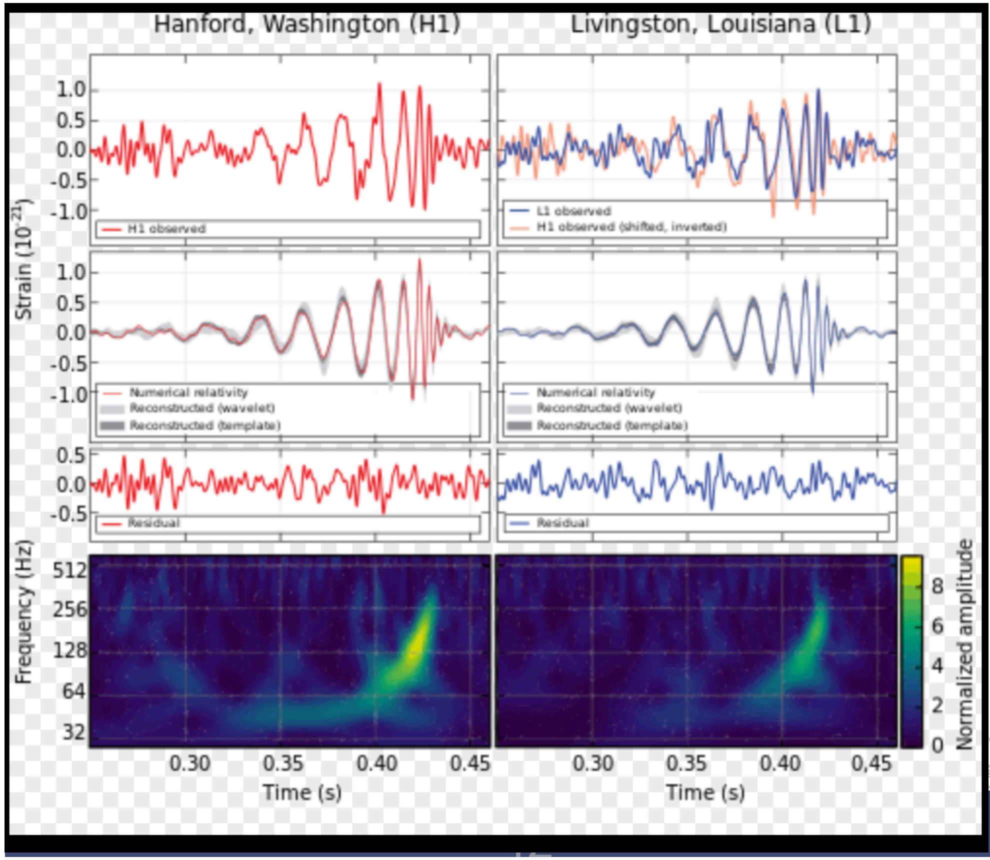
Seismic NN: elastic models



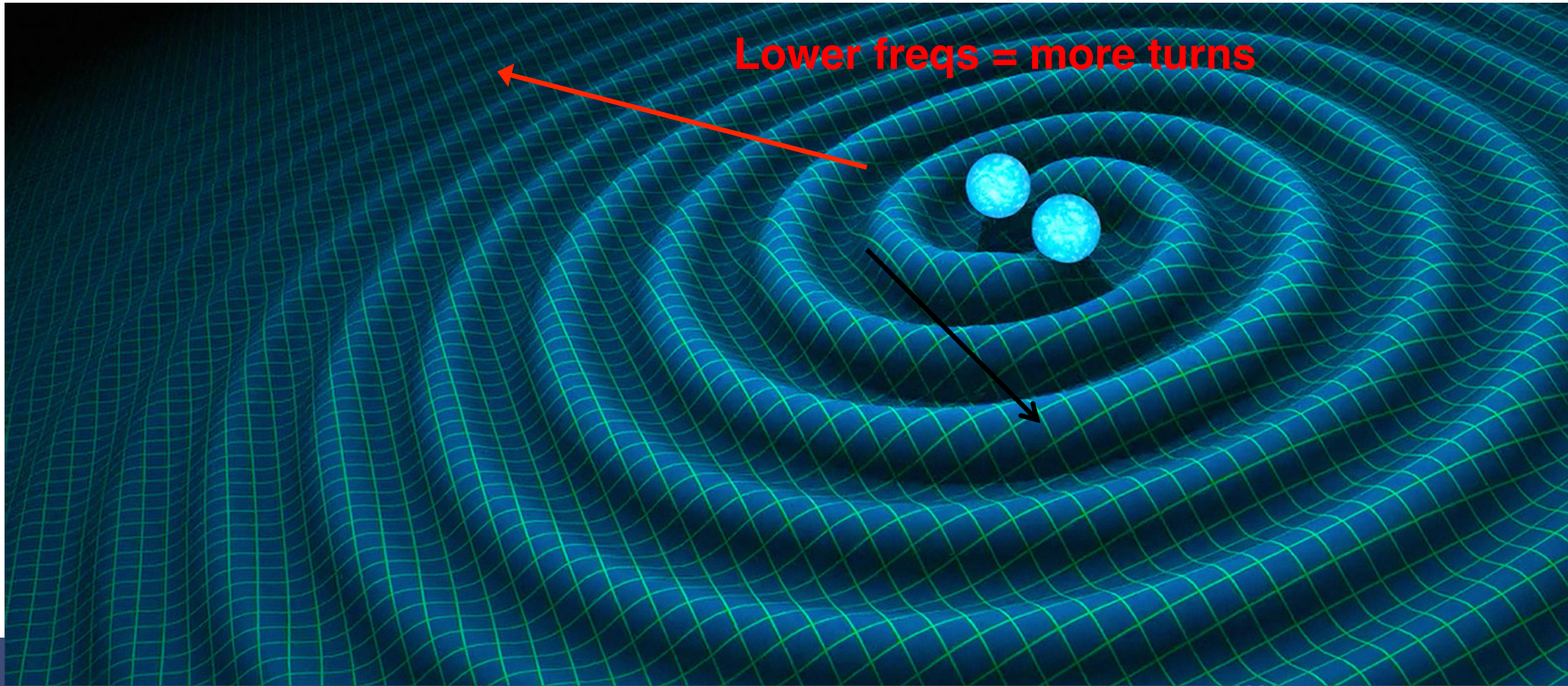
Giancarlo Cella
INFN sez. Pisa
3rd ILIAS Annual meeting
Gran Sasso INFN National Lab
February 28-March 3, 2006

Newtonian Noise (a naïve view)





Newtonian Noise (a naïve view)



Netwonian Noise

A naïve view

Main Issue: Rayleigh waves (and lacking knowledge of underground mass distribution)

Problem: model underground and surface mass distribution and land motion
(same issue with the atmosphere) to characterize and predict Rayleigh waves

Other sources of noise:

‘Environmental’

i.e.

- Acoustic
- EM
- Others...

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Multisensory Data Fusion in Robotics

Multisensor data fusion is the process of combining observations from a number of different sensors to provide a robust and complete description of an *environment* or process of interest.

Data fusion finds wide application in many areas of robotics such as object recognition, *environment mapping*, and localisation.

From: H. Durrant-Whyte, T. C. Henderson,
Multisensor Data Fusion,
Part C, Chapter 25, in B.Siciliano, O. Khatib (eds.) Springer Handbook of Robotics, 2008

Multisensory Data Fusion in Robotics

Principles

It's essentially an application of Bayes' rule:

$$P(\boldsymbol{x} \mid z) = \frac{P(z \mid \boldsymbol{x}) P(\boldsymbol{x})}{P(z)}.$$

assuming conditional independence:

$$P(z_1, \cdots, z_n \mid \boldsymbol{x}) = P(z_1 \mid \boldsymbol{x}) \cdots P(z_n \mid \boldsymbol{x}) = \prod_{i=1}^{n} P(z_i \mid \boldsymbol{x}) .$$

We get the multisensory expression:

$$\boxed{P(\boldsymbol{x} \mid \boldsymbol{Z}^n) = C P(\boldsymbol{x}) \prod_{i=1}^{n} P(z_i \mid \boldsymbol{x}) ,}$$

and its recursive form:

$$P(\boldsymbol{x} \mid \boldsymbol{Z}^k) = \frac{P(z_k \mid \boldsymbol{x}) P(\boldsymbol{x} \mid \boldsymbol{Z}^{k-1})}{P\left(z_k \mid \boldsymbol{Z}^{k-1}\right)} .$$

Multisensory Data Fusion in Robotics

Methods

- Bayes' Rule
- *Probabilistic Grids*
- The Kalman Filter (plus Extended Kalman Filters, Information Filters, etc.)
- Sequential Monte Carlo Methods
- Alternatives to Probability

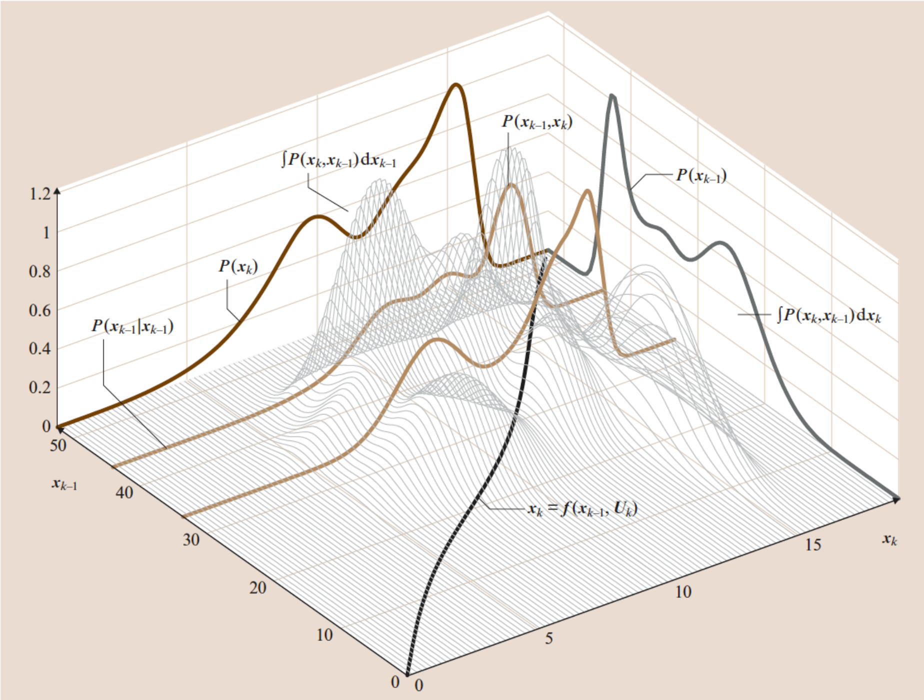


Fig. 25.1 Time update step for the full Bayes filter. At a time $k-1$, knowledge of the state $\boldsymbol{x}_{k-1}$ is summarised in a probability distribution $P(\boldsymbol{x}_{k-1})$. A vehicle model, in the form of a conditional probability density $P(\boldsymbol{x}_k \mid \boldsymbol{x}_{k-1})$, then describes the stochastic transition of the vehicle from a state $\boldsymbol{x}_{k-1}$ at a time $k-1$ to a state $\boldsymbol{x}_k$ at a time k. Functionally, this state transition may be related to an underlying kinematic state model in the form $\boldsymbol{x}_k = \boldsymbol{f}(\boldsymbol{x}_{k-1}, \boldsymbol{u}_k)$. The figure shows two typical conditional probability distributions $P(\boldsymbol{x}_k \mid \boldsymbol{x}_{k-1})$ on the state $\boldsymbol{x}_k$ given fixed values of $\boldsymbol{x}_{k-1}$. The product of this conditional distribution with the marginal distribution $P(\boldsymbol{x}_{k-1})$, describing the prior likelihood of values of $\boldsymbol{x}_k$, gives the the joint distribution $P(\boldsymbol{x}_k, \boldsymbol{x}_{k-1})$ shown as the surface in the figure. The total marginal density $P(\boldsymbol{x}_k)$ describes knowledge of $\boldsymbol{x}_k$ after state transition has occurred. The marginal density $P(\boldsymbol{x}_k)$ is obtained by integrating (projecting) the joint distribution $P(\boldsymbol{x}_k, \boldsymbol{x}_{k-1})$ over all $\boldsymbol{x}_{k-1}$. Equivalently, using the total probability theorem, the marginal density can be obtained by integrating (summing) all conditional densities $P(\boldsymbol{x}_k \mid \boldsymbol{x}_{k-1})$ weighted by the prior probability $P(\boldsymbol{x}_{k-1})$ of each $\boldsymbol{x}_{k-1}$. The process can equally be run in reverse (a retroverse motion model) to obtain $P(\boldsymbol{x}_{k-1})$ from $P(\boldsymbol{x}_k)$ given a model $P(\boldsymbol{x}_{k-1} \mid \boldsymbol{x}_k)$

H. Durrant-Whyte, T. C. Henderson, Multisensor Data Fusion, Part C, Chapter 25, in B.Siciliano, O. Khatib (eds.) Springer Handbook of Robotics, 2008

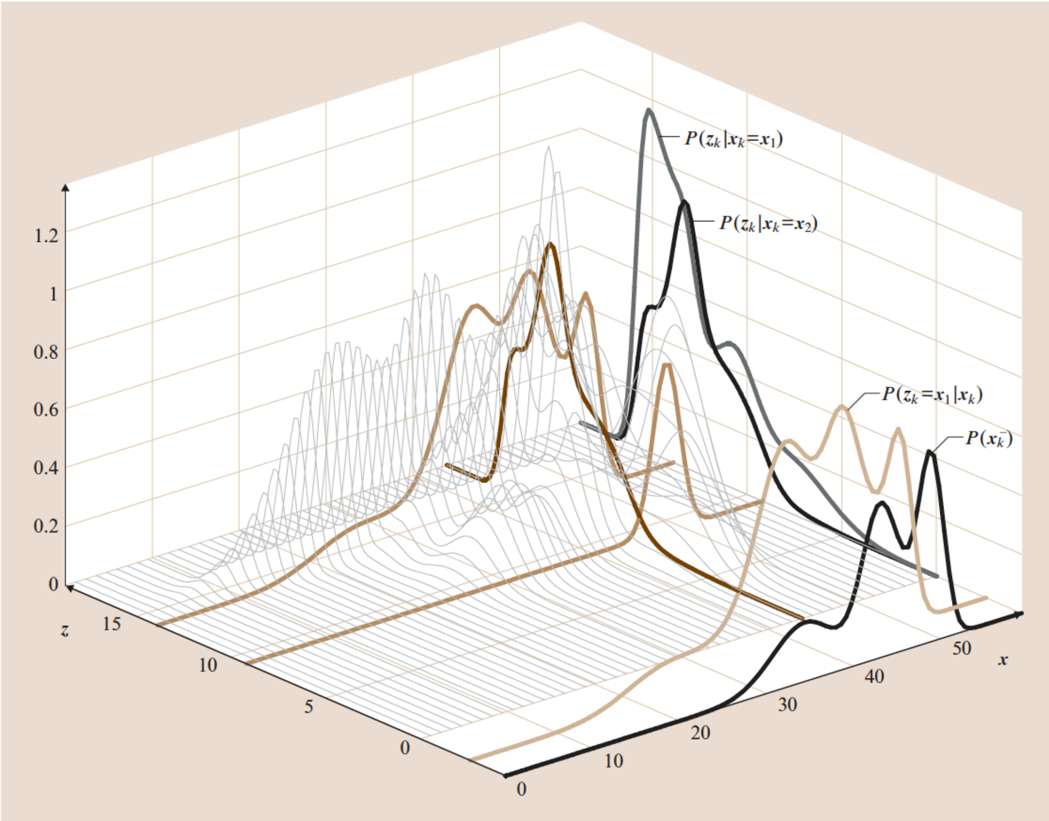


Fig. 25.2 Observation update for the full Bayes filter. Prior to observation, an observation model in the form of the conditional density $P(z_k \mid \boldsymbol{x}_k)$ is established. For a fixed value of $\boldsymbol{x}_k$, equal to $\boldsymbol{x}_1$ or $\boldsymbol{x}_2$ for example, a density function $P(z_k \mid \boldsymbol{x}_k = \boldsymbol{x}_1)$ or $P(z_k \mid \boldsymbol{x}_k = \boldsymbol{x}_2)$ is defined describing the likelihood of making the observation z_k. Together the density $P(z_k \mid \boldsymbol{x}_k)$ is then a function of both z_k and $\boldsymbol{x}_k$. This conditional density then defines the observation model. Now, in operation, a specific observation $z_k = \boldsymbol{x}_1$ is made and the resulting distribution $P(z_k = \boldsymbol{x}_1 \mid \boldsymbol{x}_k)$ defines a density function (now termed the likelihood function) on $\boldsymbol{x}_k$. This density is then multiplied by the prior density $P(\boldsymbol{x}_k^-)$ and normalised to obtain the posterior distribution $P(\boldsymbol{x}_k \mid z_k)$ describing knowledge in the state after observation

H. Durrant-Whyte, T. C. Henderson, Multisensor Data Fusion, Part C, Chapter 25, in B.Siciliano, O. Khatib (eds.) Springer Handbook of Robotics, 2008

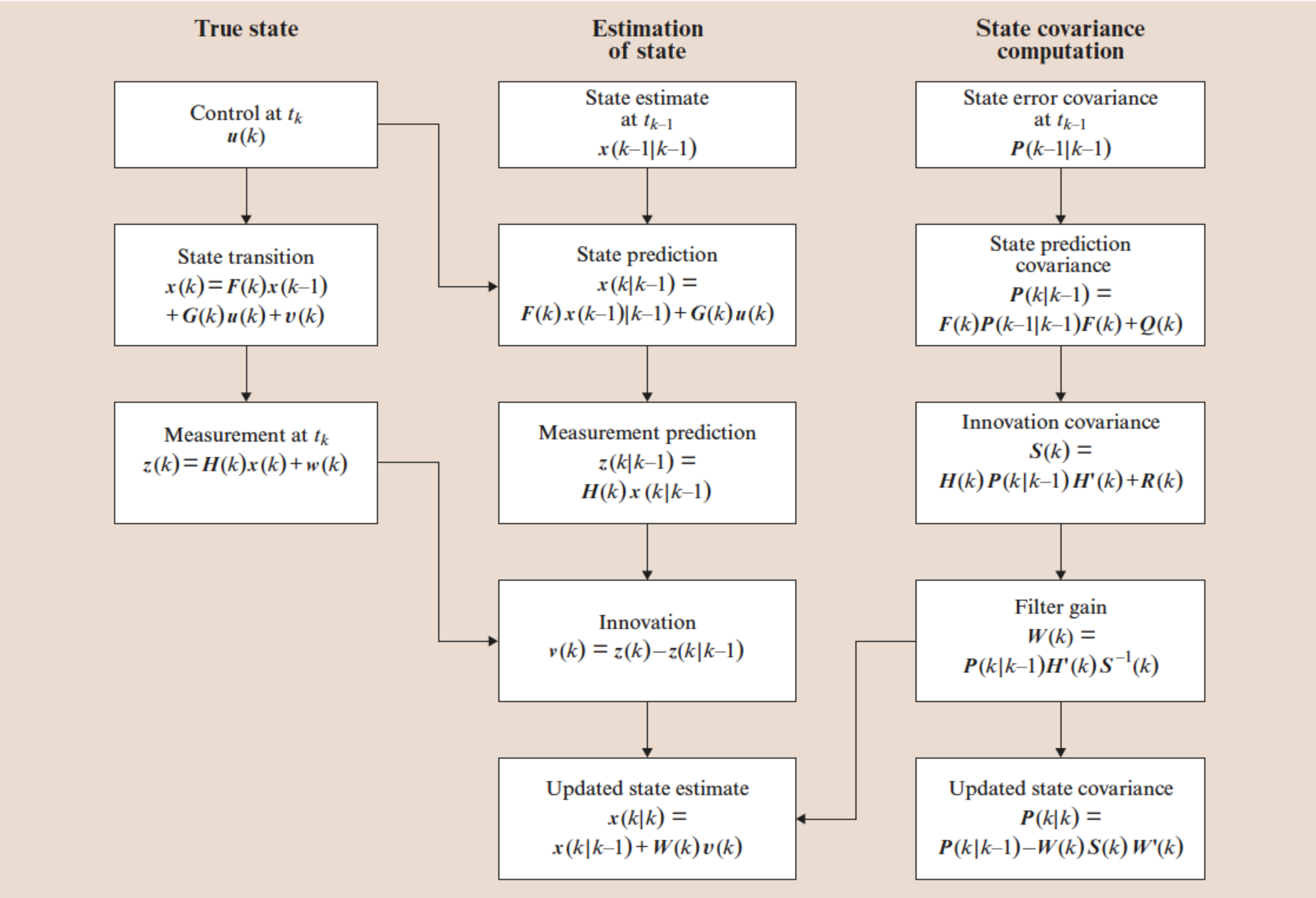


Fig. 25.3 Block diagram of the Kalman filter cycle (after *Bar-Shalom* and *Fortmann* 1988 [25.7])

H. Durrant-Whyte, T. C. Henderson, Multisensor Data Fusion, Part C, Chapter 25, in B.Siciliano, O. Khatib (eds.) Springer Handboo of Robotics, 2008

Multisensory Data Fusion in Robotics

Methods

Current directions of interest include:

- large-scale, ubiquitous sensor systems,
- bio-based or biomimetic systems,
- medical in situ applications
- wireless sensor networks.

Multisensory Data Fusion in Robotics

Applications

- dynamic system control: the problem is to use appropriate models and sensors to control the state of a dynamic system (e.g., industrial robot, mobile robot, autonomous vehicle, surgical robot, etc.).

- environment modeling: the problem is to use appropriate sensors to construct a model of some aspect of the physical environment. Typical sensors include cameras, radar, 3-D range finders, IR, tactile sensors and touch probes (CMMs), etc. The result is usually expressed as geometry (points, lines, surfaces), features (holes, sinks, corners, etc.), or physical properties. Part of the problem includes the determination of optimal sensor placement.

Multisensory Data Fusion in Robotics

Example: ANSER II: Decentralised Data Fusion

Decentralised data fusion (DDF) methods were initially motivated by the insight that the information or canonical form of the conventional Kalman filter data fusion algorithm could be implemented by simply adding information contributions from observations. As these (vector and matrix) additions are commutative, the update or data fusion process can be optimally distributed amongst a network of sensors-

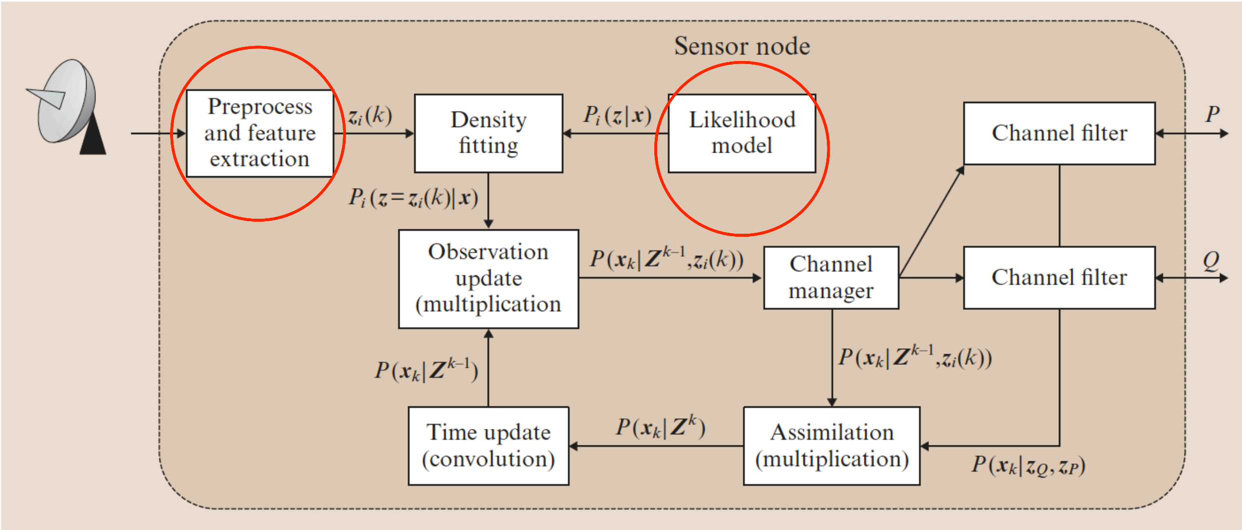
The sensor is modelled directly in the form of a likelihood function. Once instantiated with an observation, the likelihood function is input to a local fusion loop which implements a local form of the Bayesian time and observation update. Network nodes accumulate probabilistic information from observation or communication and exchange mutual information (information gain) with other nodes in the network. This mutual information is transmitted to and assimilated by other nodes in the network in an ad-hoc manner. The result is that all nodes in the network obtain a single integrated posterior probability based all node observations.

The ANSER II system consists of a pair of autonomous air vehicles equipped with infra-red and visual sensors, a pair of unmanned ground vehicles equipped with visual and radar sensors, and additional information provided by geometric and hyper-spectral data bases, along with information input by human operatives. The likelihood functions for singlesensor features are obtained **through a semi-supervised machine learning method.** The resulting probabilities are modeled in the form of a mixture of Gaussians. Each platform then maintains a bank of decentralised, non-Gaussian Bayesian filters for the observed features, and transmits this information to all other platforms. The net result is that each platform maintains a complete map of all features observed by all nodes in the network. Multiple observations of the same feature, possibly by different platforms, results in an increasingly accurate estimate of the feature location for all nodes.

The ANSER II system demonstrates a number of general principles in Bayesian data fusion methods.

Specifically the need to appropriately model sensors through the likelihood function, and the possibility of building very different data fusion architectures from the essential Bayesian form.

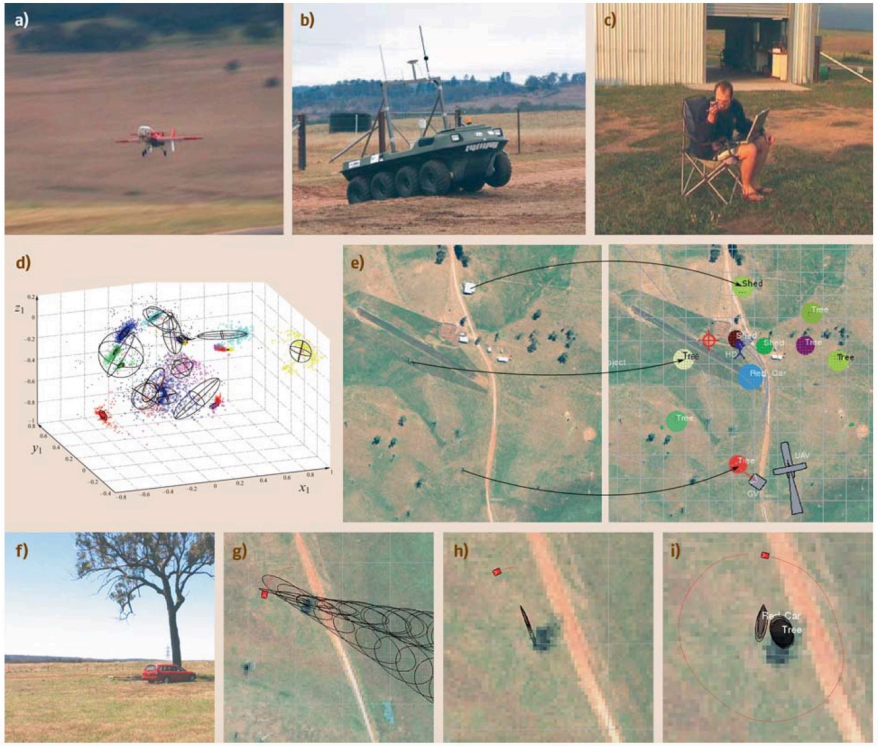
Multisensory Data Fusion in Robotics
Example: ANSER II: Decentralised Data Fusion



Mathematical structure of a decentralised data fusion node

H. Durrant-Whyte, T. C. Henderson, Multisensor Data Fusion, Part C, Chapter 25, in B.Siciliano, O. Khatib (eds.) Springer Handboo of Robotics, 2008

Multisensory Data Fusion in Robotics
Example: ANSER II: Decentralised Data Fusion



A synopsis of the ANSER II autonomous network and its operation.
(a–c) Main system components;
(a) air vehicle,
(b) ground vehicle,
(c) human operative.

(d–e) The perception process;
(d) top three dimensions of features discovered from
ground-based visual sensor data along with the derived mixture model describing these feature properties
(e) sector of the overall
picture obtained from fusing air vehicle (UAV), ground vehicle (GV) and human operator (HO) information. Each set of ellipses
corresponds to a particular feature and the labels represent the identity state with highest probability.

(f–i) Sequential fusion
process for two close landmarks: (f) a tree and a red car, (g) bearing-only visual observations of these landmarks are successively
fused, (h) to determine location and identity (i).

Note the Gaussian mixture model for the bearing measurement likelihood

H. Durrant-Whyte, T. C. Henderson,
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- Bolder approaches

NN mitigation

Preliminary ideas

- (adaptive) Modeling of the area (emi) sphere of $r \approx 5$ km by a network of robots equipped at least with onboard seismometers which change adaptively their positions

- Dynamic optimization of sensor positions (for example doubling those already installed?)

Robotics
Preliminary ideas

A solution that **doesn’t require the development of new basic science** will be the application of methods directly imported from multi robot systems to the design of new concept adaptive seismic sensor networks, where the deployment and adaptive real-time reconfiguration of a mesh of robotized seismic sensor might in principle allow a much more fine-grained and time-evolving models of the underground layers of the earth crusts, opening new potentially very useful opportunities for research.

For example, methods of deployment and re-deployment based on the maximization of the information gain [1, 2, 3, 4]

[1] A. Howard, M. J. Mataric, G. S. Sukhatme, Mobile sensor network deployment using potential fields: A distributed, scalable solution to the area coverage problem, Distributed autonomous robotic systems 5. 299-308, (2002)

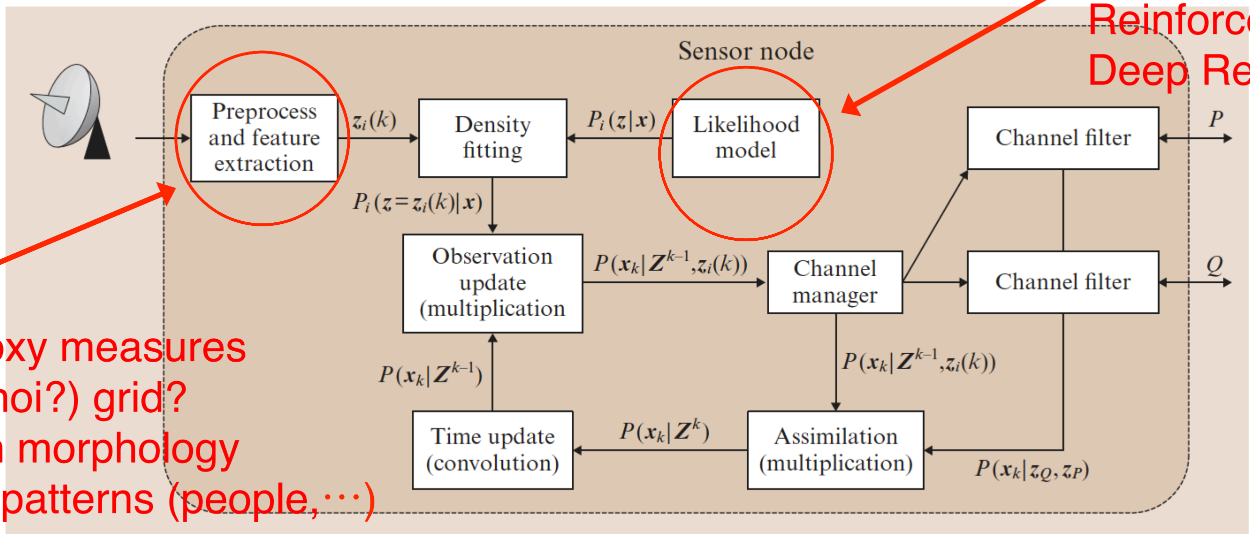
[2] B. Shucker, J. K. Bennett, Scalable control of distributed robotic macrosensors, Distributed Autonomous Robotic Systems 6, 379-388, (2007)

[3] N. Xiong, P. Svensson, Multi-sensor management for information fusion: issues and approaches, Information fusion 3.2,163-186, (2002)

[4] A. Sanfeliu, J. Andrade-Cetto, Ubiquitous networking robotics in urban settings, Proceedings of the IEEE/RSJ IROS Workshop on Network Robot Systems, (2006)

Decentralised Data Fusion like AnserII but with two main changes

Semi-supervised,
Reinforcement Learning?
Deep Reinforcement Learning



Density proxy measures
on a (Voronoi?) grid?
Also terrain morphology
and usage patterns (people,⋯)

Mathematical structure of a decentralised data fusion node

Multisensory Data Fusion in Robotics
Example: ANSER II: Decentralised Data Fusion

Quantum by INNOSEIS (a spin-out from the National Institute for Subatomic Physics in the Netherlands) is an ultra-light weight (< 1kg) wireless seismic sensor network that dramatically reduces deployment costs, while scaling up to 1 million nodes for onshore exploration. It has be designed for static Wireless, sensor networks. However, a daisy-chain small network is operating in Cascina already and no major issues prevent to mount them on mobile platforms.

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Robotics

Preliminary ideas

- Monitoring/Predictive maintenance
- Adaptation*
- Surveillance (if it is an issue)

* For example adaptive tuning/calibration of the test mass vibration insulation systems, and in general of any subsystem requiring tuning/calibration

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Bolder approaches...

Towards cheap lightweight bio-inspired autonomous vehicle, manipulation and grasping through ML/D(R)L

ML and D(R)L to the rescue?

The traditional 'mechatronic' approach to Robotics, as described in the major textbooks on the matter:

- some (typically linearized) deterministic control strategy
- multi rigid body (typically heavy) kinematical structure.
- sensor measures filtered by control observers.

This basic structure is underpinning the great majority of 'blind' robots successfully utilized by many decades in automotive factories.

ML and D(R)L to the rescue?

‘First Wave’ robots:

- follow preprogrammed trajectories with very high accuracy and precision
- have very limited – in most cases no – sensory capabilities

They are used for welding, painting and similar tasks in the final assembly of ‘big item’ manufactured products like cars, trucks, washing machines etc.

In the latest couple of decades perception (vision, haptics, torque/force sensing) and Path Planning and Object Recognition based on various AI methods have been investigated and applied in many research prototypes.

ML and D(R)L to the rescue?

‘Second Wave’ robots:

In the latest couple of decades we had steep progress in:

- Perception (vision, haptics, torque/force sensing) and Object Recognition,
- Planning, SLAM and various AI methods

Still not good enough for ‘really open-ended’ environments…

However,

Together with IoT low cost sensing and actuation they are enabling the Industry 4.0 revolution and the deployment self-driving cars

ML and D(R)L to the rescue?

- However, although already obtained results seem suitable for application in structured or semi-structured environments such as manufacturing facilities or hospitals, they lack robustness and adaptivity for their application in open-ended environments and in general the long awaited and promised applications of service robotics (elder care, home assistance etc.).

ML and D(R)L to the rescue?

- A characteristic issue with the ‘traditional’ robot arms is that to make possible linear modeling at high speeds of structures with a non-linear dynamics you need heavy weights and as a consequence bad ‘payload ratios’ (the payload ratio is the ratio between the weight that a robot can move and the weight of the robot itself, for example a ratio 10 kg vs 200-300 kgs of ‘robot body’ weight is not uncommon). Another issue is that a rigid structure radically limits, for example, the grasping and manipulation capabilities of the robot.

ML and D(R)L to the rescue?

Reducing weights and increasing compliance lead to:

- a dramatic increase in non-linearities
- more uncertainties in the dynamics and the measures
- scene and object recognition and related point clouds dimensionality dramatic growth

Most widely used methods are less reliable (or useless).

ML and D(R)L to the rescue?

- Machine Learning methods have been increasingly applied in Robotics for example Belief Space Planning
- Deep Learning methods have been recently applied to Robotics
- Solutions have been proposed, for example, leveraging on the group regularities in the movement and local displacements of mechanical structures
- A very radical approach is pursued by Sporns/Lungarella, Bonsignorio and others on the basis of Theoretical Information Science methods

ML and D(R)L to the rescue?

- Machine Learning methods and DL methods show great promise for robotic research and application in particular for the application to the control of future soft bodied distributed sensing and actuation robots, were more established methods show their inherent limitations.
- Data science methods have so far not been applied in this are and may help both modeling and control.

The problems of learning in physical natural and artificial intelligent systems will be core issues, in particular for (partially) soft robots in the new FET-Flagship Proof-of-concept RoboCom++ project, [9], on ‘next generation robotics’.

ML and D(R)L to the rescue?

- All those issues are difficult to cope with ‘traditional methods’ while seem well suited for ‘fast’, asynchronous, reinforcement learning schemes.

- ML and DRL methods that have been already successfully applied in Robotics may actually be adapted and applied to GW detectors expanding their detection capability.

ML and D(R)L to the rescue?

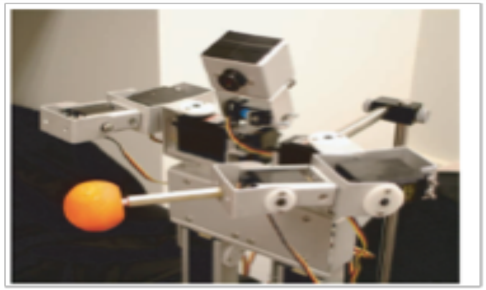
Methods from GW and Data Science and the ML community may help experimental methods and benchmarking in robotics.

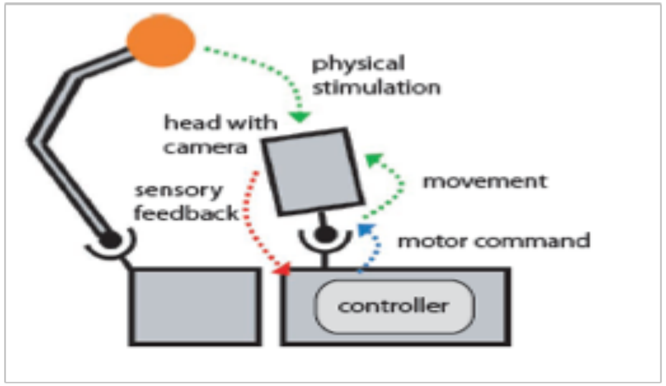
- Reproducibility of results and performance evaluation (benchmarking) are widely recognized issues in robotics
- one of the most serious reprducibility bottleneck is given by the huge amount of data generated by even trivial robotic experiments.

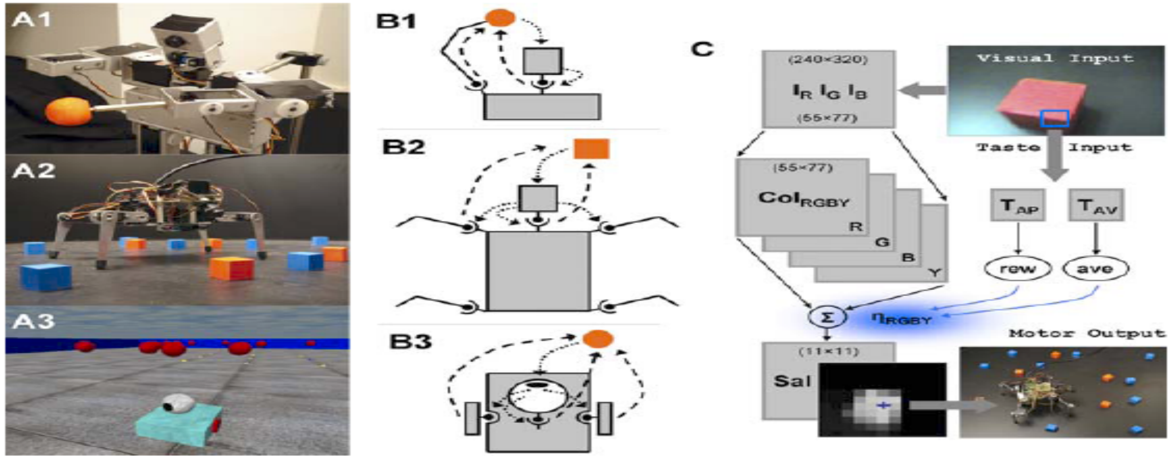
Looking for new paths forward...
For example: Information self-structuring

Experiments:

Lungarella and Sporns, 2006
Mapping information flow
in sensorimotor networks
PLoS Computational Biology







Lungarella, Sporns (2006)

Figure 1. Robots, Sensorimotor Interactions, and Neural Control Architecture
(A1) *Roboto* has a total of 14 DOF, five of which are used in the current set of experiments. Note the head-mounted CCD camera, the pan-tilt head system (2 DOF), and the moveable left arm with shoulder, elbow, and wrist joints (3 DOF). The object is a red ball (1.25 inches diameter) attached to the tip of the last joint.
(A2) *Strider* has a total of 14 DOF, with four legs of 3 DOF each and 2 DOF in the pan-tilt head system. Objects are red and blue blocks (1 inch cubes). *Strider* is situated in an environmental enclosure with black walls.
(A3) *Madame* has 4 DOF, with 2 DOF in the pan-tilt system and 2 DOF for the wheels, which are both located on an axis vertical to the main body axis. The environment is a square arena bounded by blue walls containing 20 red-colored floating spheres.
(B1) *Roboto* engages in sensorimotor interactions via the head system and arm movements; sensory → motor (dotted arrows), motor → sensory (dashed arrows).
(B2) *Strider* engages in sensorimotor interactions via the head system, as well as via steering signals generated by the head and transmitted to the four legs.
(B3) *Madame*'s behavior consists of a series of approaches to colored objects and ovations. Fixations to the objects are maintained by independent action of head and body.
(C) Neural control architecture. The architecture common to all robots is composed of color image arrays I_R, I_G, I_B, color- intensity map $\boldsymbol{Col}_{RGBY}$, and saliency map *Sal* (see text for details). The peak of the saliency map (blue cross) determines the pan-tilt camera motion and body steering. In addition, *Strider*'s neural system contains a value system with taste sensory inputs relayed via a virtual taste sensor (blue square in visual image) to taste neurons ($T_{AP,AV}$), which in turn generates reward and aversiveness signals (rew, ave). These signals are used to modulate the strengths of the saliency factors η_{RGBY} (see text for details).
DOI: 10.1371/journal.pcbi.0020144.g001

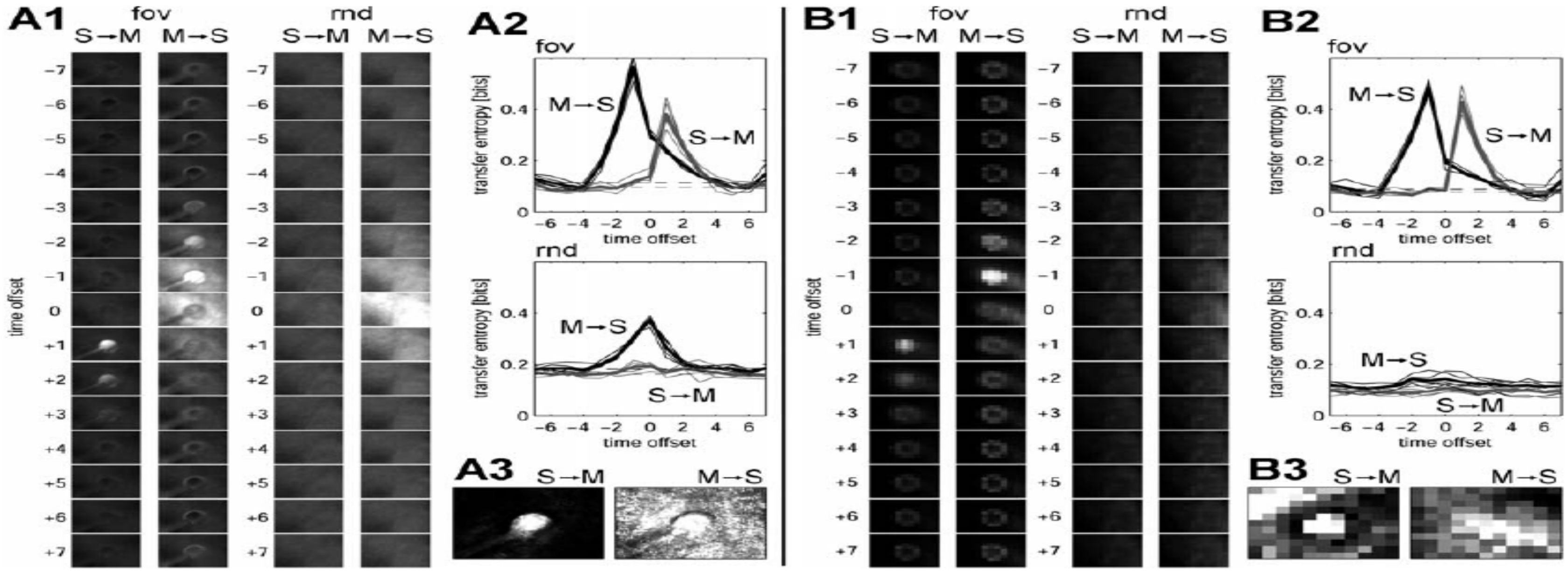


Figure 3. Information Flow (Transfer Entropy) between Sensory Input, Neural Representation of Saliency, and Motor Variables in *Roboto*

(A1) Transfer entropy between array I_R (variable S) and pan-tilt amplitude (variable M). Series of plots show maps of transfer entropy from S to M (S $\rightarrow$ M) and from M to S (M $\rightarrow$ S) over visual space (55 $\times$ 77 pixels), calculated for offsets between -7 ("M leading S") and $+7$ ("S leading M") time steps. Plots show data for conditions "fov" and "rnd." The gray scale ranges from 0.0 to 0.5 bits (for all plots in panels A1 and B1).

(A2) Curves show transfer entropy for five individual runs (thin lines) as well as the average over five runs (thick lines) between the single central pixel of array I_R (S) and pan-tilt amplitude (M), for directions M $\rightarrow$ S (black) and S $\rightarrow$ M (gray).

(A3) z-Score maps of significant image regions (plotted between $z = 0$ and $z = 6$). The z-scores are expressed as number of standard deviations above background at time offset $+1$ (S $\rightarrow$ M) and -1 (M $\rightarrow$ S). Mean and standard deviation of background is calculated from transfer entropy values at maximal time delays (-7,$+7$ time steps).

(B) All three panels have the same format as (A), but the neural activations of the saliency map *Sal* are substituted as variable S (11 $\times$ 11 neural units).

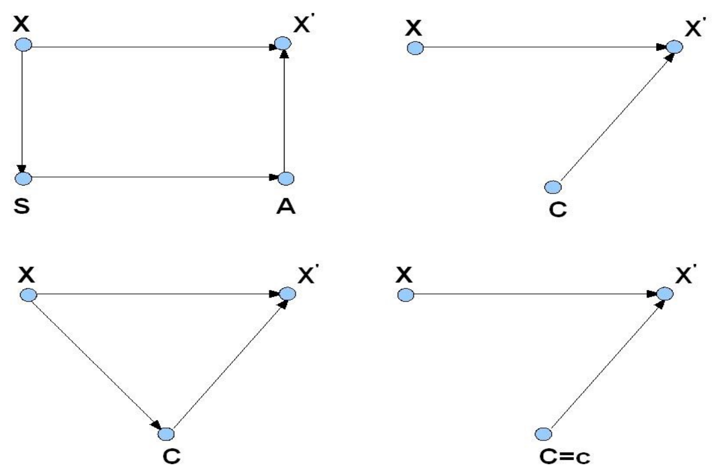
DOI: 10.1371/journal.pcbi.0020144.g003

Probabilistic Model Of Control

- Although it may seem strange only in recent times the classical results from Shannon theory, have been applied to the modeling of control systems.
- As the complexity of control tasks namely in robotics applications lead to an increase in the complexity of control programs, it becomes interesting to verify if, from a theoretical standpoint, there are limits to the information that a control program must manage in order to be able to control a given system.

Probabilistic Model Of Control

Touchette, Lloyd (2004)



Directed acyclic graphs representing a control process. (Upper left) Full control system with a sensor and an actuator. (Lower left) Shrinked Closed Loop diagram merging sensor and actuator, (Upper right) Reduced open loop diagram. (Lower right) Single actuation channel enacted by the controller's state C=c.

Models of ‘Morphological Computation’

In [59], the network of agents, where each word is initially represented by a subset of three or more nodes with all (possible) links present, evolves towards an equilibrium state represented by fully connected graph, with only single links.

The statistical distribution, necessary to determine the information managing capability of the network of physical agents and to link to equation (2) can be obtained from equations derived in the statistical physics of network domain.

From (2) it is possible to derive the relations recalled here below (these relations are demonstrated in the appendix).

$$K(X)\overset{+}{\leq}\log\frac{W_{closed}}{W_{open}^{\max}} \qquad \text{(I)}$$

As told, relation (I) links the complexity ('the length') of the control program of a physical intelligent agent to the state available in closed loop and the non controlled condition. This shows the benefits of designing system structures whose 'basin of attractions' are close to the desired behaviors in the phase space.

$$\Delta HN+\sum_{i}^{n}\Delta H_{i}-\Delta I\leq I(X;C) \qquad \text{(II)}$$

Relations (II) links the mutual information between the controlled variable and the controller to the information stored in the elements, the mutual information between them and the information stored in the network and accounts for the redundancies through the multi information term *ΔI*.

Relations (III) links the program complexity of the controller to the information stored in the elements, the mutual information between them and the information stored in the network.

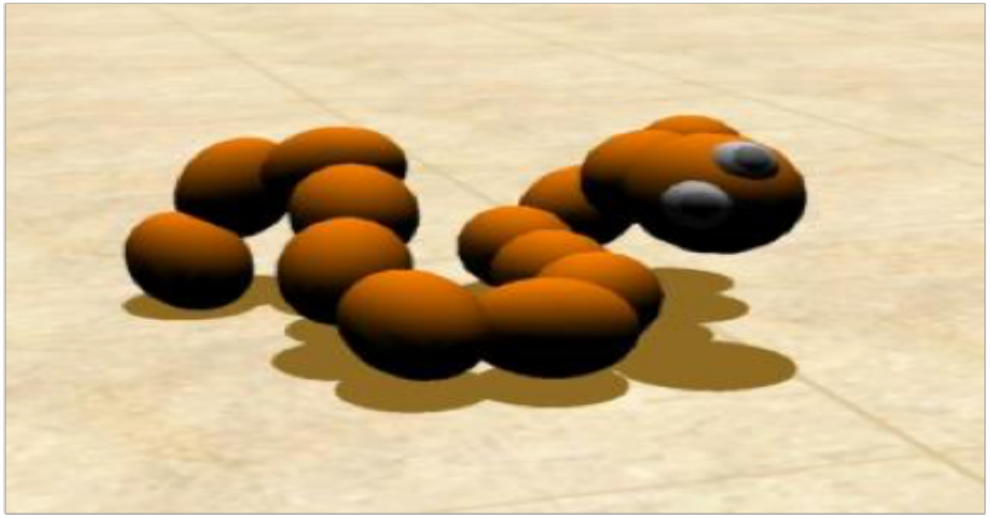
$$K(X)=\Delta HN+\sum_{i}^{n}\Delta H_{i}-\Delta I \qquad \text{(III)}$$

Relations (IV) links the program complexity of the controller to the information stored in the elements the mutual information between them and the information stored in the network.

$$\Delta HN=\log\frac{\Omega_{closed}}{\Omega_{open}^{\max}}+\Delta I \qquad \text{(IV)}$$

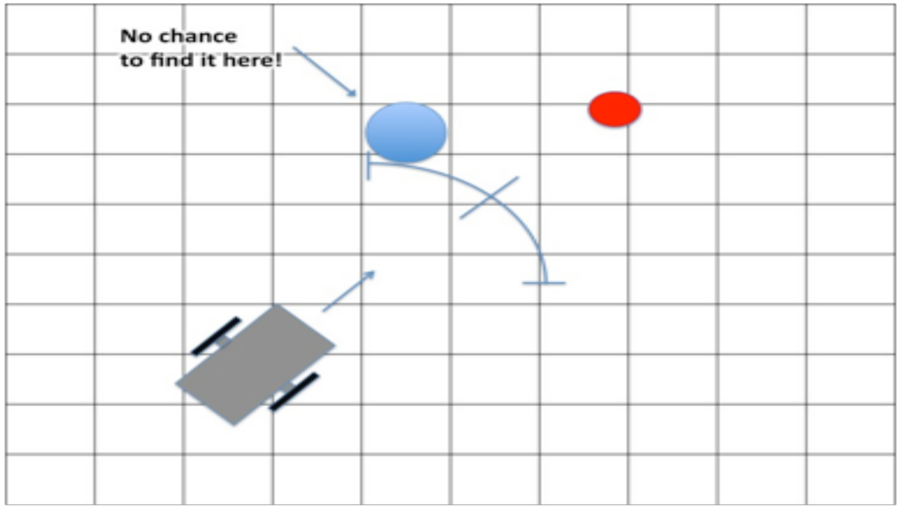
These relations are quite preliminary, and perhaps need a more rigorous demonstration, but give an insight on how information is managed within a network of physical elements or agents interacting with a given environment in a finalized way. They suggest how the cognitive adaptation is at network level: in any environment niche it is possible with small networks of highly sophisticated individual agents, like in human societies, or with many limited autonomy individuals like in ant colonies, with a great variety of possibilities in the middle.

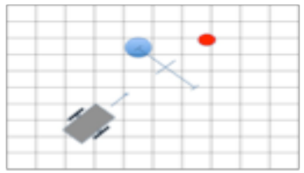
Snakebot



see: **Tanev et. al, IEEE TRO, 2005**

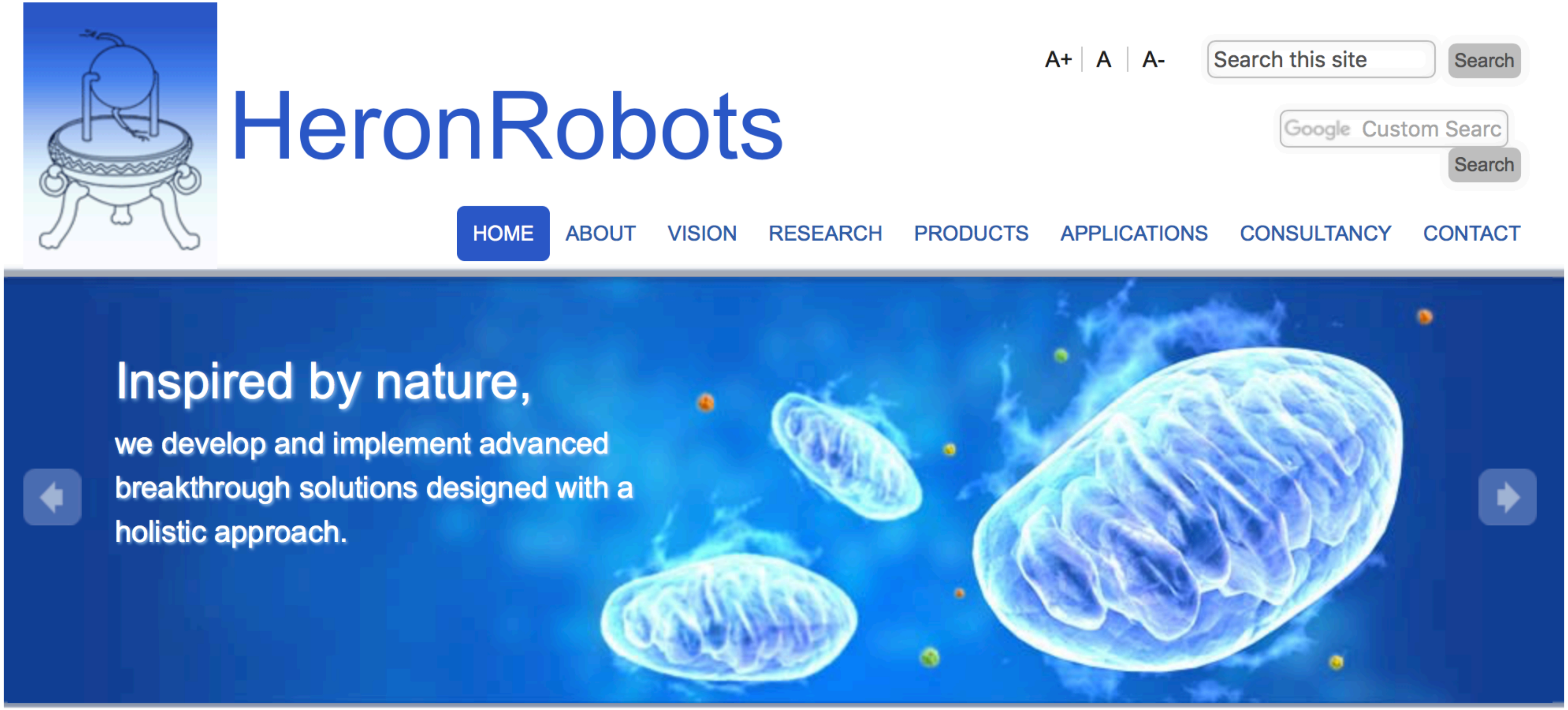
Maybe not GOF Euclidean space? :-)

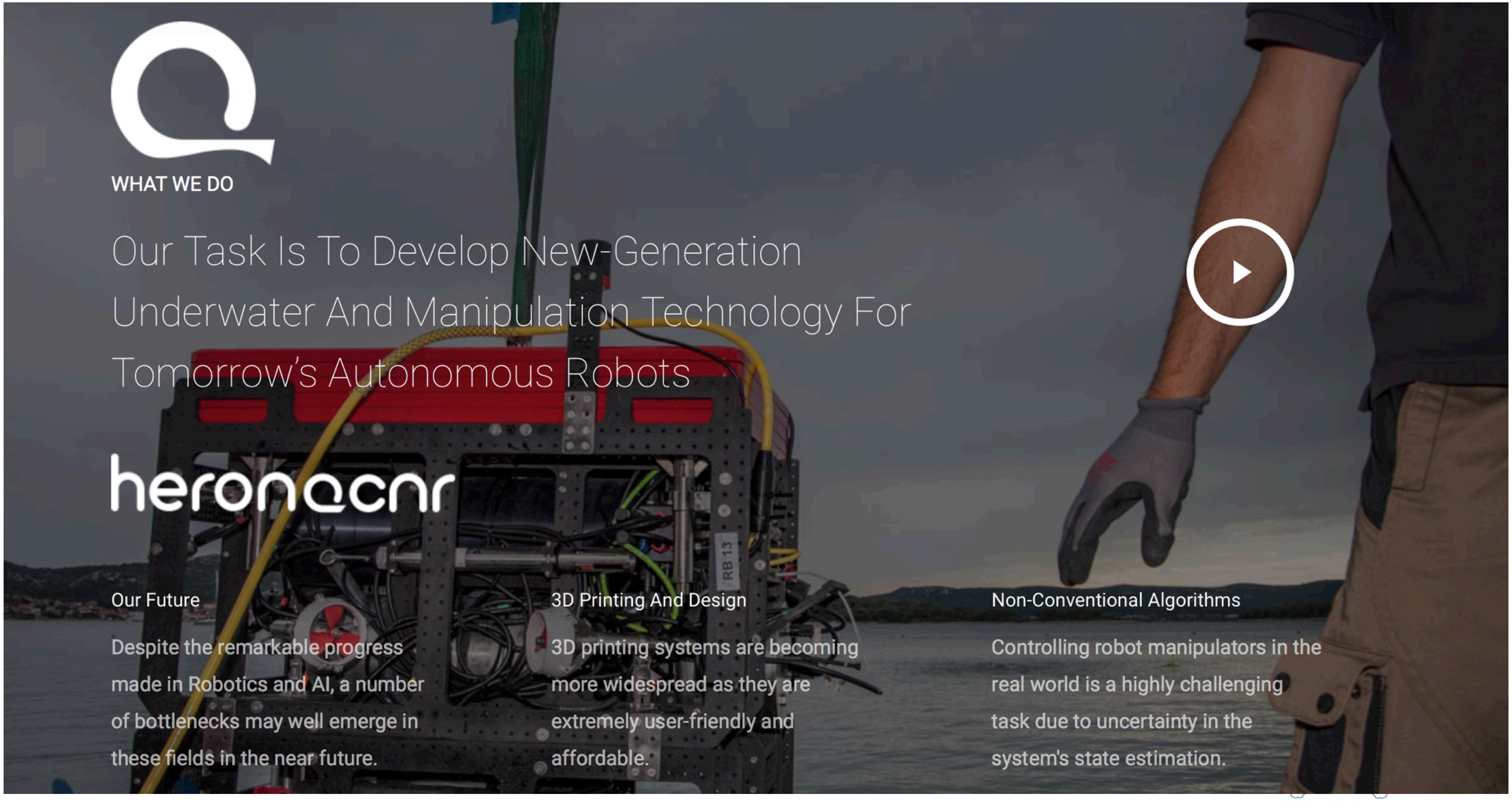


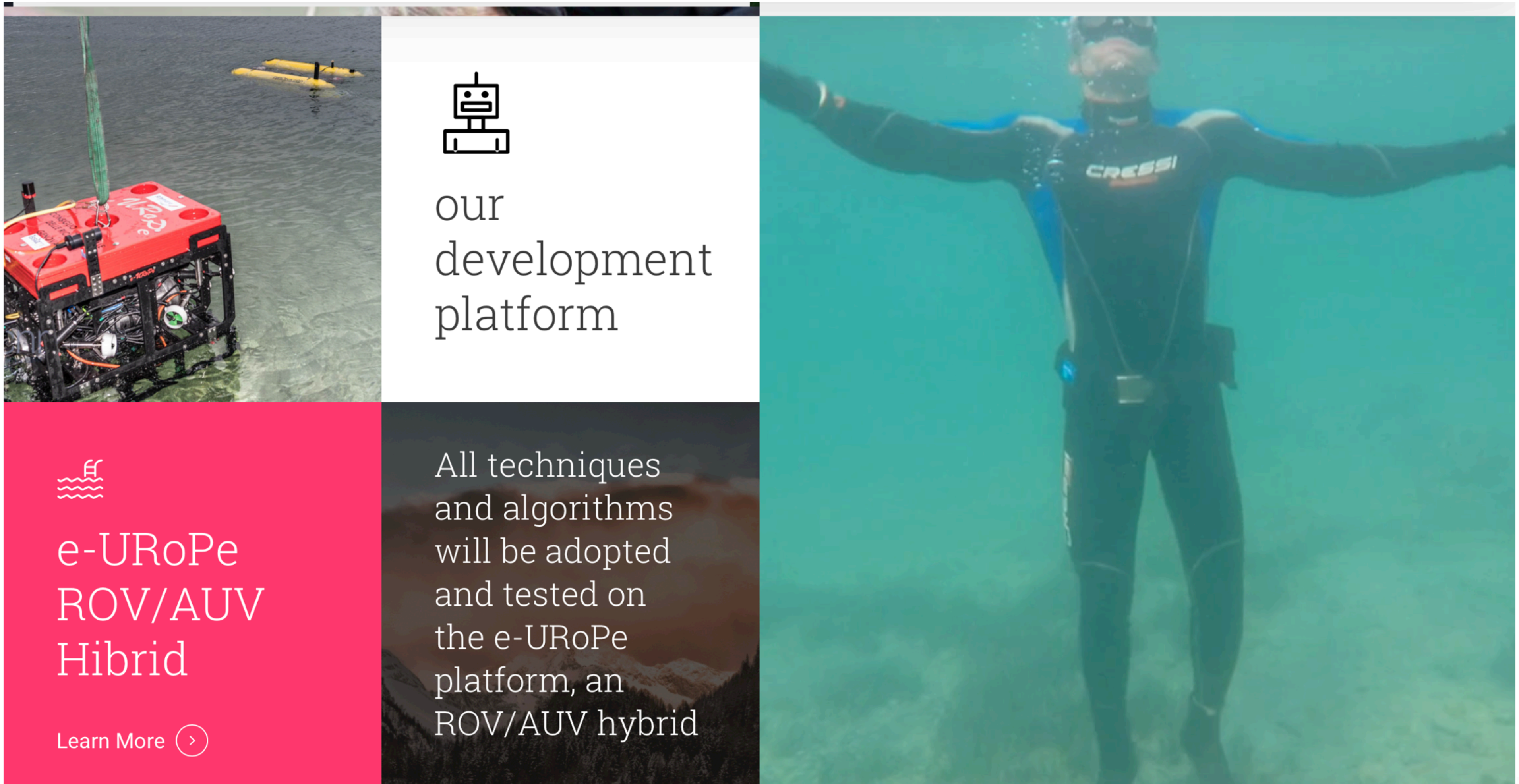


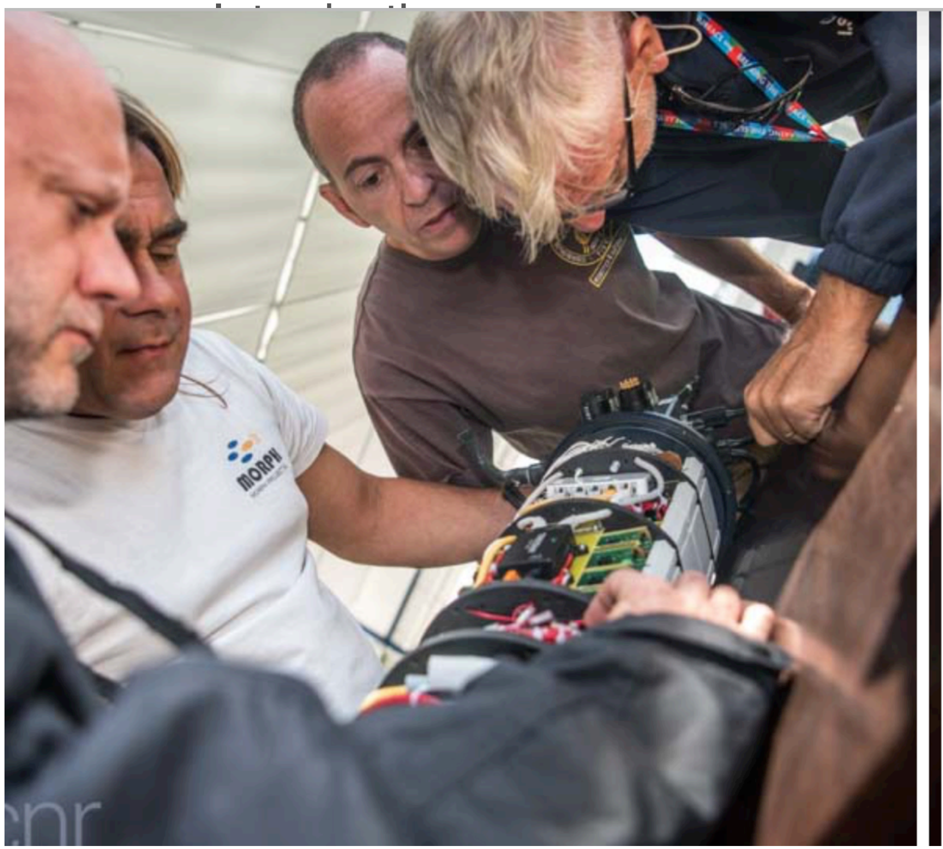
see: **Bonsignorio, Artificial Life, 2013**

Introduction




WHAT WE DO
Our Task Is To Develop New-Generation Underwater And Manipulation Technology For Tomorrow's Autonomous Robots
heronacnr
RB 13
Our Future
Despite the remarkable progress made in Robotics and AI, a number of bottlenecks may well emerge in these fields in the near future.
3D Printing And Design
3D printing systems are becoming more widespread as they are extremely user-friendly and affordable.
Non-Conventional Algorithms
Controlling robot manipulators in the real world is a highly challenging task due to uncertainty in the system's state estimation.


our development platform
e-URoPe ROV/AUV Hibrid
Learn More
All techniques and algorithms will be adopted and tested on the e-URoPe platform, an ROV/AUV hybrid



Our Research Mission

Is To Expand Scientific And Technical Knowledge In The Field Of Underwater Manipulation,

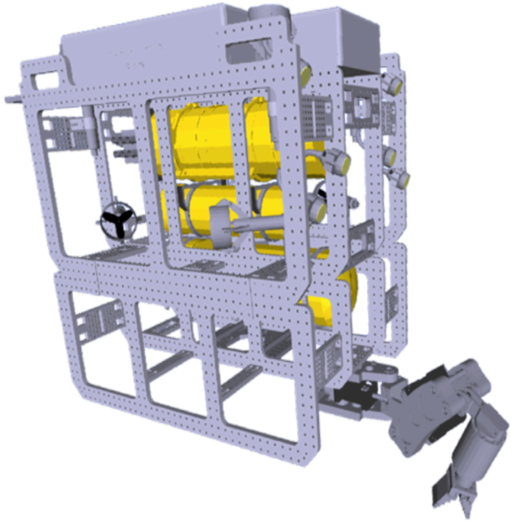
more generally, in marine robotics, with an eye to pursuing new solutions which are "disruptive" at the scientific and technical level.

Introduction

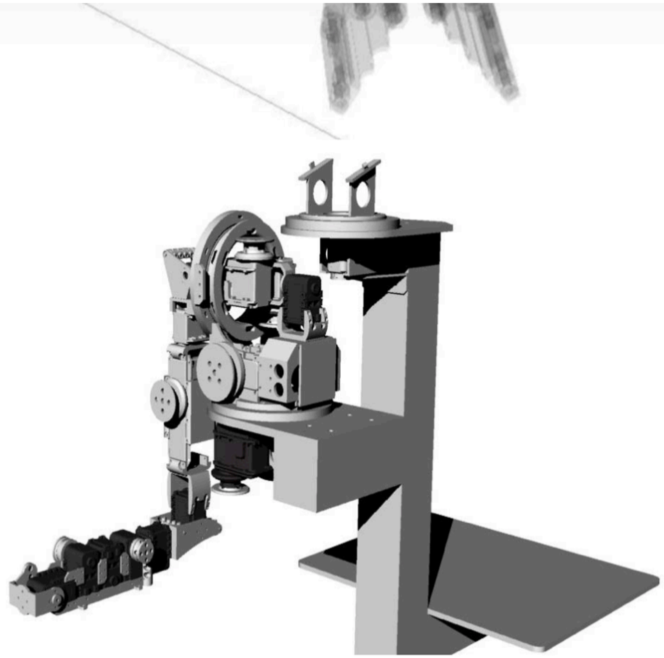
H_2Arm

Marine Robotics Manipulation

Best Solutions. Zero Compromises.



ARM 5E MICRO
produced by ECA Robotics

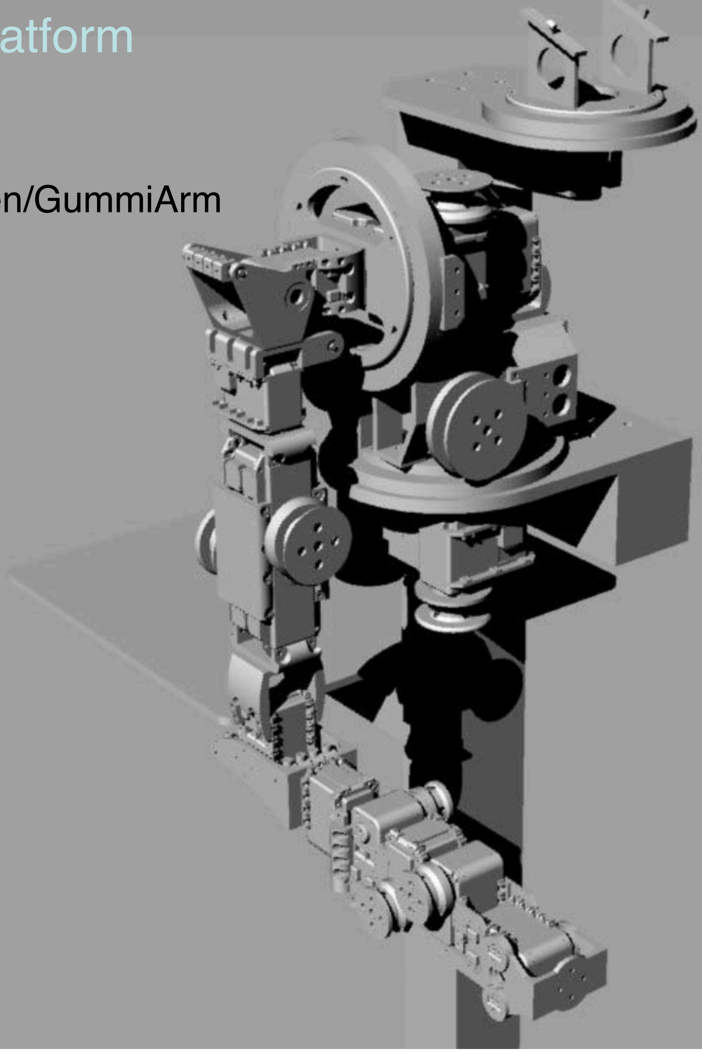


GummiArm

Open Source HW Platform

GummiArm

https://github.com/mstoelen/GummiArm



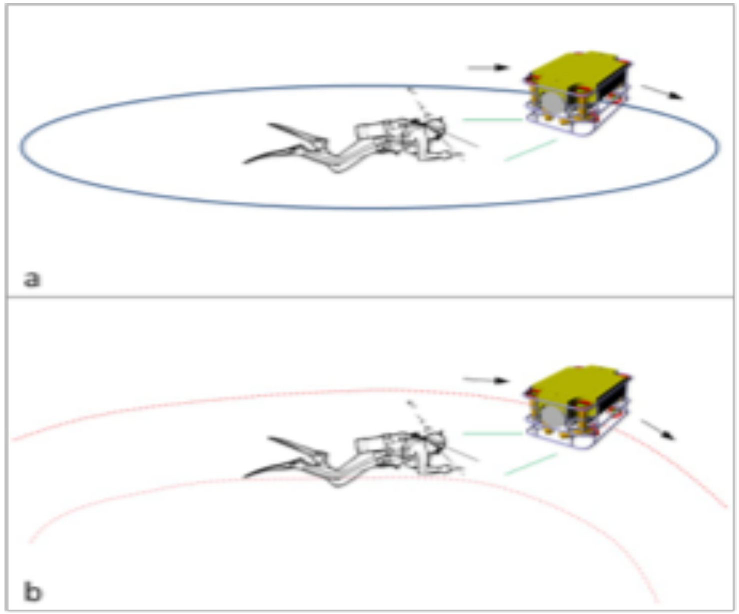
Early trials …

“Motion planning in the belief space for compliant behaviour of a (NB: *rigid*) diver companion robot”

(on a ‘standard’ arm: ARM 5E MICRO produced by ECA Robotics)

Enrica Zereik, Marco Bibuli, Gabriele Bruzzone, Francesco Gagliardi,
National Research Council of Italy, Institute of Marine Engeneering
Fabio Bonsignorio, Heron Robots

Problem statement



ARM 5E MICRO
produced by ECA Robotics

Belief State Approach

In order to cope with the previously mentioned underwater scenario we model the possible and even significant measurements errors of the system as linear Gaussian and we apply a belief state planning technique to reduce uncertainty and to be able to move the vehicle in the desired final position with a given precision.

As demonstrated by \cite{c1} the assumption of maximum likelihood observation for the measurements makes possible to adopt comparatively frugal optimization techniques in the belief space such as direct transcription and LQR (Linear Quadratic Regulation); for further details see \cite{REFCHI11}. The state of the system is therefore the most probable state according to the acquired measurements and the performed actions.

A position in belief-space can be seen as a Gaussian PDF (Probability Density Function); an opportune planned trajectory in the belief space moves towards a a goal position characterized by a mean value and lower variance; for example 1D motion in the belief state of a material point can be represented as a line in the 2D mean-variance plane.

Following the approach proposed by \cite{c1} we a-priori planned a trajectory in the belief space by direct transcription method and then we apply LQR method to stabilize the trajectory taking in account the upgrading measurements gathered by the system. The process is iterated until the desired position with lower variance is reached. The planning is therefore performed in higher dimensional space than the state space; as consequence we deal with a non-linear, stochastic and under-actuated dynamic (number of inputs smaller than state space dimension). The assumption of linear Gaussian system helps to simplify the problem: it has been demonstrated by \cite{c1} that it generates reasonable behaviour in the region near the linearization point.

In our simulation we model the observation on the vehicle position $z_t \in Z$ as a non linear stochastic function of the d-dimensional state vector *d* $ {x_t} \in X $ $x_t \in X$

.

$$z_t = g(x_t) + \omega$$

$$x_{t+1} = f(x_t, u_t)$$

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STITUTE
Scuola Superiore Sant'Anna

Belief State Approach

where g is a deterministic function of measurements and ω is a zero mean Gaussian noise with covariance W_t dependent on the state of the system.
Two consecutive time dependent states are linked by a control action u_t

$$x_{t+1} = f(x_t, u_t)$$

where f,g are differentiable functions of x_t and u_t

The system model can be further simplified assuming belief state described by a Gaussian PDF

$$\Sigma_t : P(x) = \mathcal{N}(x / m_t, \Sigma_t)$$

and by linearization of the belief space dynamic that leads to:

$$x_{t+1} = A_t(x_t - m_t) + f(m_t, u_t)$$

$$z_t = C_t(x_t - m_t) + g(f(m_t, u_t)) + \omega$$

where \$ m_t is the mean of the belief state and A_t and \$ C_t are the Jacobian matrices

$$A_t = \frac{\delta f}{\delta x}(m_t, u_t), C_t = \frac{\delta g}{\delta x}(m_t)$$

In this hypotheses it is possible to derive a series of states $b_{\tau T}$ and of action $u_{\tau T}$ finding local minima of the cost function J by a standard SQP (Sequential Quadratic Programming) algorithm.

Belief State Approach

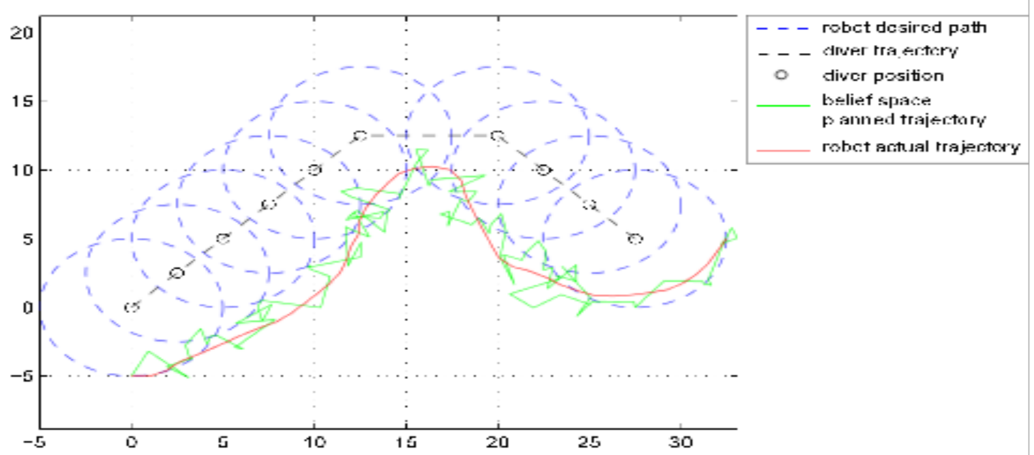
$$J\left(b_{\tau:T},u_{\tau:T}\right)=\sum_{i=1}^{k} w_i\left(\hat{n}_i^T\Sigma_t\hat{n}_i\right)^2+\sum_{t=\tau}^{T-1}\tilde{m}_t^T Q\hat{m}_t+\tilde{u}_t^T R\tilde{u}_t$$

Where Q and R are weight matrices, the n_i, are the unit vectors of belief space along which the optimization is performed. Σ_T is the covariance matrix at the end of the segment, m_t^T the value of the mean of the Gaussian of the measures.

The actions in the belief space weight the objective to reduce and keep the relative distance from the diver with the objective of reducing the uncertainty on the measures.

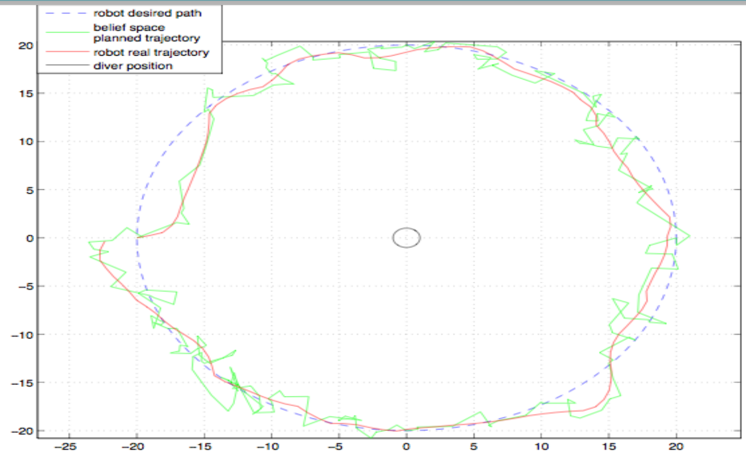
This hybrid approach aiming to blend the motion objectives with those related to the reduction of the uncertainties on the measures seems very suitable to the underwater, in particular marine, environment where the uncertainties in the measurements are usually relevant and a stochastic approach to control is needed, in order to achieve acceptable robustness of the behaviors.

Simulations



Simulation of the first scenario: the diver is performing a task in a specific spot and the robot is moving in a circular path around him/her in order to monitor his/her health status and reactively respond to possible requests coming from the diver.

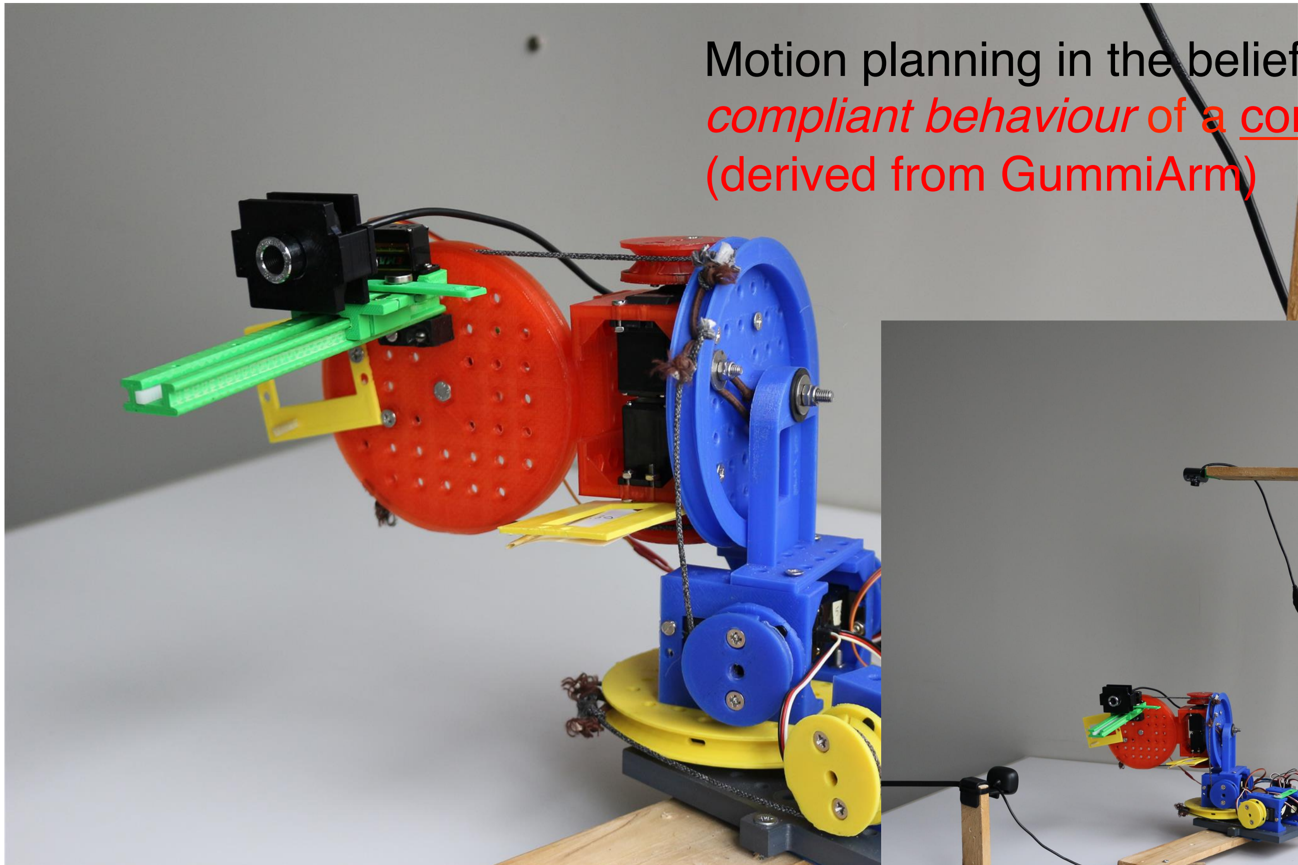
Simulations

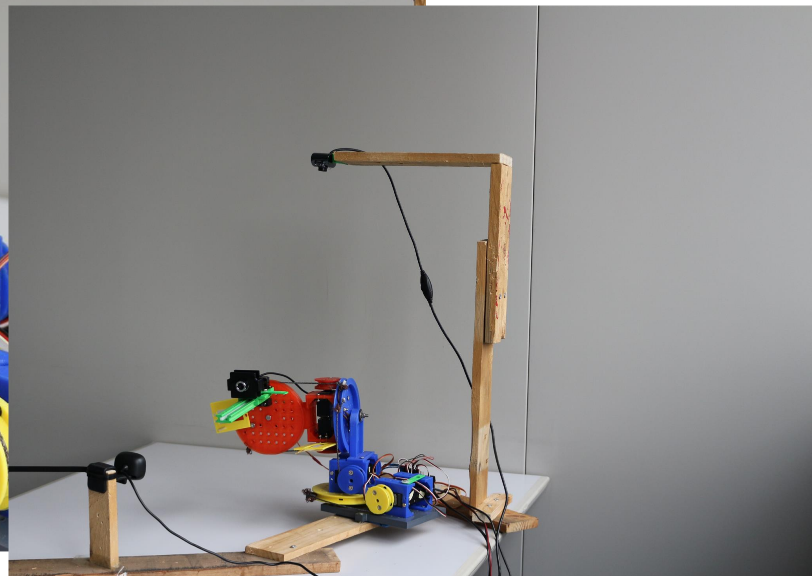


Simulation of the second scenario: the diver is exploring the underwater environment and the robot is asked to move in a circular path around him/her while translating in a compliant way with respect to the diver motion.

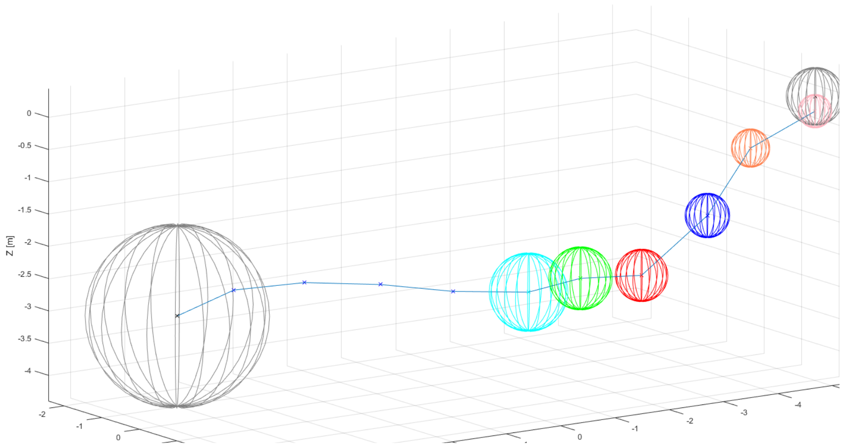
Note that, in case the diver arrives to a stop to perform another taskin a specific spot (e.g. because he/she has seen something interesting), the robot buddy will switch to the first scenario moving again along a circular path around the diver.

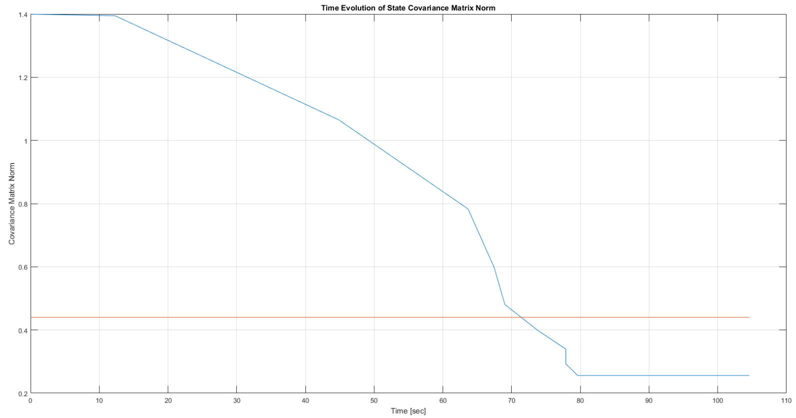
Motion planning in the belief space for
compliant behaviour of a compliant arm
(derived from GummiArm)

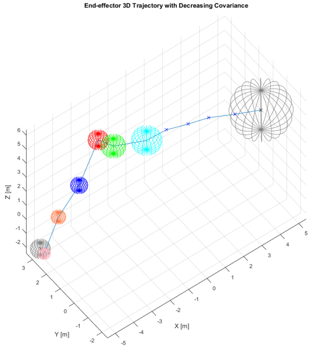


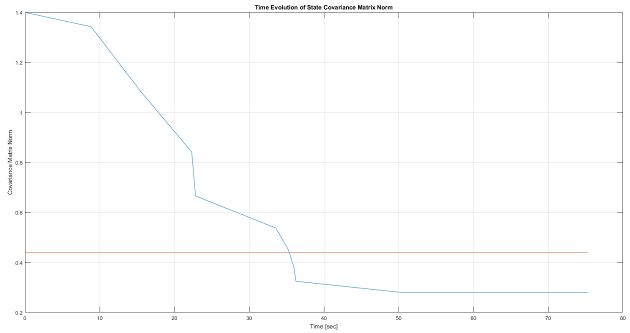


Introduction

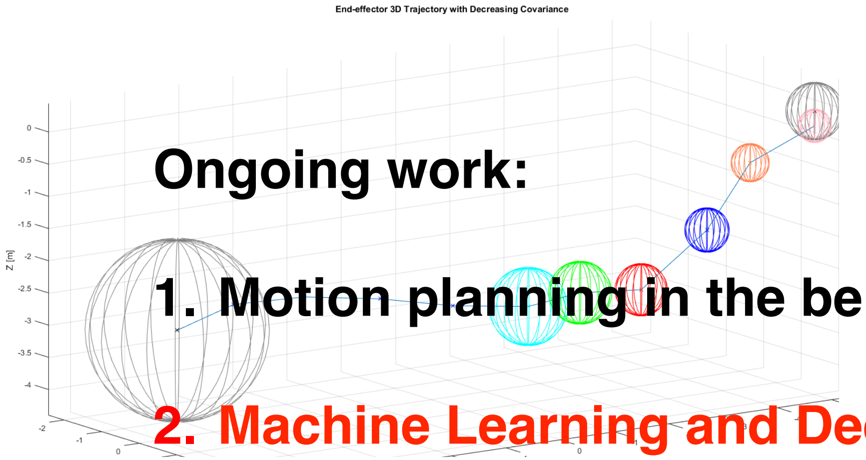








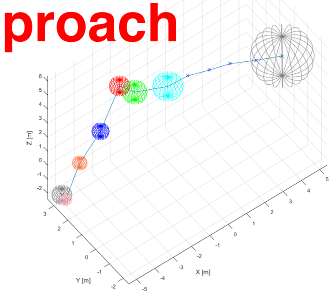
Introduction

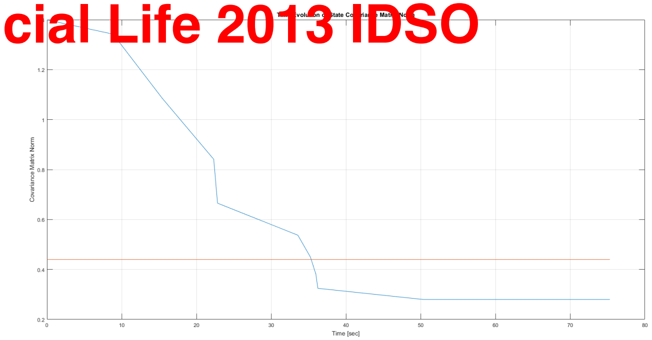


Ongoing work:

1. **Motion planning in the belief space Lie-Group aware**

2. **Machine Learning and Deep Learning Lie-group aware implementing/adapting Artificial Life 2013 IDSO approach**





The Road Ahead

rking Tools

CA COST Action CA17137

A network for Gravitational Waves, Geophysics and Machine Learning

The breakthrough discovery of gravitational waves on September 14, 2015 was made possible through synergy of techniques drawing from expertise in physics, mathematics, information science and computing. At present, there is a rapidly growing interest in Machine Learning (ML), Deep Learning (DL), classification problems, data mining and visualization and, in general, in the development of new techniques and algorithms for efficiently handling the complex and massive data sets found in what has been coined "Big Data", across a broad range of disciplines, ranging from Social Sciences to Natural Sciences. The rapid increase in computing power at our disposal and the development of innovative techniques for the rapid analysis of data will be vital to the exciting new field of Gravitational Wave (GW) Astronomy, on specific topics such as control and feedback systems for next-generation detectors, noise removal, data analysis and data-conditioning tools.The discovery of GW signals from colliding binary black holes (BBH) and the likely existence of a newly observable population of massive, stellar-origin black holes, has made the analysis of low-frequency GW data a crucial mission of GW science. The low-frequency performance of Earth-based GW detectors is largely influenced by the capability of handling ambient seismic noise suppression. This Cost Action aims at creating a broad network of scientists from four different areas of expertise, namely GW physics, Geophysics, Computing Science and Robotics, with a common goal of tackling challenges in data analysis and noise characterization for GW detectors.

(Descriptions are provided by the Actions directly via e-COST.)

COST Association COST Action CA17137

- **Description**
- Parties
- Management Committee

General Information*

Proposer of the Action:
Dr Elena Cuoco

Science officer of the Action:
Dr Ralph STUEBNER

Administrative officer of the Action:
Ms Rose CRUZ SANTOS

Downloads*

Action Fact Sheet
Download AFS as .RTF

Memorandum of Understanding
Download MoU as PDF

http://www.cost.eu/COST_Actions/ca/CA17137

Summary

- HeronRobots and CNR-ISSIA (now part CNR-INR) work together on a potentially disruptive deeply bio inspired mobile manipulation and grasping technology especially suited for underwater applications. To this purpose they constituted the Joint Lab Heron@CNR (http://www.issia.cnr.it/wp/heroncnr/)
- As a first goal, we are developing a new tendon-based manipulation system – loosely connected to an underwater (semi) autonomous vehicle- which does not require significant mechanical accuracies in the joints and in the limbs.
- The system will exploit morphological computation and the Lie Group underlying structure of the arm motion.

Summary

- The main issues with Deep (reinforcement) Learning , and in general Machine Learning, methods when applied to robotics is their data inefficiency.
- The learning system operates in a huge abstract state space which consider way too many physically impossible configurations and does not consider the underlying group transformation structure of the possible motions.
- Our system will overcome (or at least mitigate) those limitations.

Summary

- To our knowledge this is the first time that a compliant robotic system is governed by a DRL system inherently exploiting morphological computation and body dynamics.
- This will hopefully ☺ allow implementing autonomous underwater vehicle manipulation with unprecedented dexterity at low cost.

Bottom Line: Physics Matters!

Coping with the common underlying theoretical issues implied by the application of ML and DL to physical systems might have deep and wide scientific and technological impact (for example protein folding.. DeepMind AlphaFold!)

Thank you!