Why having mobile sensors matters?

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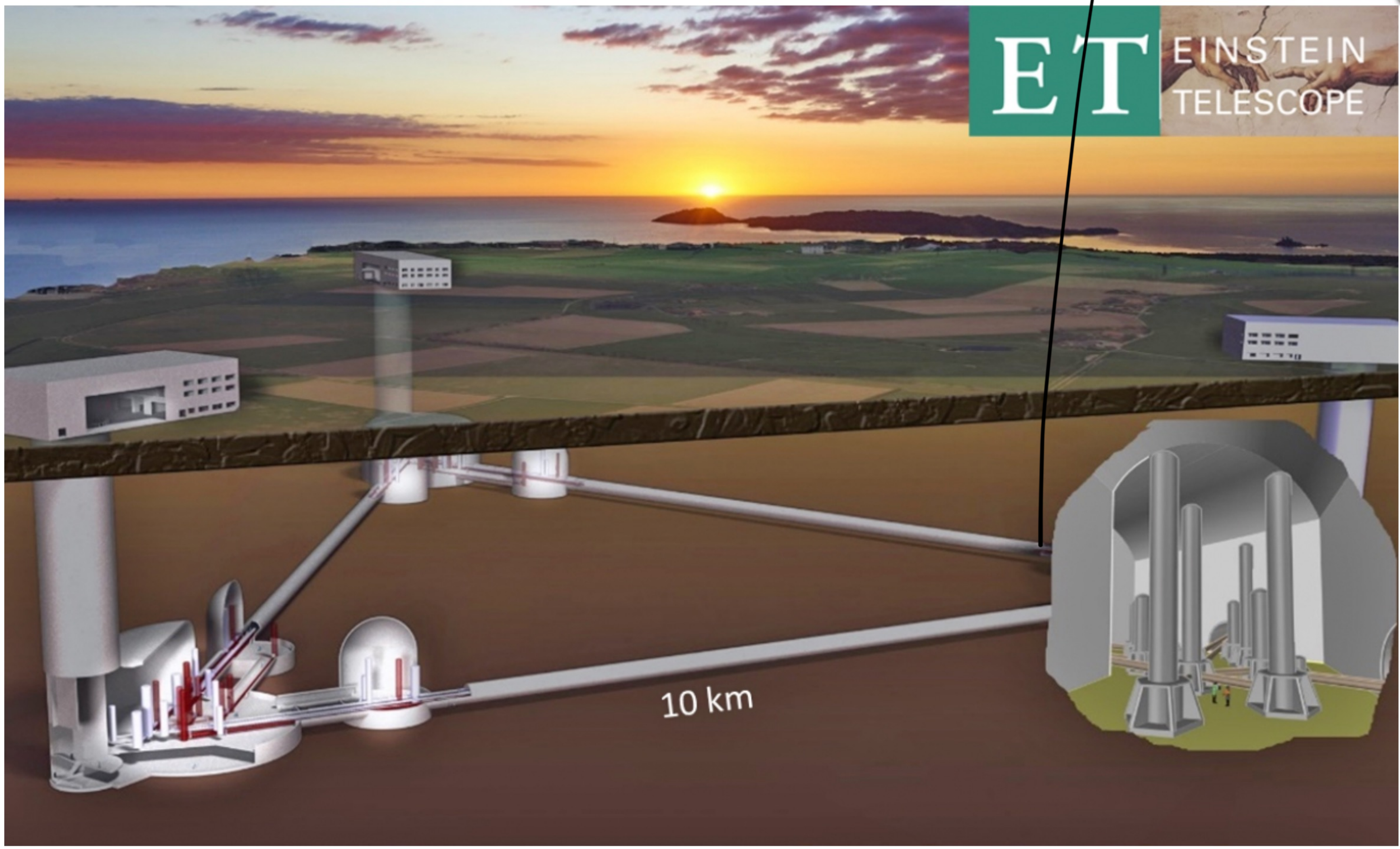
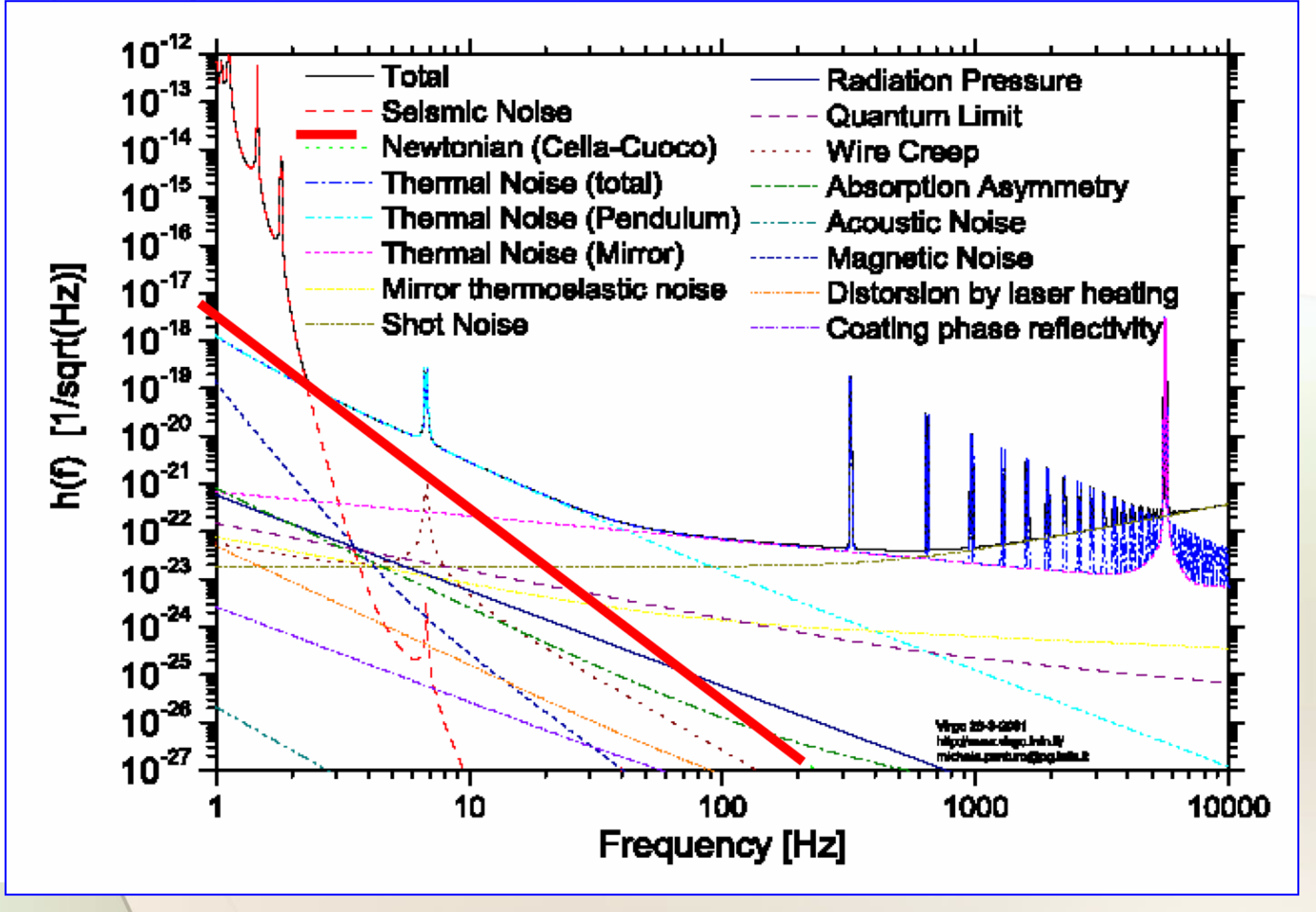
www.heronrobots.com

ET



Seismic NN: elastic models



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

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...

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

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

NN mitigation

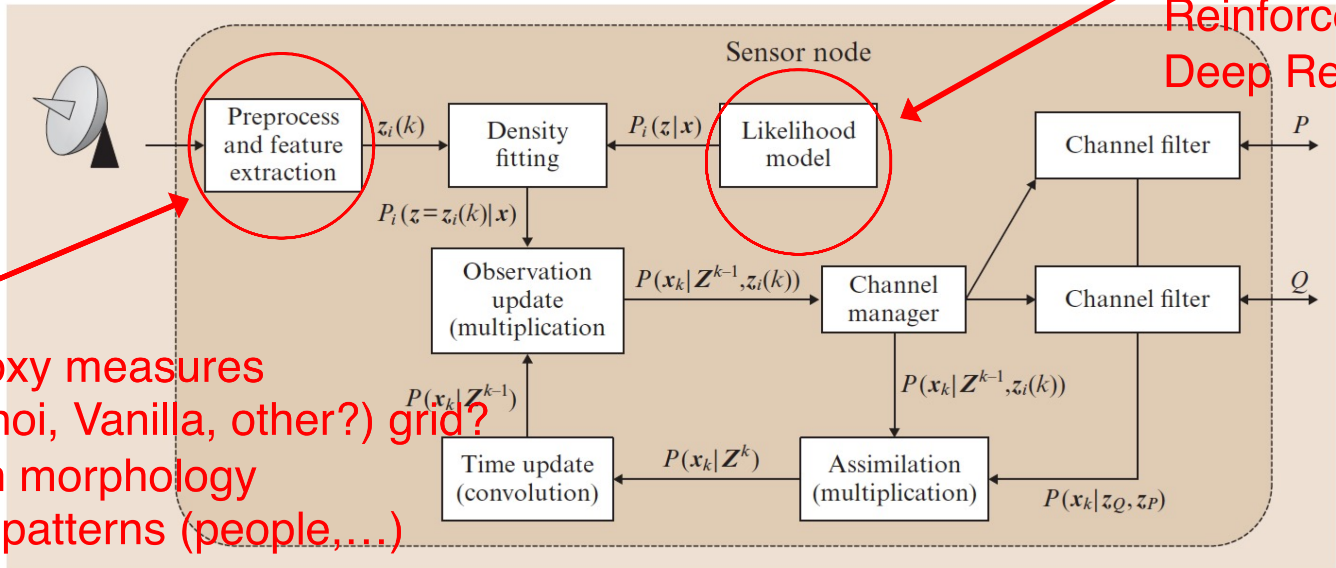
Preliminary ideas

- (adaptive) Modeling of the area (emi) sphere of r ≈ 10 m to 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?)

Decentralised Data Fusion like AnserII but with two main changes

Semi-supervised,
Reinforcement Learning?
Deep Reinforcement Learning



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

Mathematical structure of a decentralized 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.

T. Bulik and team's geophone

Infrasound microphone

Needed to characterize the infrasound field, **Low cost, Sensitivity in the range of 1-30Hz, lots of uses: geophysics, volcanology etc**, Potential industrial applications, **Prototype ready – network to be installed in Virgo this year**

Methods

Signal modeling by GP regression

Information Gain

Multi-robot coordination and task allocation

Discussion

1) spatiallly distributed stochastic sources of noises (e.g. newtonian noise, but not only)

2) the spatial distribution of noise sources changes over time

3) network sensor optimization should change over time (no way to obtain trustable distributions under ergodic assumptions) EKF and similar needed?

Discussion

1) mass density distribution originates newtonian tensor of noise according to classical gravity on the detector interference ‘points’, not really continuous field, not stationary, true for many relevant noises

2) Earth is a dynamical geophysical system, a chaotic one

3) Sensor (for example seismic sensors, but not only) must be moved over time. Geology is (most of the times) slow so human intervention is an option

Discussion

3) Sensor (for example seismic sensors, but not only) must be moved over time. Geology is (most of the times) slow so human intervention is an option

Humans are slower, more mechanically noisy and the human generated noise is more difficult to model

Discussion

Mobile sensor networks like those considered here will generate huge flows of data to be interpreted in quasi-real time.

That will need massive utilization of data science, ML/DL and in general AI methods.

Discussion

Together, Robotics and AI/ML/DL can enable a giant leap in GW detector technologies and geoscience alike

Thank you!

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