LEONARDO

Electronics Division

SCIENCE AND TECHNOLOGY ORGANISATION

SPECIALISTS' MEETING on

DISTRIBUTED MULTI-SPECTRAL AND MULTISTATICS SENSING

NATO-SET-312/RSM

organized by the Sensors and Electronics Technology Panel, MSE Focus Group

23-24 May 2022, Bled (SVN)
NATO UNCLASSIFIED open to AUS, CHE, FIN, SWE

KNS 3Towards Mature AI-driven Sensing – Aspects from a Realization Perspective

ALFONSO FARINA (Speaker) President of Radar and Sensors Academy, Leonardo S.p.A. (Italy)
Luca TIMMONERI (LDO), Valerio GARDELLI (LDO), Massimo LOFFREDA (LDO)
Pasquale FERRARA (LDO LaBs)

Bled (SVN)

23-24 May 2022,

Electronics

Helicopters

Aircraft

Cyber & Security

Space

Unmanned Systems

Aerostructures

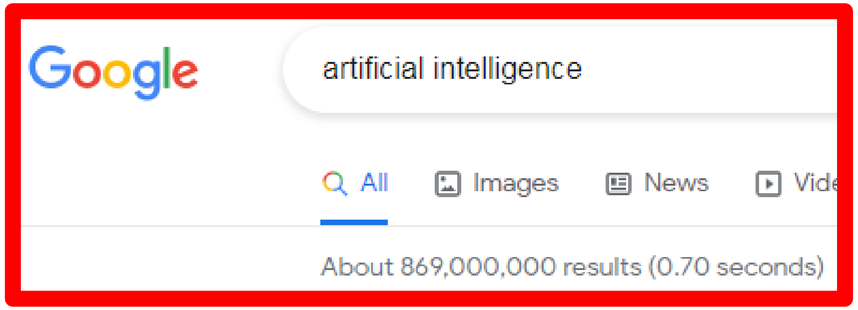
SUMMARY

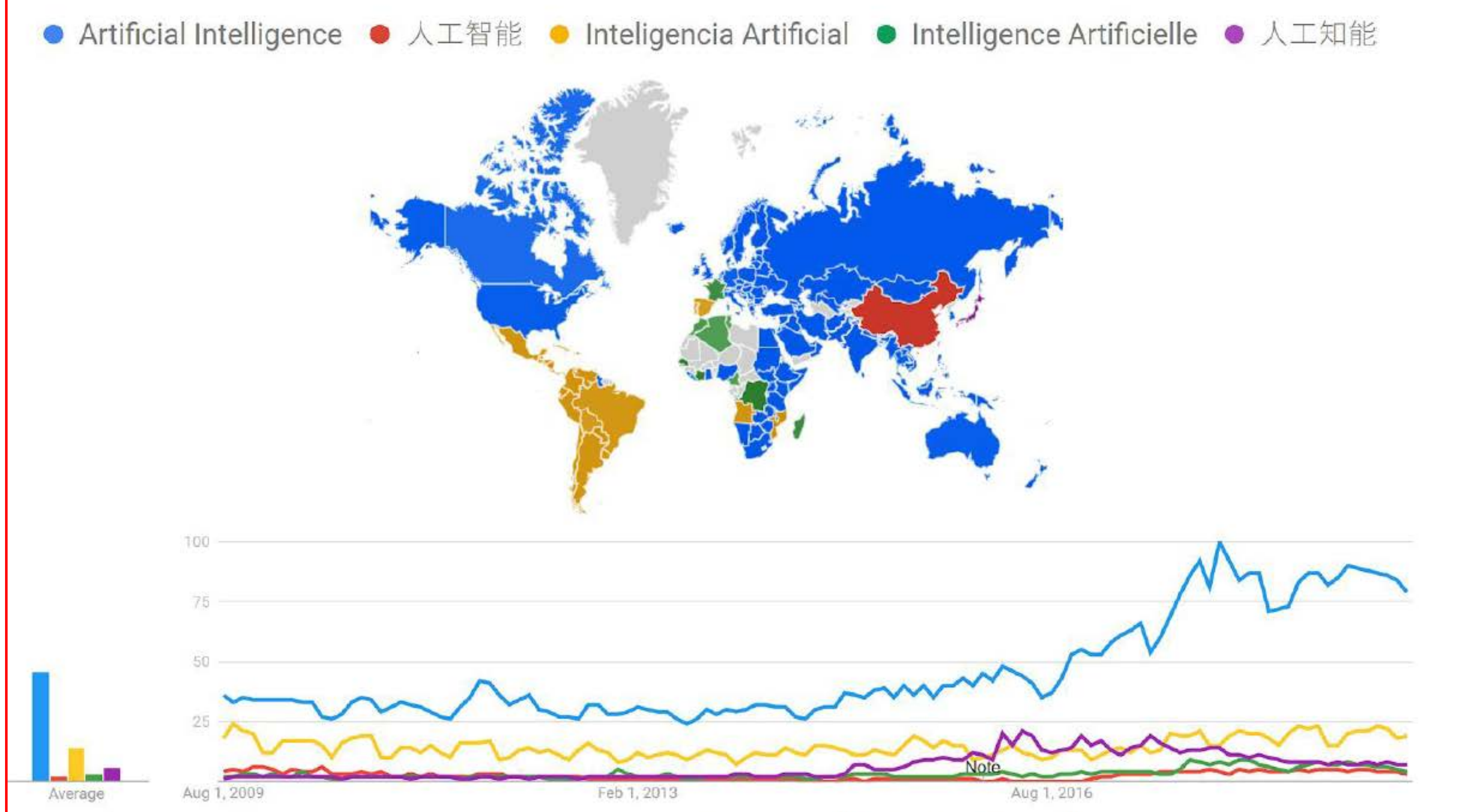
- Artificial Intelligence
  - Definition and Dissemination
  - Sustainable Development Goals of United Nations
  - Story in Leonardo (LIA (80’s-90’s))
- Intelligence in Radar: Adaptivity and Cognitivity in Radar
- Wide Situation Awareness: Role of Big Data and Measurement of Complexity
- Learning from Connectome of Worms C-elegance and Dragonfly
- Continuing to learn from Nobel Prize laureate in Neuroscience
  - Visual comprehension → Convolutional Neural Network
- Study cases
  - Target classification via AI
  - Image processing
  - Clutter cancellation
- Points of Criticism of AI
  - Risks associated to AI
  - Ethic of AI
- Way ahead
  - Cognitivity and quantum mechanism → Consciousness
  - Coordination of 1200 drones
- References

Artificial Intelligence (AI) Definition and Dissemination

- AI definition:
- https://en.wikipedia.org/wiki/Artificial_intelligence

Artificial intelligence (**AI**) is intelligence demonstrated by machines, as opposed to the **natural intelligence** displayed by animals including humans. AI research has been defined as the field of study of intelligent agents, which refers to any system that perceives its environment and takes actions that maximize its chance of achieving its goals.



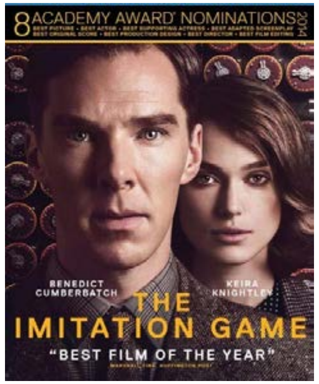


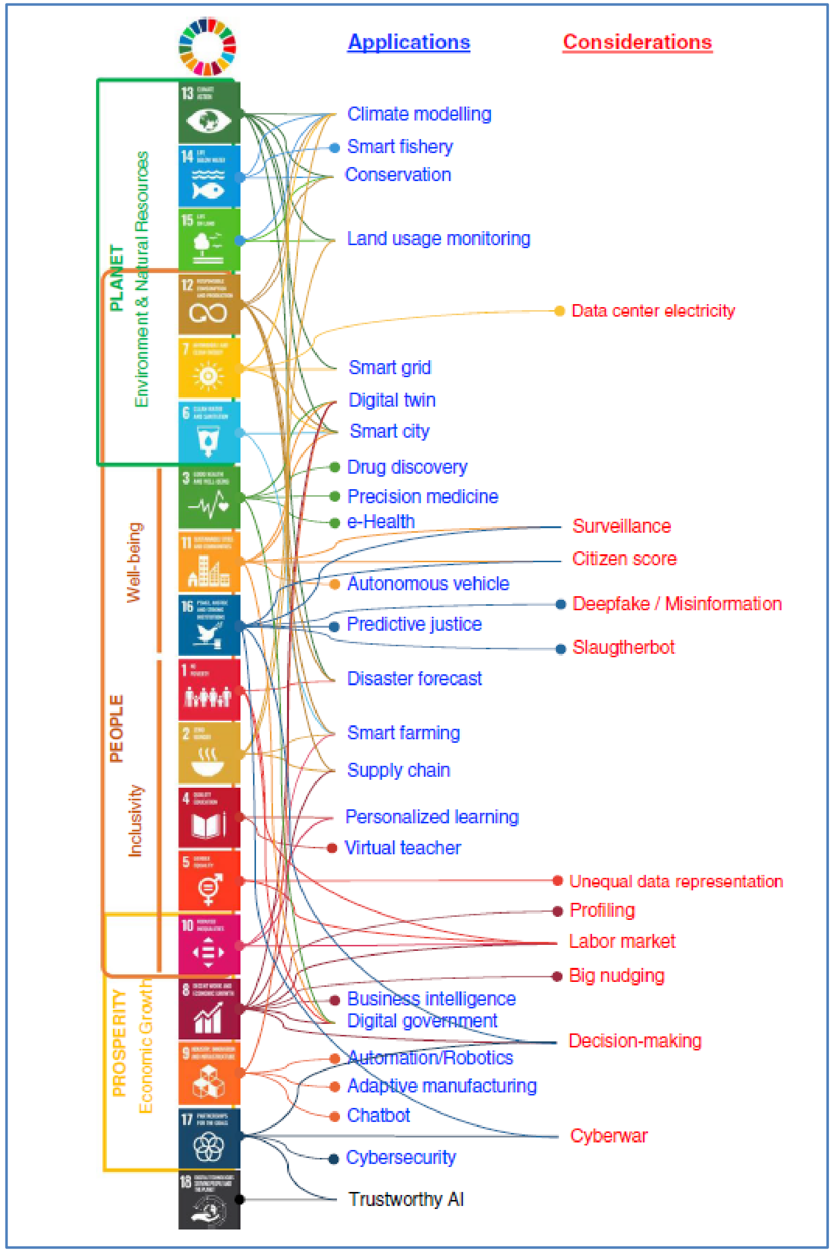
Analysis of queries on the Google search engine for the keyword "Artificial Intelligence" in English, Chinese, Spanish/Portuguese, French and Japanese between August 2009 and August 2019 via the Google Trends tool.*

https://ec.europa.eu/futurium/en/system/files/ged/vincent-pedemonte_ai-for-sustainability_0.pdf

How Artificial Intelligence (AI) intercepts the 17 SDG of UN

The Sustainable Development Goals (SDGs) were set in 2015 by the international community as part of the UN 2030 Agenda for Sustainable Development through which countries of the world collectively pledged to eradicate poverty, find sustainable and inclusive development solutions, ensure everyone's human rights, and generally make sure that no one is left behind by 2030.



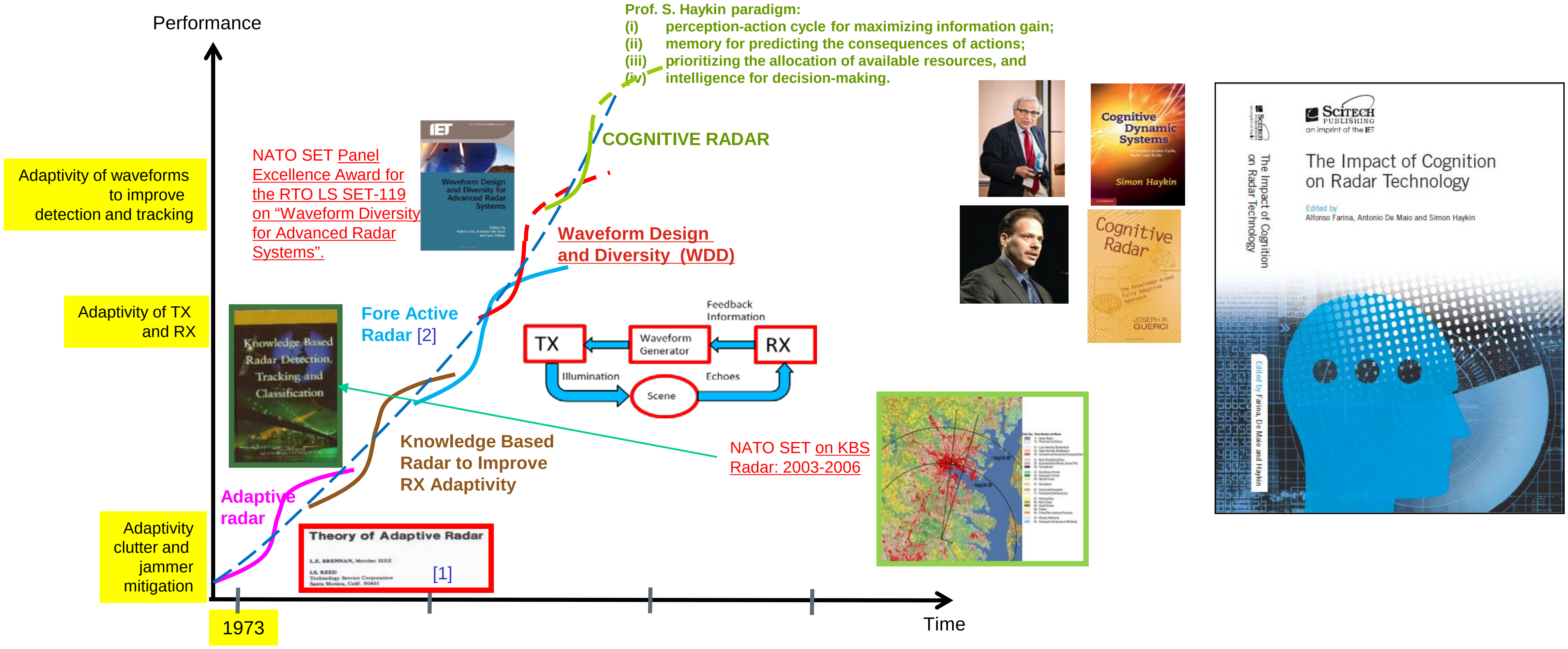


https://ec.europa.eu/futurium/en/system/files/ged/vincent-pedemonte_ai-for-sustainability_0.pdf

THE SELENIA LABORATORY FOR ARTIFICIAL INTELLIGENCE

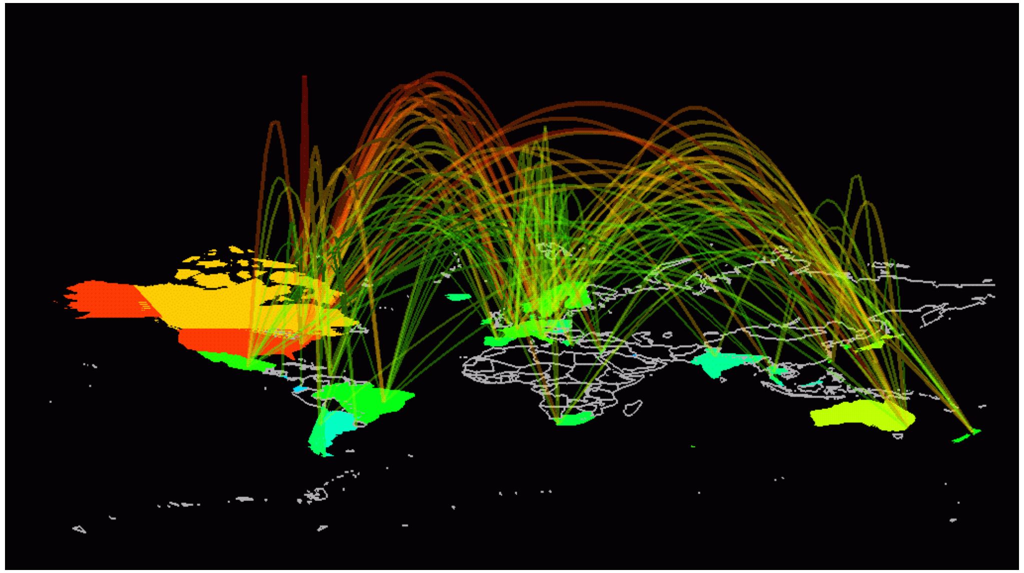
The LIA (Laboratorio di Intelligenza Artificiale-Artificial Intelligence Laboratory) was founded (1985, renamed LTI: Lab information Technology, in 1990) after an idea of **Luigi Stringa**, at the time General Director of Selenia. The Lab was composed by a group of enthusiastic young researchers selected both in the Company and from the university. **Giovanna Ballaben** was the first Director of that Lab. The LIA mission was to research in the field of AI with the aim of understanding the Company's needs and then transferring the knowledge acquired to the Divisions in order to provide AI skills within the products. We believe that a similar mission could be still valid and applicable.

Intelligence in Radar: From “Adaptive” to “Cognitive Radar”. Jumping the technology S-Curves!



[1] L. Brennan and I. Reed, IEEE Trans. on Aerospace And Electronic Systems , Vol. AES-9, No. 2, March 1973.
[2] D. J. Kershaw and R. J. Evans, “Optimal waveform selection for tracking systems”, IEEE Trans. IT, 40, pp. 1536-1550, 1994.

Wide Situation Awareness: Role of Big Data and Measurement of Complexity



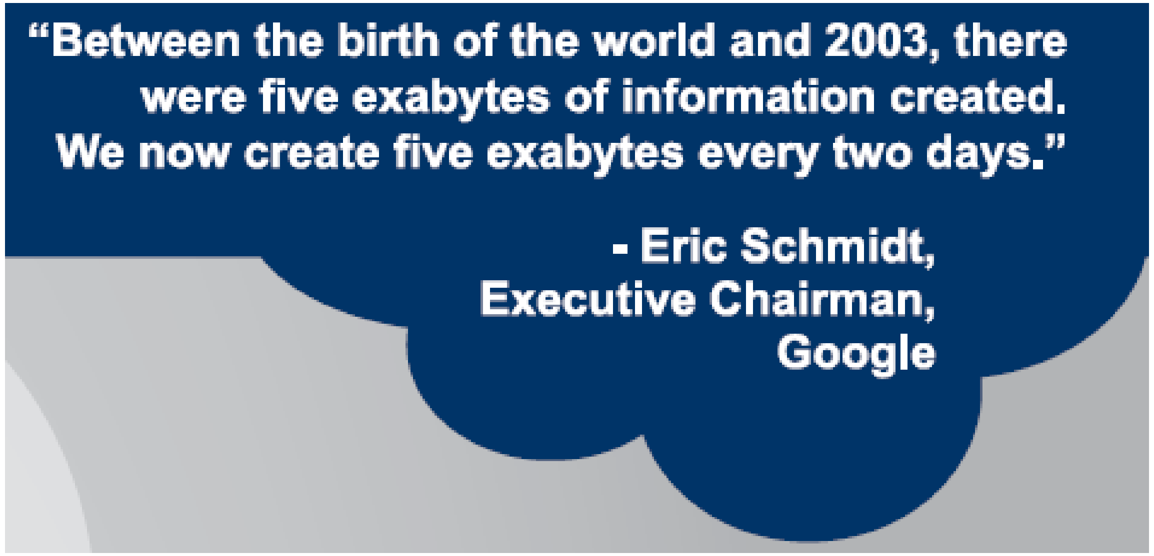
3D Geographic Network Display, Eick et al., 1996.

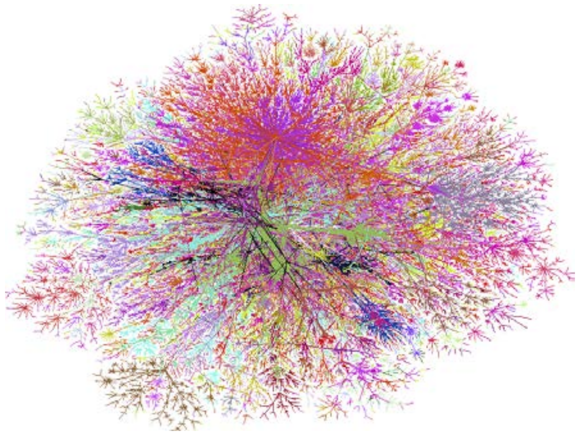
The number of IoT (Internet of Things) connections within the EU28 will increase from approximately 1.8 billion in 2013 (the base year) to almost 6 billion in 2020

Real-time Big Data applications will become increasingly widespread.

European ICT Market ~ 587 $ Bill, 2014

BIG DATA volume→ 35 zettabytes (ZB) by 2020.



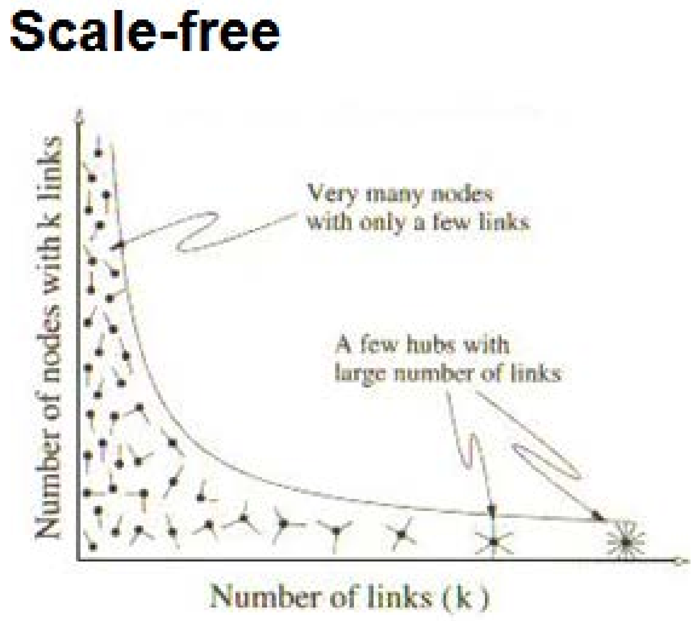


Data & Infrastructures:

- Big data→ topology analysis tool →*needle in haystack*
- Large critical infrastructures & supporting networks
- Civil-military cooperation in integrated networks
- Cyber security

Ubiquitous networks:

- Non-standard characteristics: e.g., probability density function with *heavy tails*
- *Long range dependence* in the net, typically arise in cyber security data.



Mathematical tools for network/graphs:

- Signal Processing on Graphs (e.g.: Graph Fourier Transform)
- Data Processing (e.g.: detection of special subgraphs in whole graph)
- Virus spread in networks: interplay of topology and epidemics
- Graph Laplacian → first two eigenvalues →network connectivity
- ***Adaptive net topology*** increasing spectral gaps against cyberattack
- *Epidemiological/Cyber spreading* related to spectral radius $\lambda_{max}(A)$ of network, i.e. to largest eigenvalue of its adjacency matrix

Definition of Complexity and Potential Measurements

Current quantitative and quantitative definitions of complexity are ambiguous. Quantitative measures of complexity include:

- ❑**Kolmogorov complexity** → the length of the shortest binary computer program that describes the object.
- ❑**Cyclomatic complexity** → the number of linearly independent control paths of the software program.
- ❑**Plecticity** (*)→ refers to the ability of a connected set of agents to act synergistically via the connectivity between them.

(*) **Murray Gell-Mann, “The Quark and the Jaguar: Adventures in the Simple and the Complex”, 1994.**
1969 Nobel Prize in physics for his work on the theory of elementary particles.
One of the Founders of the Santa Fe Institution

WIKIPEDIA

Santa Fe Institute

The **Santa Fe Institute** (**SFI**) is an independent, nonprofit theoretical research institute located in Santa Fe, New Mexico, United States and dedicated to the multidisciplinary study of the fundamental principles of complex adaptive systems, including physical, computational, biological, and social systems. The institute is ranked 24th among the world's "Top Science and Technology Think Tanks" and 24th among the world's "Best Transdisciplinary Research Think Tanks" according to the 2020 edition of the *Global Go To Think Tank Index Reports*, published annually by the University of Pennsylvania.[1]

Greek → *plektos*
Latin → *plexus*

simplex → "once" as in "simple"

Plecticity

complexus → "together" as in "complex"

Learning from Connectome of Worms C-elegans

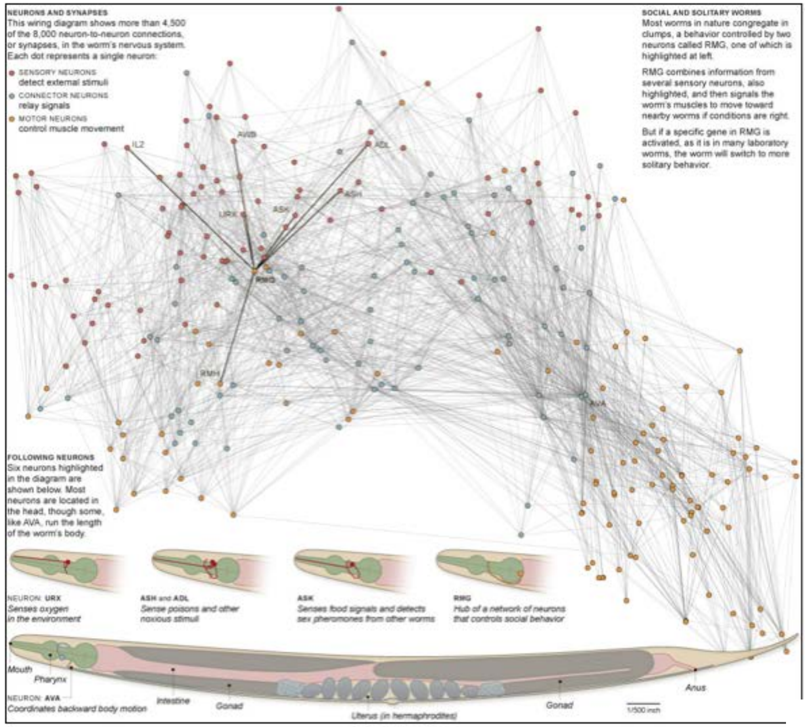
Human Connectome too complex to exploit.

*The human brain implements the adaptivity by means of a complex network of connections, 60 trillions (=60x10^{12}) of **synapses**, among about **30 billion** (=30x10^{9}) neurons.*

35M<Neurons in the brain<275M

Connectome of bat brain… not known yet

https://en.wikipedia.org/wiki/List_of_animals_by_number_of_neurons



Connectome of the ‘Caenorhabditis elegans’ worm’s nervous systems (302 neurons).

https://en.wikipedia.org/wiki/Caenorhabditis_elegans

https://www.genome.gov/25520394/online-education-kit-1998-genome-of-roundworm-c-elegans-sequenced

Learning from Connectome of Worms C-elegans

- Free living transparent roundworm
- About 1 mm length, blind
- Lives in temperate soil environments
- It is the most studied organism in terms of connectome

WORM C. ELEGANS

https://commons.wikimedia.org/w/index.php?curid=2680458

Study Case

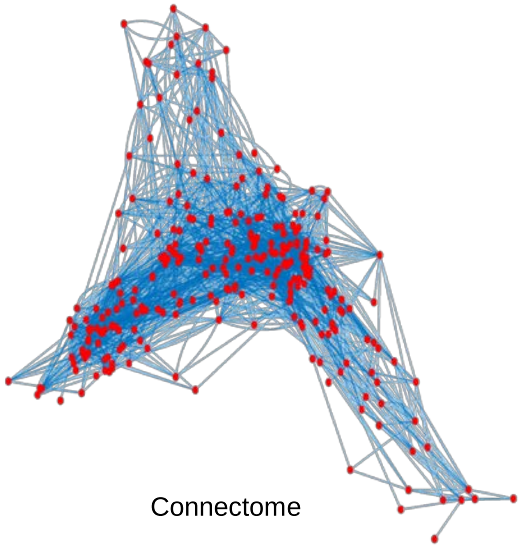
- 277 neurons
- 2105 connections
- Unweighted adjacency matrix

Kaiser M, Hilgetag CC (2006), “Non-Optimal Component Placement, but Short Processing Paths, due to Long-Distance Projections in Neural Systems”, *PLoS Computational Biology*

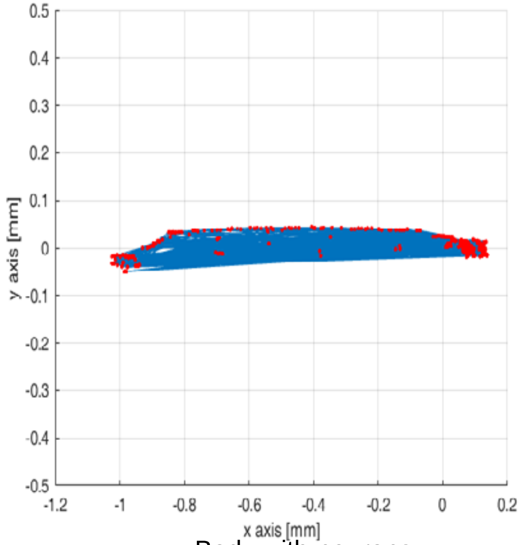
https://www.dynamic-connectome.org/?page_id=25

Weights	Feature	C. Elegans
NO	Mean length shortest path	4.284
	Maximum betweenneess centrality	0.1182
	Mean betweenneess centrality	0.0094
	Plecticity	12.5905

Learning from Connectome of Worms C-elegans



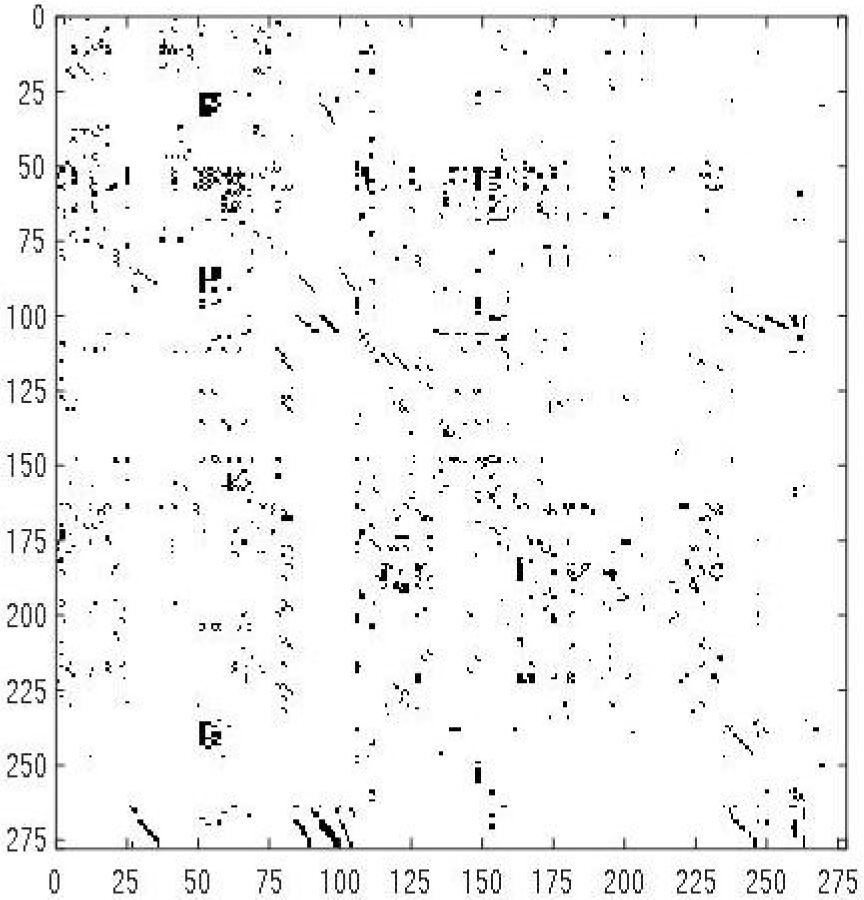
Connectome



Body with neurons

C. ELEGANS GRAPH (277 NODES)

Adjacency Matrix of a portion of the connectome

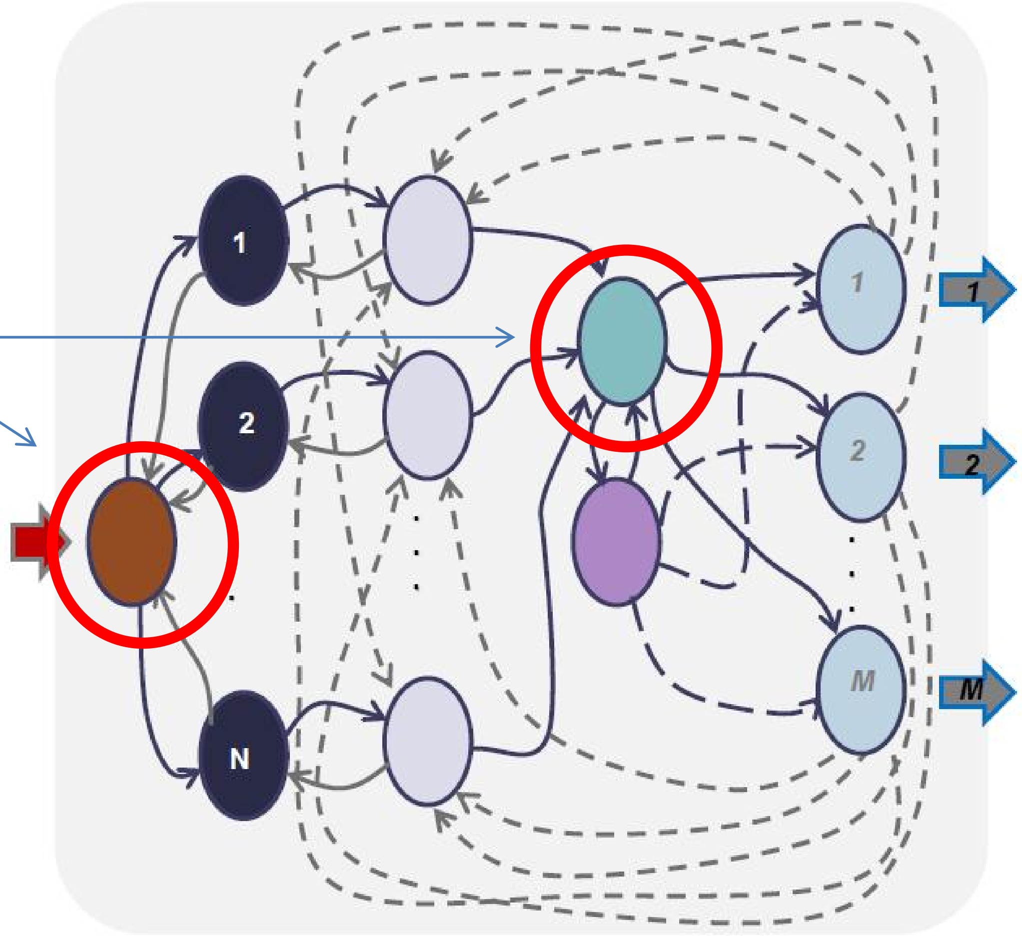


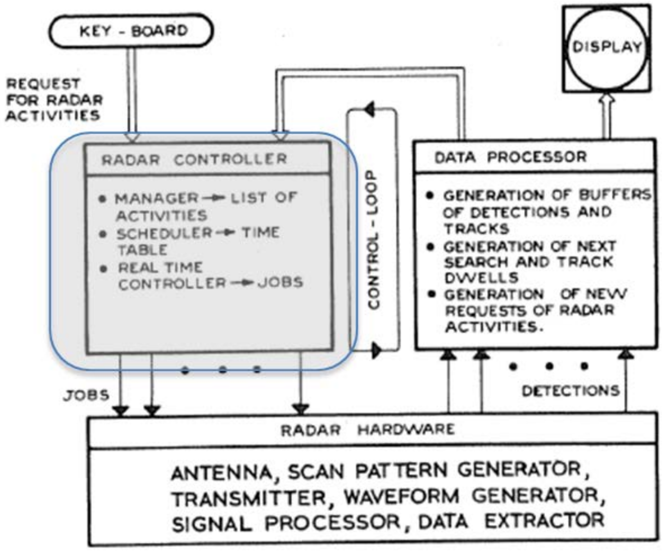
Learning form Connectome of Worms C-elegans

A GENERIC SYSTEM PERFORMING A SEQUENCE OF TASKS (GSPST)

to assign resources to perform N functions and provide them to M outputs

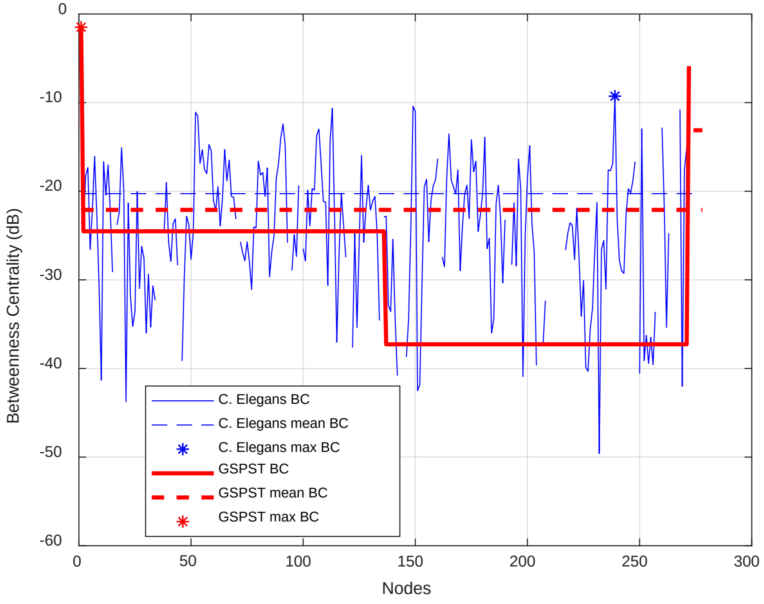
System Hubs





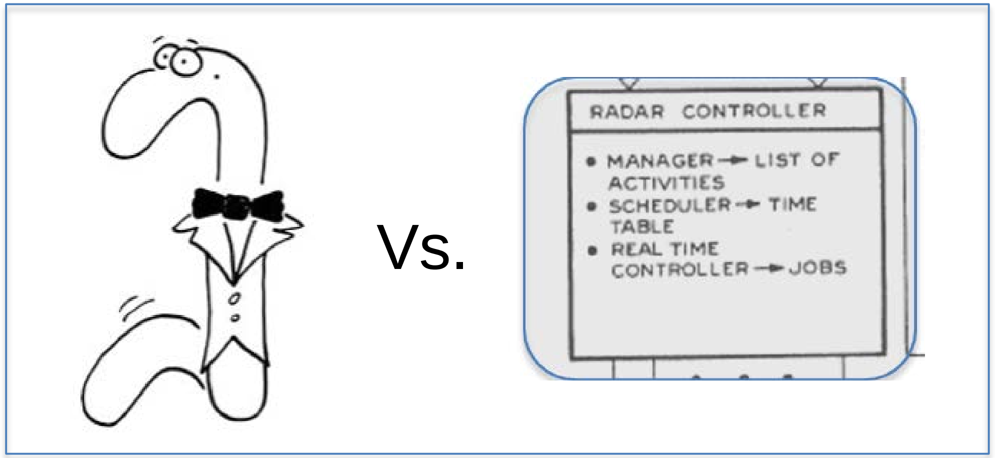
Learning form Connectome of Worms C-elegans

Logarithmic scale



	#of Nodes	# of Edges	Plecticity
C. Elegans	277	2105	**12.59**
GSPST	278	1362	**115.13**

Higher plecticity of the GSPST due to the centralized nature of the Graph (Hub nodes play a key role with respect to all the other nodes)

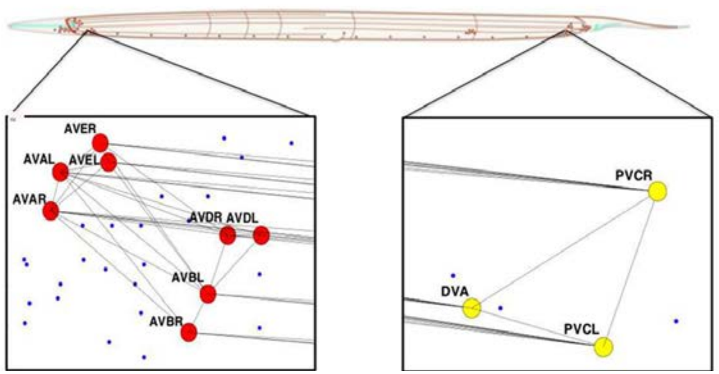


Learning form Connectome of Worms C-elegans

LESSON LEARNED FROM NATURE……

….. find the blend between distributed and concentrated architectures

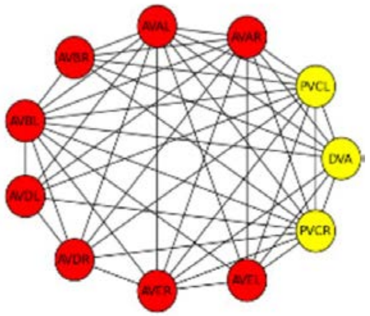
Worm C. Elegans



Rich club of the C. Elegans nervous system
(Nodes in yellow are located in the tail and those in red are located in the head)

Rich club neurons: connector hubs with high betweenness centrality, and many intermodular connections to nodes in different modules

Rich club neurons (N=11) comprise almost exclusively the interneurons of the locomotor circuits, with known functional importance for coordinate movement



A pure topological view of the rich club network

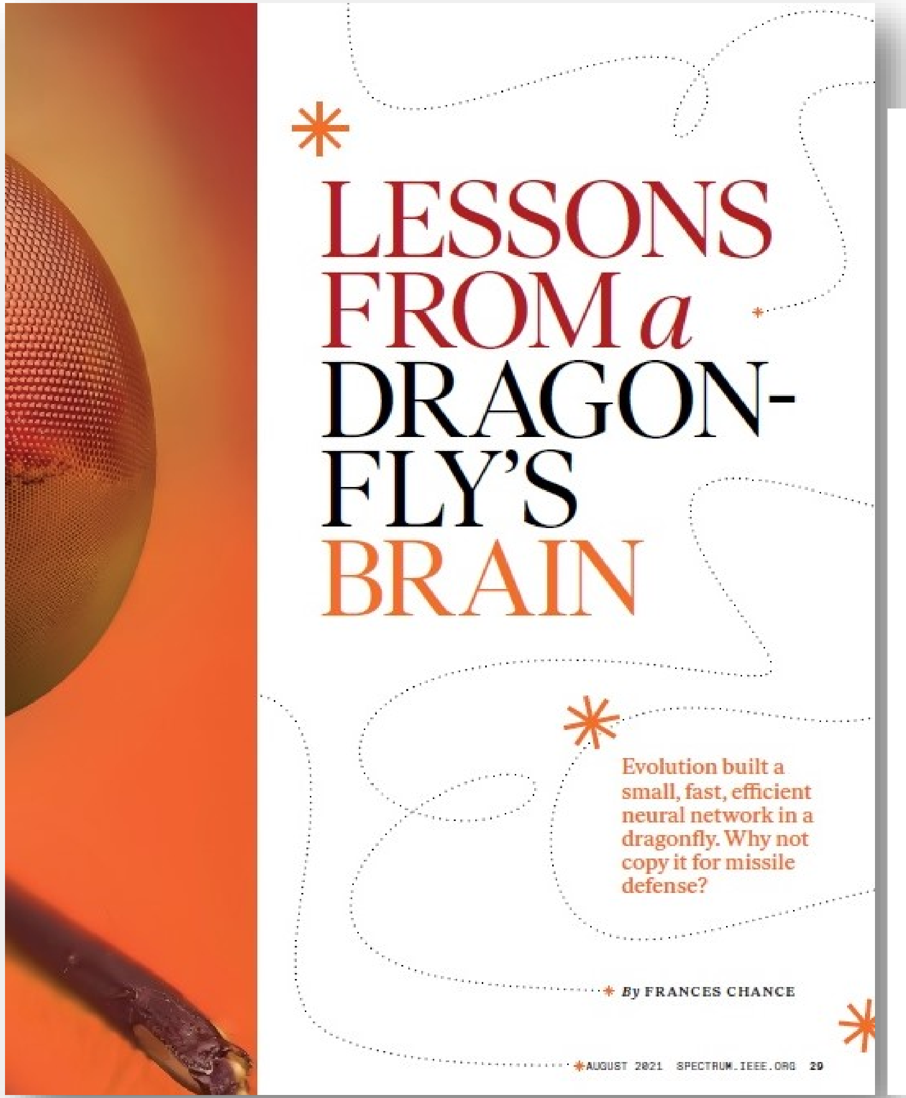
OPPORTUNITIES FOR COGNITIVE RADAR DESIGN

Towlson EK, Vértes PE, Ahnert SE, Schafer WR, Bullmore ET, "The Rich Club of the C. elegans Neuronal Connectome", Journal of Neuroscience 10 April 2013, 33 (15) 6380-6387 http://www.jneurosci.org/content/33/15/6380

Linking Controllability and Complexity of networks: A. Farina, A. De Maio, S. Haykin, (Editors), "The impact of Cognition on Radar Technology", Scitech Publishing, an Imprint of the IET Publisher, 2017. **Ch. 10,** 10.3.1.1 Linking Controllability and Complexity of two Notional Networks.
Y. Y. Liu, J. J. Slotine, and A. L. Barabasi, "Controllability of Complex Networks," Nature, pp. 167-173, July and October 2011.

Learning from Connectome of Dragonfly

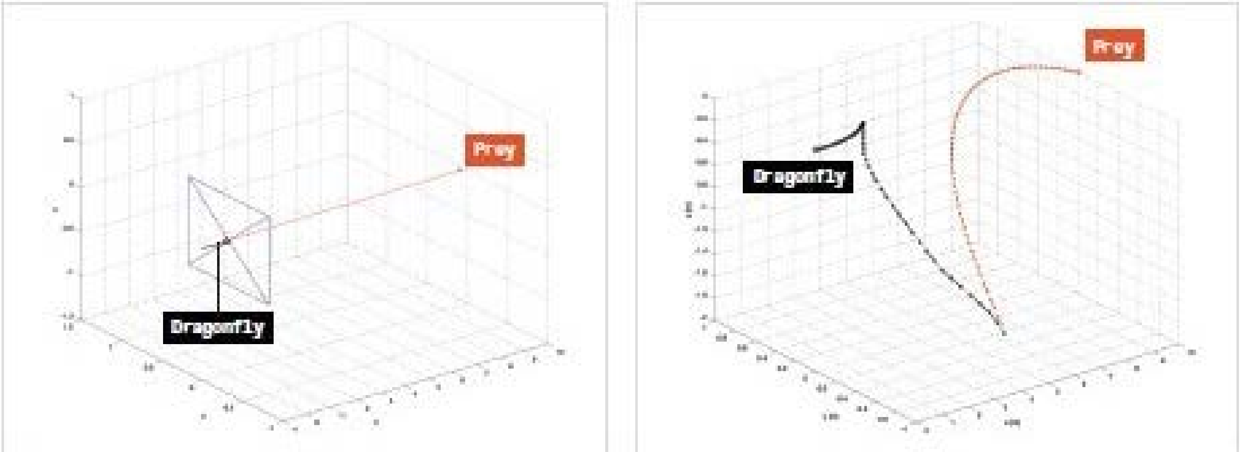
Helping to select an effective neural network (NN) architecture for intercept guidance law


LESSONS FROM a DRAGON-FLY'S BRAIN

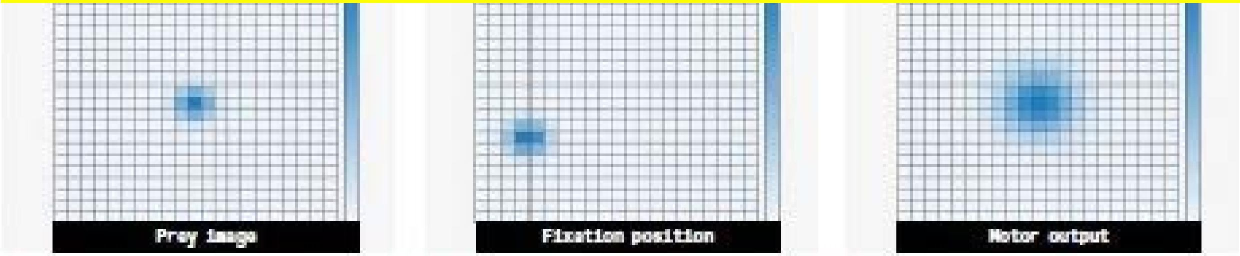
Evolution built a small, fast, efficient neural network in a dragonfly. Why not copy it for missile defense?

By FRANCES CHANCE

AUGUST 2021 SPECTRUM.IEEE.ORG 29



Infrared signature of NN activation during predating path



The model dragonfly reorients in response to the prey's turning [upper left]. The black circle is the dragonfly's head, held at its initial position. The solid black line indicates the direction of the dragonfly's flight; the dotted blue lines are the plane of the model dragonfly's eye. The red star is the prey's position relative to the dragonfly, with the dotted red line indicating the dragonfly's line of sight. On the upper right, the figure shows the dragonfly engaging its prey. Below are three heat maps of the activity patterns of neurons at the same moment; the first set represents the eye, the second represents those neurons that specify which eye neurons to align with the prey's image, and the third represents those that output motor commands.

Courtesy of IEEE SPECTRUM

Continuing to learn from Nobel Prize laureates in Neuroscience: few examples…..

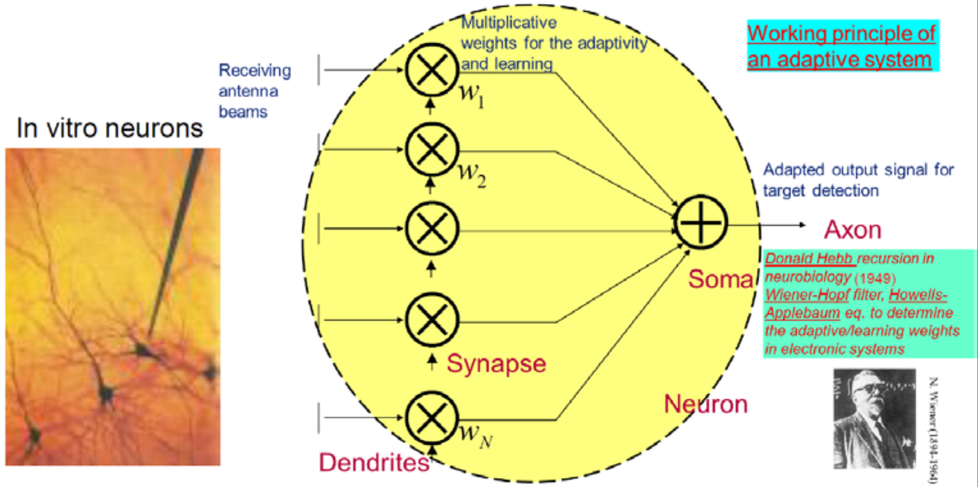
https://faculty.washington.edu/chudler/nobel.html

Nobel Prize - Neuroscience

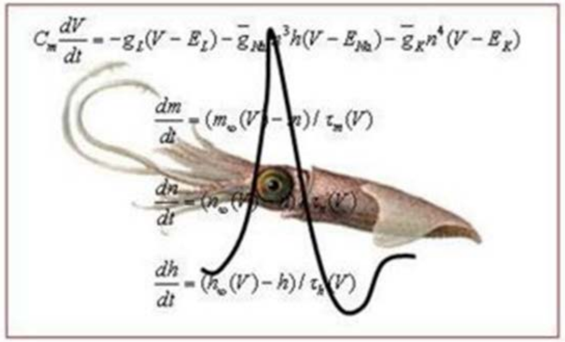
Year of Award	Name(s)	Birth and Death Dates	Nationality/Citizenship	Field of Study
1906	Golgi, Camillo	7/7/1843 to 1/21/1926	Italian	Structure of the Nervous System
	Ramon y Cajal, Santiago	5/1/1852 to 10/18/1934	Spanish	Structure of the Nervous System

1963	Eccles, Sir John Carew	1/27/1903 to 5/2/1997	Australian	Ionic mechanisms of nerve cell membrane
	Hodgkin, Sir Alan Lloyd	2/5/1914 to 12/20/1998	British	Ionic mechanisms of nerve cell membrane
	Huxley, Sir Andrew Fielding	12/22/1917 to 5/30/2012	British	Ionic mechanisms of nerve cell membrane

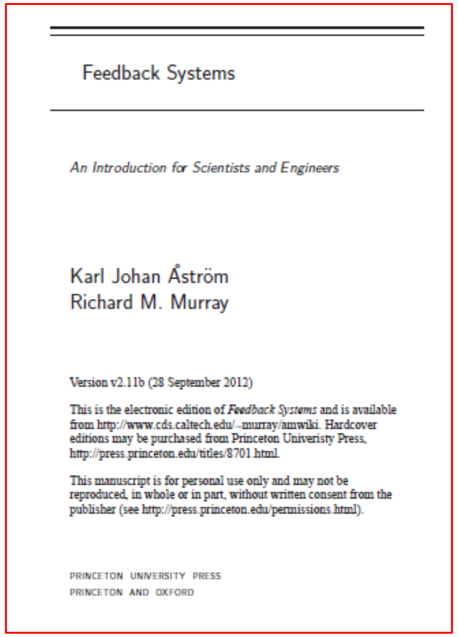
*The human brain implements the adaptivity by means of a complex network of connections, 60 trillions (=60x10^{12}) of **synapses**, among about **30 billion** (=30x10^{9}) neurons.*



Alan L. Hodgkin



Andrew F. Huxley



Feedback Systems

An Introduction for Scientists and Engineers

Karl Johan Åström
Richard M. Murray

Version v2.11b (28 September 2012)

This is the electronic edition of *Feedback Systems* and is available from http://www.cds.caltech.edu/~murray/amwiki. Hardcover editions may be purchased from Princeton University Press, http://press.princeton.edu/titles/8701.html.

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Continuing to learn from Nobel Prize laureates in Neuroscience: few examples…..

1981	Hubel, David Hunter	2/27/1926 to 9/22/2013	Canadian, American Citizen	Information processing in the visual system
	Sperry, Roger Wolcott	8/20/1913 to 4/17/1994	American	Functions of the right and left hemispheres of the brain
	Wiesel, Torsten N.	6/3/1924 to	Swedish, American Citizen	Information processing in the visual system

The New York Times https://www.nytimes.com/2019/03/27/technology/turing-award-ai.html

Turing Award Won by 3 Pioneers in Artificial Intelligence

By Cade Metz

March 27, 2019

SAN FRANCISCO — In 2004, Geoffrey Hinton doubled down on his pursuit of a technological idea called a neural network.

It was a way for machines to see the world around them, recognize sounds and even understand natural language. But scientists had spent more than 50 years working on the concept of neural networks, and machines couldn't really do any of that.

Backed by the Canadian government, Dr. Hinton, a computer science professor at the University of Toronto, organized a new research community with several academics who also tackled the concept. They included Yann LeCun, a professor at New York University, and Yoshua Bengio at the University of Montreal.

On Wednesday, the Association for Computing Machinery, the world's largest society of computing professionals, announced that Drs. Hinton, LeCun and Bengio had won this year's Turing Award for their work on neural networks. The Turing Award, which was introduced in 1966, is often called the Nobel Prize of computing, and it includes a $1 million prize, which the three scientists will share.

Over the past decade, the big idea nurtured by these researchers has reinvented the way technology is built, accelerating the development of face-recognition services, talking digital assistants, warehouse robots and self-driving cars. Dr. Hinton is now at Google, and Dr. LeCun works for Facebook. Dr. Bengio has inked deals with IBM and Microsoft.

"What we have seen is nothing short of a paradigm shift in the science," said Oren Etzioni, the chief executive officer of the Allen Institute for Artificial Intelligence in Seattle and a prominent voice in the A.I. community. "History turned their way, and I am in awe."

Drs. LeCun and Bengio in 2017 with Dr. Hinton, who created a research program dedicated to "neural computation and adaptive perception" in 2004. Re•Work

Visual comprehension (Convolutional Neural Network)

History

CNN are often compared to the way the brain achieves vision processing in living organisms.[23]

Receptive fields in the visual cortex

Work by Hubel and Wiesel in the 1950s and 1960s showed that cat visual cortices contain neurons that individually respond to small regions of the visual field. Provided the eyes are not moving, the region of visual space within which visual stimuli affect the firing of a single neuron is known as its receptive field.[24] Neighboring cells have similar and overlapping receptive fields. Receptive field size and location varies systematically across the cortex to form a complete map of visual space. The cortex in each hemisphere represents the contralateral visual field.

Their 1968 paper identified two basic visual cell types in the brain:[10]

- simple cells, whose output is maximized by straight edges having particular orientations within their receptive field
- complex cells, which have larger receptive fields, whose output is insensitive to the exact position of the edges in the field.

Hubel and Wiesel also proposed a cascading model of these two types of cells for use in pattern recognition tasks.[25][24]

https://en.wikipedia.org/wiki/Convolutional_neural_network

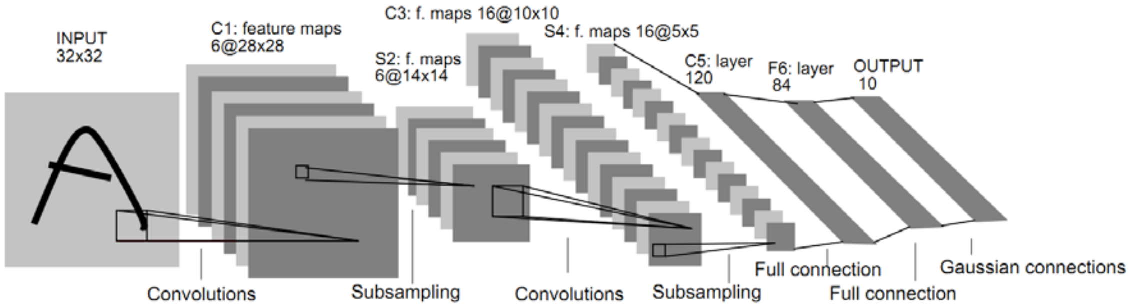


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

https://pythonmachinelearning.pro/introduction-to-convolutional-neural-networks-for-vision-tasks/

Problem description: AI application to C2

Function	Description	Time-frame	Notes
Classification	Determination of the type / class of the target	Near term	Conventional solutions have shown their limits, AI based solutions may provide better performance
Threat Assessment	Determination of the threat level of a target	Near term	Need to manage different situations based on context (e.g. peacetime, crisis). Importance of real data for various situations.
Generation of "Smart" Red Forces	Training and Wargaming	Near term	Creation of novel situations.
Analysis / understanding of the situation and determination of the action	Situation Awareness and Decision Support / Making to support the Human Operator	Medium term	Very broad class, to be implemented and verified on increasingly complex scenarios.
Management / use of resources	Support to mission planning	Medium term	Problems with many variables and constraints, generally solved with heuristic techniques.
Damage/Kill Assessment	Evaluation of damage inflicted to the enemy	Near term	Not much real data is available, more work should be dedicated towards reliable automatic solutions.

- AI promises to improve the speed and accuracy of just about everything from logistics to battlefield planning and speed in this case is not about the velocity of an airplane or an ammunition. Speed is about decision making, making the right decisions first and shortening the Command and Control cycle. From the military perspective, **Artificial Intelligence can represent a remarkable force multiplier**.



- One of the most challenging requirement relates to provide fast surveillance and **target classification everywhere, at every time, for every domain,** with guaranteed low level of false alarm rate and according to privacy and national–international regulations

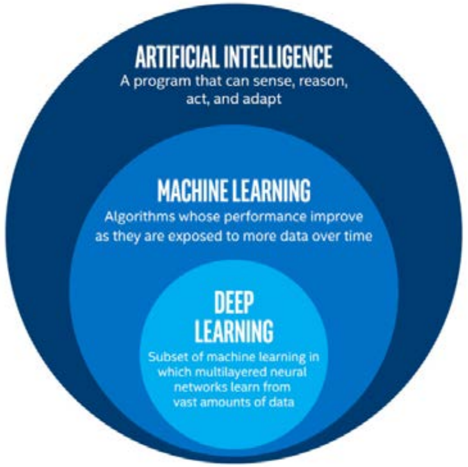
- **Targets classification is currently one of the most promising areas of application of Deep Learning (DL)** , since it shares an essential aspect of big data, i.e. there are a large number of targets detected by the sensors, which must be assessed in near real time, in order to reduce the necessary operators and system resources

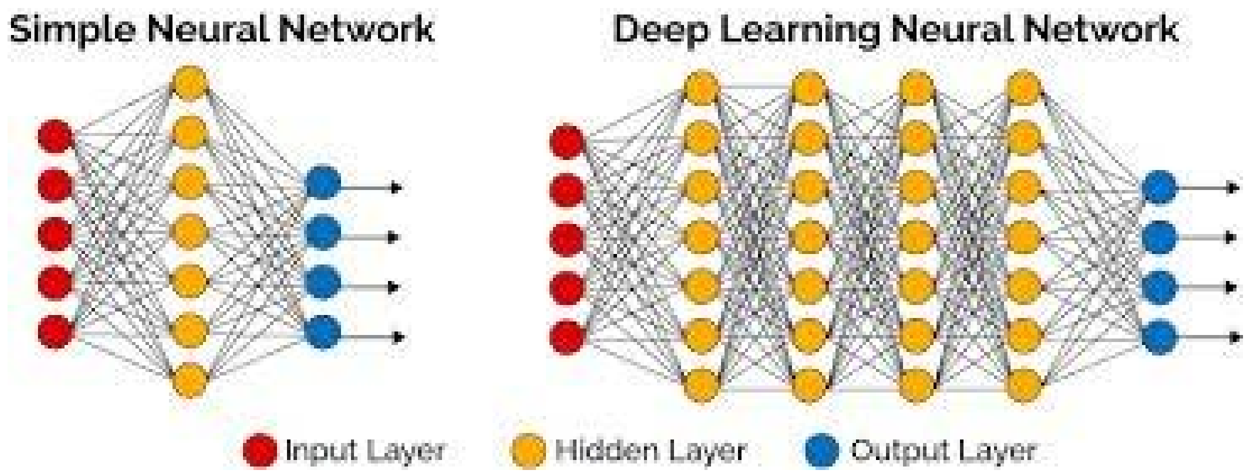


Proposed Approach

- **Our aim is to conceive, implement and test a classification architecture based on DL fully independent by any type of database**

- **Deep Learning is the subset of Machine Learning based on multilayered neural networks, which has triggered this latest revival in Artificial Intelligence.** DL is the best realization so far of a computational model that can address visual pattern recognition and natural language processing and for this reason, the investigation of DL appears quite natural for the target classification.



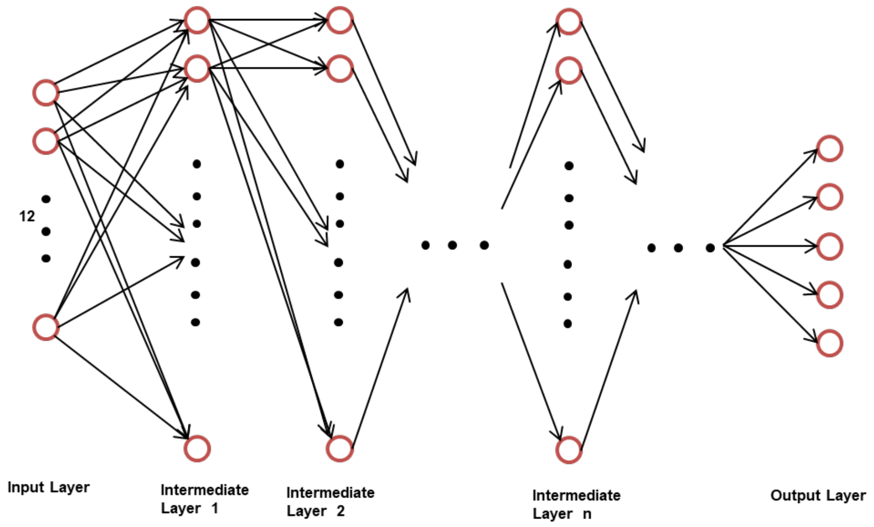


towardsdatascience.com/cousins-of-artificial-intelligence-dda4edc27b55

- The approach with neural networks is influenced by the **training methods and dataset composition**. A large amount of data is needed to train the network.

Neural Network – tools and typology

- To implement and train our neural network we use **TensorFlow**, a free and open-source software library for dataflow and differentiable programming across a range of tasks (https://www.tensorflow.org/). It is used for machine learning applications such as neural networks
- We have used a high-level TensorFlow API named ‘Estimator’. Estimators encapsulate the main actions useful to:
  - Training a network
  - Evaluate the results
  - Predict
  - Export and distribute
- **The implemented Neural Networks pertain to Multilayer Perceptron (MLP), a class of feedforward artificial Neural Network, that contains an input layer, a variable number of hidden layers and an output layer. The activation function used in each node is the standard Rectified Linear Unit (ReLU).**
- **The first layer contains 4 nodes (Latitude, Longitude, Height and Velocity) for each sensor plot**



Dataset preparation

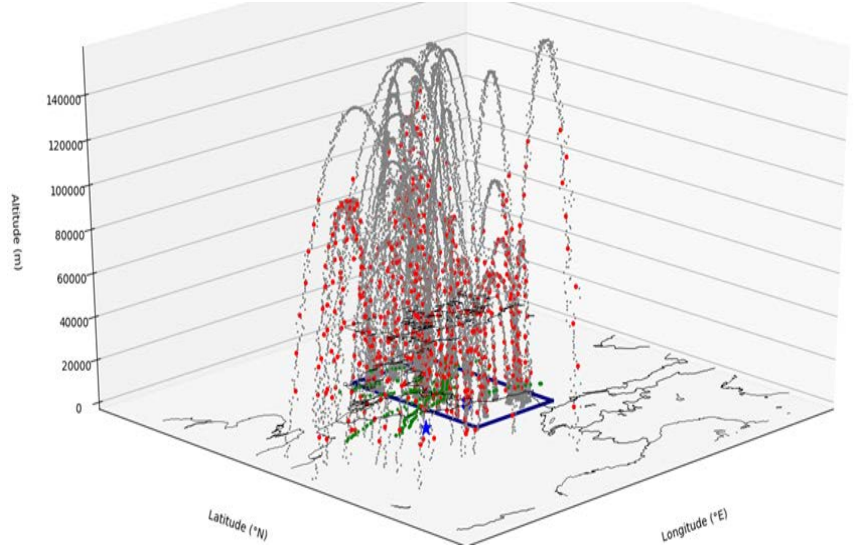
Real data

We used data from a 30’ live recording of a Leonardo secondary radar installed near to a Terminal Maneuvering Area mixed with simulated tracks of Ballistic Missiles (BMs). 1260 meaningful tracks were extracted from a live registration of a secondary radar (commercial flights)

Simulated data

- Various trajectories profiles of BMs were simulated during the three phases: boost, cruise and re-entry.

- The used BMs simulator considers:
  - one stage ballistic missile.
  - Three main forces affect the BM motion: thrust, drag and gravity.
  - Initial parameters:
    - Missile diameter, dry mass, fuel mass, thrust, Specific Impulse (ISP).
  - Other main parameters that act on the rocket in the different flight phases:
    - air density and pressure at current altitude, angle from horizontal



Achieved results

Neural network characterization: Six different neural networks have been implemented varying the number of layers from 2 to 5 and the nodes of each layer ranging from 10 to 1500.

Type of sensors: two category of sensors have been emulated pertaining to Long Range class (plot rate 12 sec and detection range 1000km) and Multifunctional class (plot rate 1 sec and detection range 150km). Ideal Pd (=1) and Pd equal to 0.8 has been introduced.

Study cases: measurement errors have been emulated using typical radars values (i.e. range error in the order of 100mt and angle error around 0.5). The number of plots available for the classification has been varied from 3 to 10.

Metric: a very simple metric has been used declaring a positive result if the network has correctly classified the target (Air Breathing Target (ABT) or BM) and, in case of BM, if the correct Class (170km, 300 km or 500 km) has been identified.

Errors						Net
No	TBM1	TBM2	TBM3	Airliner	Perc	Model
269	142	0	219	43	39,97%	60-30-10
487	71	32	65	25	71,62%	60-30-10
584	10	11	45	30	85,88%	60-30-10
270	139	1	214	49	40,12%	60-30-10
635	9	8	11	10	94,35%	500-300-50
645	9	6	8	5	95,84%	500-500-300-50
643	9	6	9	6	95,54%	500_500_300_100_50
644	8	6	8	7	95,69%	1500-1000-500-250-50
654	4	13	7	4	95,75%	1500-1000-500-250-50
655	6	5	12	4	95,90%	500_500_300_100_50
665	6	3	5	3	97,36%	1500_1500

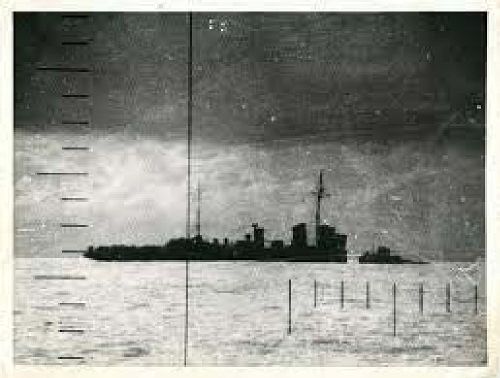
Network not optimised

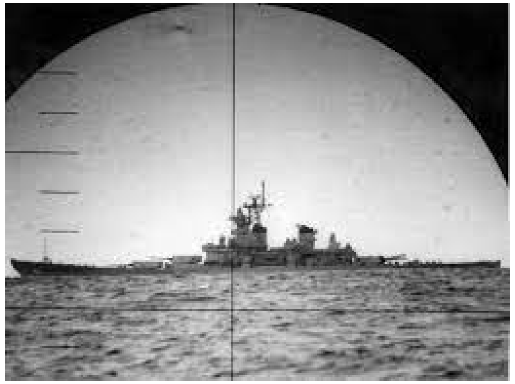
Network optimization

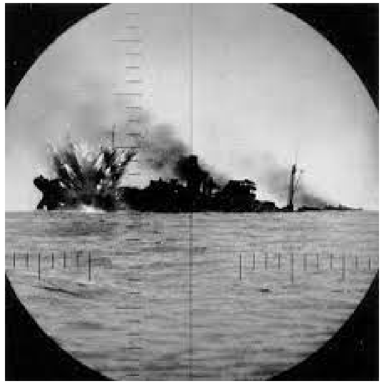
Network optimised

Problem description: image processing

- One of the needs that we want to investigate is the recognition and classification of images taken from a periscope.
- In more complex scenarios, the need arises to recognize multiple ships in the image
- Tracking in the video from the periscope
- The approach undertaken is based on neural networks which are quite effective in the classification of images
- For the feasibility study we did not receive real images from submarines and we were based on datasets available from the internet





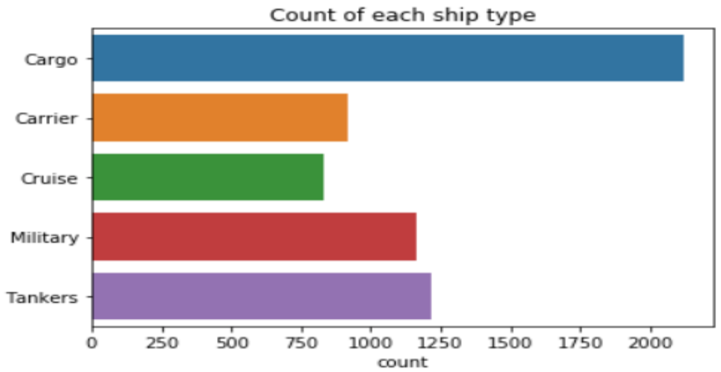


From open sources

Dataset preparation

- The starting dataset included 8932 images of different sizes, with low resolution and small dimensions
- The images are classified with the following categories:

Cargo 2120
Tankers 1217
Military 1167
Carrier 916
Cruise 832
Name: ship, dtype: int64



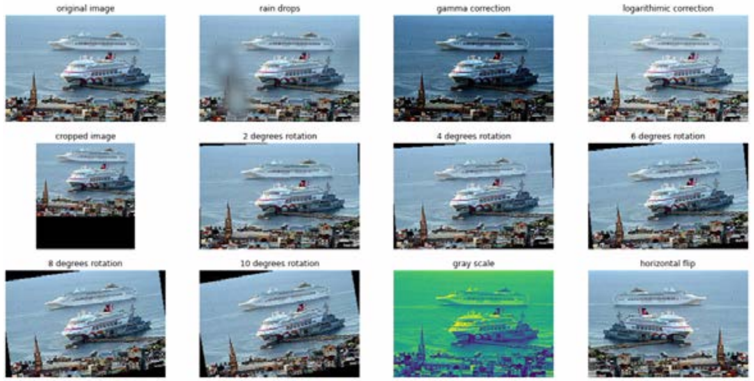
From open sources

Achieved results (example)

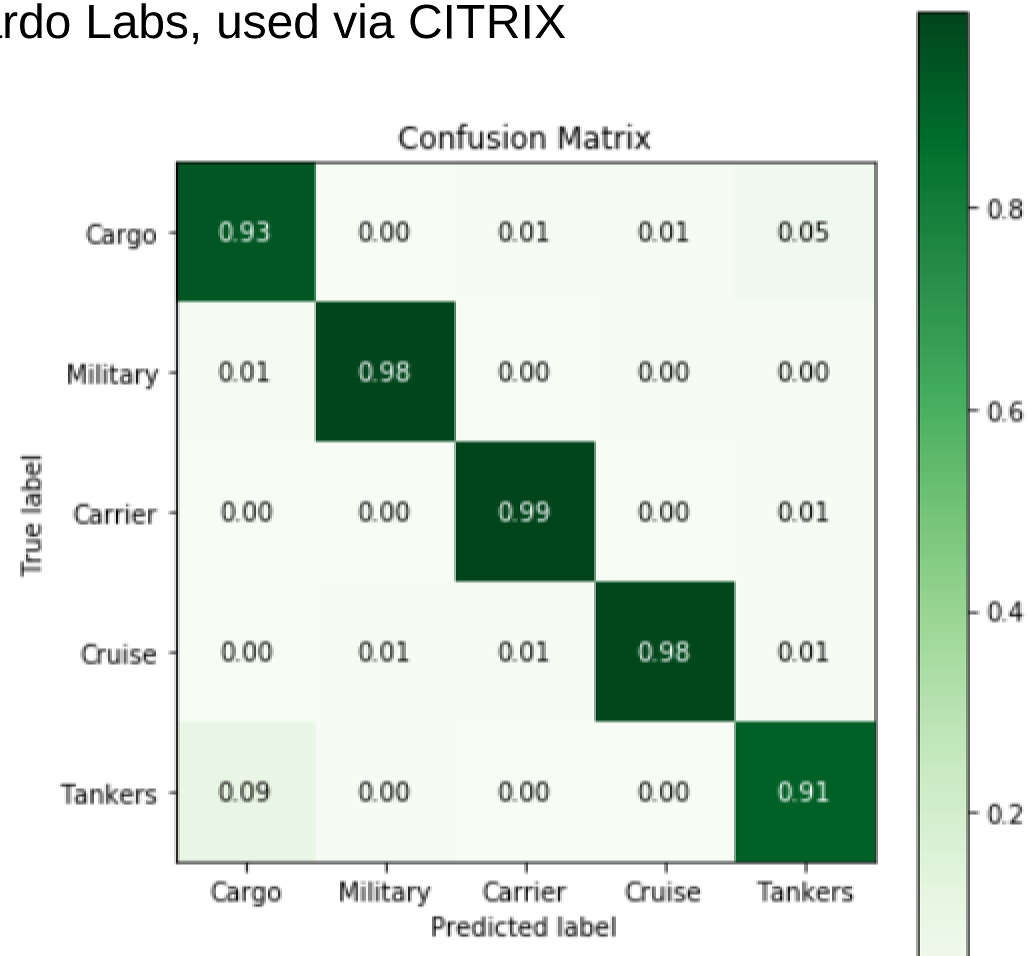
Computational resources

VMWARE Virtual Machine being tested for Leonardo Labs, used via CITRIX

- **UBUNTU 18**
- **GPU NVIDIA**
- **8 CPU**
- **124GB RAM**
- **HD 1 TB**



Training set generated by modifications of original images (rotation, flipping, correction…)

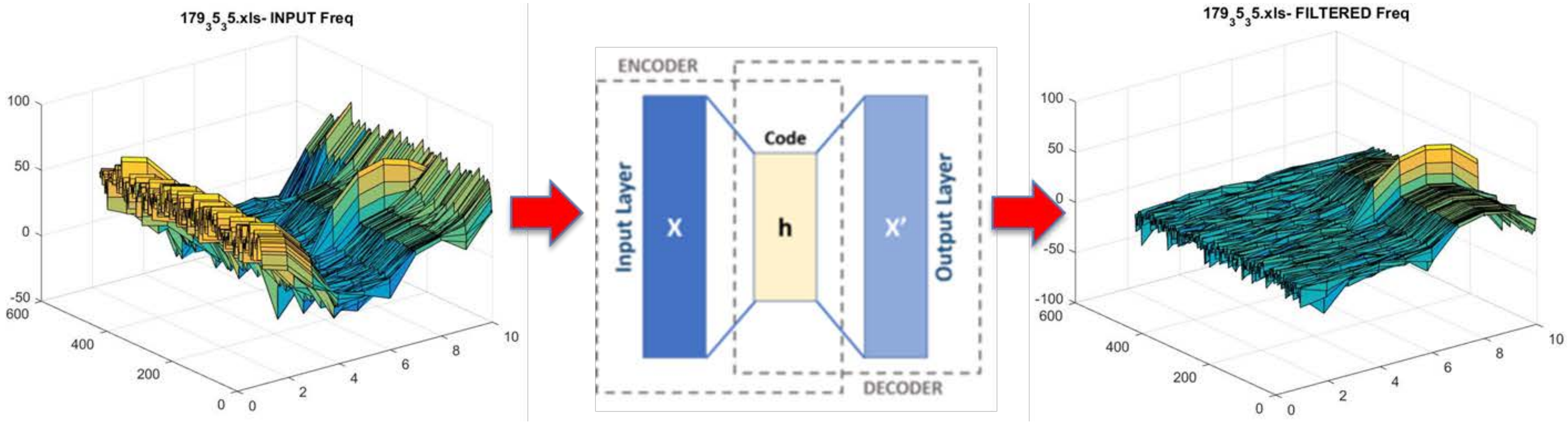


Images used for test: **2680**

Problem description: radar clutter cancellation

- The feasibility study aims to explore the possibility of introducing Artificial Intelligence technologies in the radar processing chain
- The study, in this first phase, was limited to a subset of functionalities of the processing chain, and more particularly to the Clutter Cancellation function.
- The objective is to demonstrate, through a neural network, the ability to obtain processing performance comparable or superior to those of the new generation radar.

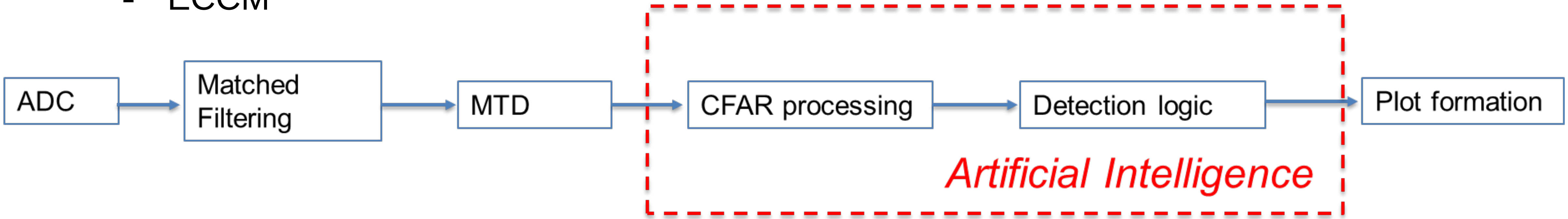
Supervised end-to-end training (signal with Clutter -> signal without Clutter).



Neural Network

Rationale of the study

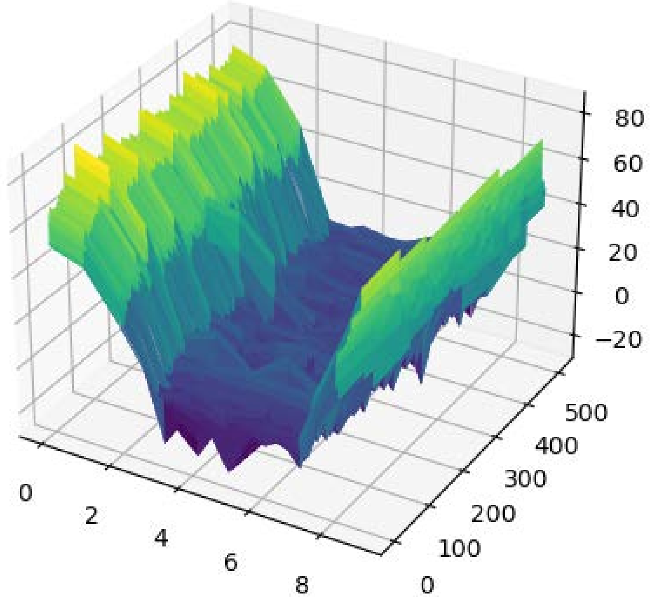
- Performance improvement in terms of accuracy and processing times
- Reduction of the complexity of the processing chain
- High flexibility and scalability on any type of radar
- HW reduction (MTBCF, cost, SWAP, logistics, maintenance)
- Quick reconfiguration and updating based on new target / clutter models and new customer requests
- Algorithm update / retraining based on data and operational experience to optimize performance in terms:
  - Clutter rejection
  - ECCM



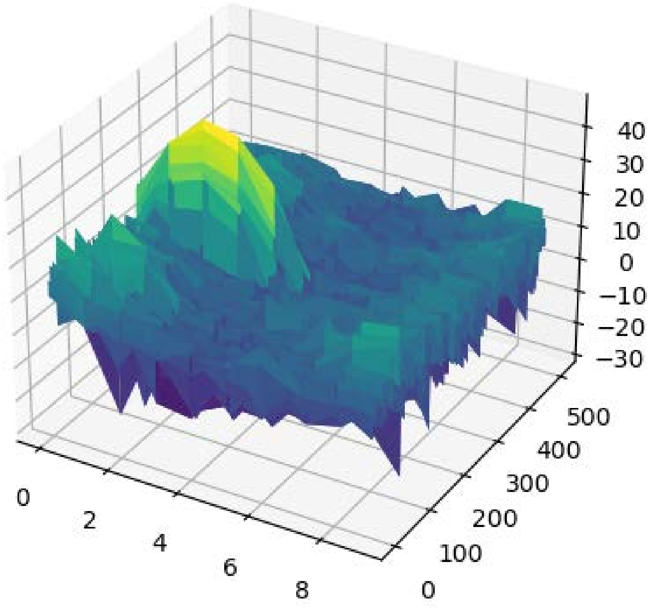
Example of results

Input

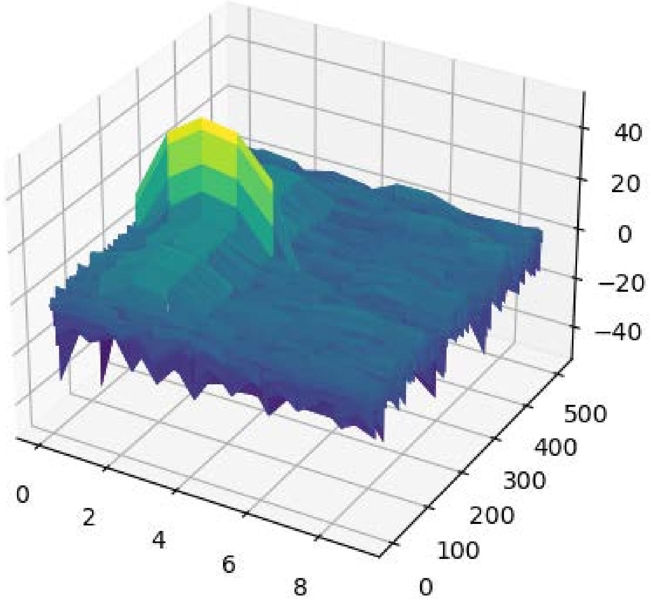
- Range: 228
- Target: 22 dB
- Target Speed: 118 m/s
- Clutter: 45 dB



Output



Target (ideal)

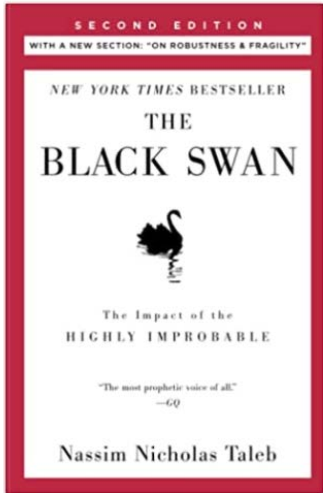


Points of criticism of AI

Data + Computing power → Data-Driven algorithms

Though, cannot give up *model-based* techniques until quality, reliability, stability and reproducibility of data-driven algorithms can be guaranteed

- **Learning requirements**: amount of data for training and over-tuning to particular datasets
- **Reproducibility**: ensure required performance levels under all operating conditions
- **Reliability**: graceful degradation
- **Understanding**: explain performance levels, network architecture and impact
- **Rare and unforeseen events**: how to simulate «unforeseen» events, how the system responds to such events (Taleb, N. N. *The Black Swan: The Impact of the Highly Improbable*. New York, NY: Random House, 2007.)



- **How to test hybrid (model-based + data-driven systems)**: how to test the interaction between different types of systems
- **Design for testability**: design AI to facilitate forensic analysis
- **Validation of training data and robustness to training data**: handle errors in ''ground truth''.

Points of criticism of AI

- AI provides little to no insight into the ‘how’ and ‘why’ of the decisions made by neural networks. It **needs to become more explainable** and interpretable to make the technology more acceptable. (Explainable AI: XAI, Explainable ML: XML) https://en.wikipedia.org/wiki/Explainable_artificial_intelligence. AI’s ACHILLES’ HEEL: **AMBIGUITY**, 22 MAY 2019, SPECTRUM.IEEE.ORG, p. 22
- AI needs of big data for specific applications
- How to make DL work well for applications where little or only weakly annotated data is available,
- **Caveats**: as Model-Driven approach, present AI systems don’t reason at the counterfactual level (If I had not taken an aspirin, would my headache have gone away?). They make decisions based on association unlike humans who can also make decisions based on counterfactual reasoning.
- **Correlation** is not to be confused with causality (or cause and effect). Firefighter and fire: firefighter near the fire → it does not mean that it is the fireman who produced the fire!
- **Learnability can be undecidable**, Nature Machine Intelligence, 07 January 2019. Machine Learning comes up against unsolvable problem. Researchers run into a logical paradox discovered by famed logician, mathematician and philosopher **KURT GÖDEL.**

BOOK REVIEW REFLECTION

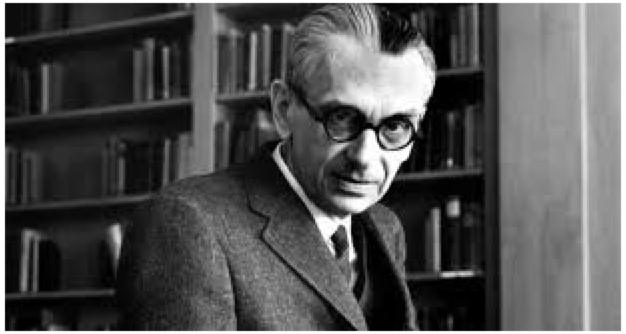
CAUSAL INFERENCE IN STATISTICS: AN ATTEMPT AT SOME REFLECTION

It is a great pleasure and a distinct honor to be invited to read and, possibly, offer some comments to Dr. Lawrence D.

(the cause) with another (the effect), where the first is understood to be partly responsible for the second. *Reality* is the state of things as they actually

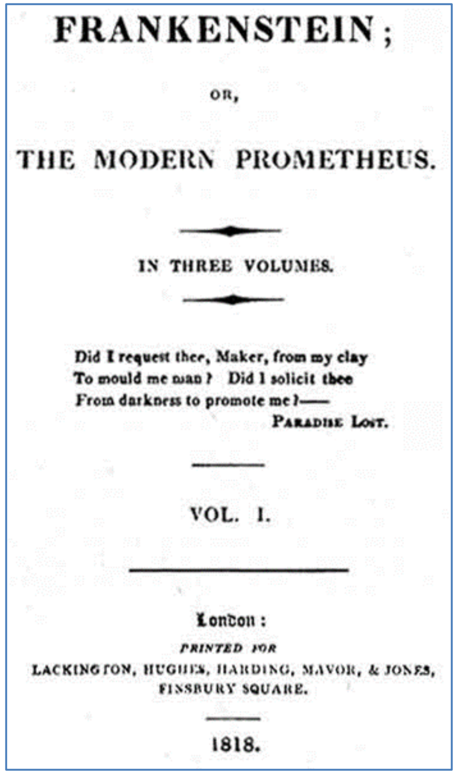
Alfonso Farina
SELEX ES (retired)
Rome, Italy
alfonso.farina@outlook.it

A., Farina, “Causal Inference in Statistics. An attempt at some reflection.” ISIF Perspectives On Information Fusion, vol. 3, 2020, pp. 36-39.



Risks associated to AI

Mary Wollstonecraft Shelley (1797 – 1851)



FRANKENSTEIN;

OR,

THE MODERN PROMETHEUS.

IN THREE VOLUMES.

Did I request thee, Maker, from my clay
To mould me man? Did I solicit thee
From darkness to promote me?——
PARADISE LOST.

VOL. I.

London:
PRINTED FOR
LACKINGTON, HUGHES, HARDING, MAVOR, & JONES,
FINSBURY SQUARE.

1818.

SPECTRAL LINES_ 02.17

What Frankenstein Can Teach Engineers

Designing technology with the best intentions can still lead to disaster

When a designer of smartphone cases made a Frankenstein Monster model for the Samsung Galaxy Note 7, the company eerily presaged the fate of what has become the most notorious digital device of the decade. Banned from airplanes and the source of sundry injuries because of a penchant for bursting into flames, the Galaxy 7 deserves to be studied by engineers for lessons about responsible practice.

Samsung discontinued the phone in October 2016 and—at least publicly—has never given a comprehensive explanation as to why the doomed phone produces so many infernos. The mystery serves as a reminder that failure has much to teach engineers—and so does *Frankenstein; or, the Modern Prometheus*, the prescient 1818 novel by English author Mary Wollstonecraft Shelley.

This year is the 200th anniversary of Shelley's completion of her novel, in May 1817. Her scenario is simple: A man creates a living being, which, grown monstrous, turns on its creator. The experience of the fictional Victor Frankenstein, who used electricity to give life to an inanimate body, shows how the best intentions can lead to unintended consequences that mock and imperil creators.

To highlight the value of engineers confronting "the fundamental questions of creativity and responsibility," MIT Press will issue in May 2017 a new edition of *Frankenstein*, specially annotated to illuminate the challenges facing technologists. "Mary was not a Luddite opposed to new technologies," writes the late Charles E. Robinson, a Shelley scholar, in his lucid introduction. Not only was she tutored in contemporary understandings of electricity and biomedicine, she grasped the risks of acting on "forbidden knowledge and playing God," Robinson writes.

While engineers and computer scientists don't design and build live, walking, talking monsters, they do create devices that have the qualities of living things. Who has not mistaken the synthesized speech of a networked computer for an actual person? Who hasn't received emails from a bot and thought, Isn't that person nice?

Digital networks don't literally have eyes and ears, but they now hold over us the power of life and death. Many medical procedures depend on the accuracy of digital instruments. So do our electricity systems, commercial airplanes, subways, and of course, the Web. Every minute of every day, in short, the specter of a digital Frankenstein monster looms.

In Shelley's novel, the chemist, Waldman, issues a similar warning, insisting that technologists "have acquired new and almost unlimited powers; they can command the thunders of heaven, mimic the earthquake, and even mock the invisible world with its own shadows."

Today, few would dismiss this assessment. What then can engineers do to reduce, if not eliminate, the chances of unwittingly creating a Frankenstein monster? Here are a few ideas:

(1) Resist the temptation to pursue projects simply because they are beautiful or too cool to resist. As the philosopher Heather E. Douglas explains in a companion essay in the new MIT edition of the novel, creative engineering often inspires feelings of awe and wonder that can obscure or erase an awareness of design challenges. When euphoria reigns, stop and take a breath!

(2) Technologists do best when they solve problems of value to people and the planet. Pursuing possibilities without regard to utility invites unforeseen blowback.

(3) Engineers should act as if creation is a shared responsibility, because their knowledge at least partly comes from others and the effects of their work inevitably extend further than themselves.

These dictums are easier theorized than put into practice, so let's give the last words to Mary Shelley, whose sense of complexity still impresses us. "Invention," she wrote in an introduction to the 1831 revised edition of *Frankenstein*, "does not consist in creating out of void, but out of chaos." For their own benefit, inventors must "give form to dark, shapeless substances." —G. PASCAL ZACHARY

G. Pascal Zachary is a professor of practice at Arizona State University's School for the Future of Innovation in Society.

- Resist the temptation to pursue projects simply because they are beautiful or too cool to resist.
- Technologists do best when they solve problems of value to people and the planet.
- **Engineers should act as if creation is a shared responsibility, because their knowledge at least partly comes from others and the effects of their work inevitably extend further than themselves.**

Feature Article:

DOI. No. 10.1109/MAES.2021.3066841

On Digital Ethics for Artificial Intelligence and Information Fusion in the Defense Domain

Wolfgang Koch, Fraunhofer FKIE, Wachtberg 53343, Germany

IEEE A&E SYSTEMS MAGAZINE JULY 2021, pp. 94-111.

AI-based Defense Systems – How to Design them Responsibly?

HEINRICH BÖLL STIFTUNG
TEL AVIV

Spotlight In order to protect their common heritage of culture, personal freedom and the rule of law in an increasingly fragile world, democracies must be able "to fight at machine speed" if necessary. For this reason, digitization in defense cannot not be confined to logistics, maintenance, intelligence, surveillance, and reconnaissance, but must equally enable responsible weapons engagement.

30 December 2021 by Wolfgang Koch

https://il.boell.org/en/2021/12/24/ai-based-defense-systems-how-design-them-responsibly

Way Ahead

Microtubules and Consciousness

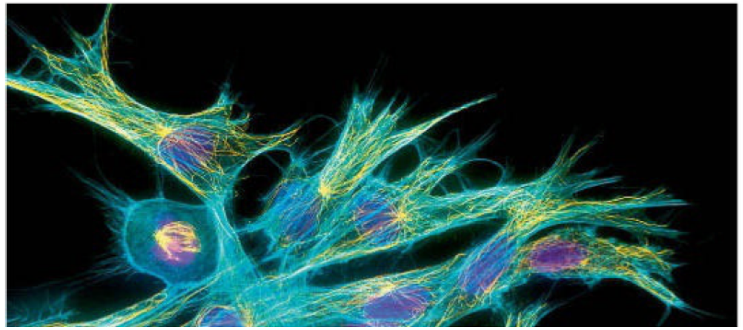
News

Quantum physics

A quantum of consciousness

Experiments on tiny structures in brain cells bolster the idea that quantum effects might explain consciousness, finds **Thomas Lewton**

THE controversial idea that quantum effects in the brain can explain consciousness has passed a key test. Experiments show that anaesthetic drugs reduce how long tiny structures found in brain cells can sustain suspected quantum excitations. Because anaesthetic switches consciousness on and off, the results may imply that



building blocks within tubulin in microtubules. The excitation diffused through microtubules far further than expected.

When Scholes and Kalra added anaesthetic into the mix, they also found that the unusual microtubule behaviour was suppressed. "The anaesthetic does interact with the microtubules and changes what happens. That

8 | New Scientist | 23 April 2022

A recent experiment displays the connection between microtubules and consciousness as put forward by Roger Penrose (Nobel prize, 2020). The effect is pure quantum.

Courtesy of Marco Frasca (MBDA)

Ideas on microtubules and cognition were put forward in our recent work (to appear). This idea was needed to connect quantum radar and cognitive radar.

Chapter 1

Quantum radar and cognition: looking for a potential cross fertilization

Alfonso Farina[1] Marco Frasca[2] and Bhashyam Balaji[3]

"What a piece of work is a man! How noble in reason, how infinite in faculty! In form and moving how express and admirable! In action how like an angel, in apprehension how like a god! The beauty of the world. The paragon of animals. And yet, to me, what is this quintessence of dust?" (Hamlet, William Shakespeare)

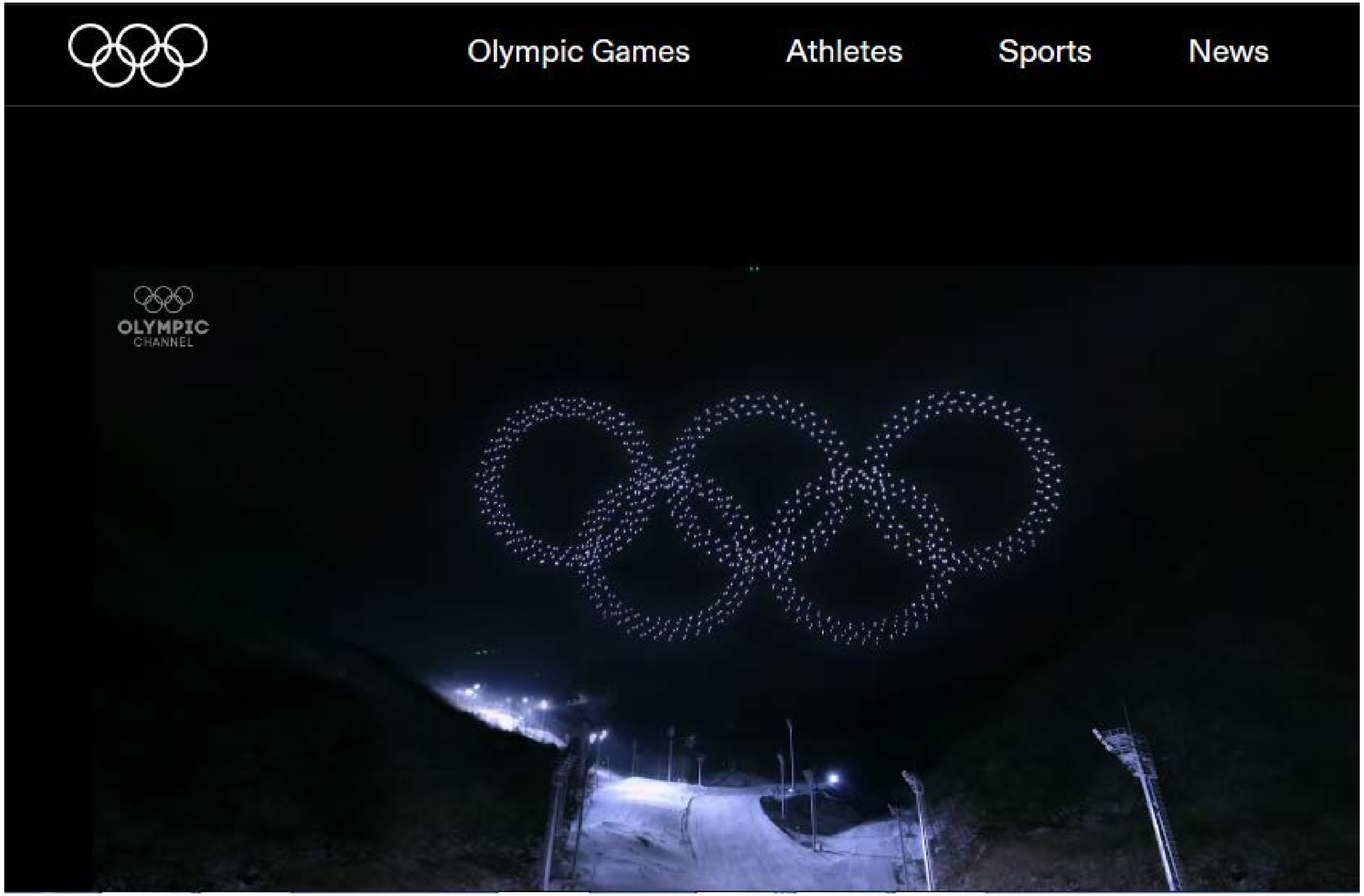
1.1 Introduction

The purpose of this chapter is to try to establish a connection between cognitive radar (being the focus of this entire book) – which is the most recent evolution of state of the art radar – with quantum physics, quantum technology and quantum sensing when it will be practically feasible.

"Next generation cognitive radar systems", IET Scitech, Editors: M. Rangaswamy, Kumar Vijay Mishra, Bhavani Shankar Mysore Ram Rao. IET Press. To appear.

Way Ahead

Computer generated images from 1200 drones: the future is now!



https://olympics.com/en/video/spectacular-drone-show-impresses-again-at-closing-ceremony?uxreference=playlist

References on AI: Long story short

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