Intelligent Embedded Systems



Intelligence for Embedded Systems (introduction to the course)

Ph. D. and Master Course

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Information about the course

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Intelligent Embedded and Cyber-physical Systems



Embedded and Cyber-physical Systems: the application scenarios



Applications, Systems and World





The Challenges

The ever-growing number of devices



Fonte: https://www.ncta.com

An example of Intelligent Embedded Systems: Rock collapse and landslide forecasting



Complex systems in remote and harsh environments



Image: Second Second





Some examples ...



PERSONAL TECH

Just How Accurate Are Fitbits? The Jury Is Out

By MIKE McPHATE MAY 25, 2016



Fitbit Charge HR Tony Cenicola/The New York Times

Many users of <u>activity trackers</u> have always harbored suspicions: How accurate are these things?

A handful of tests by <u>journalists</u> and researchers have tried to bring clarity to the issue. Results, alas, have been mixed.

The <u>latest study</u>, released by the plaintiffs <u>in a class-action lawsuit</u> against Fitbit, found that the pulsemonitoring technology used in the company's wrist-bound Surge and Charge devices was "highly

inaccurate during elevated physical activity."

Researchers from California State Polytechnic University, Pomona, had 43 subjects wear the devices as they ran, jogged and jumped rope, among other activities, and then compared the readings with those of an electrocardiogram.







FINDING ONE FACE In a million

A new benchmark test shows that even Google's facial recognition algorithm is far from perfect

Helen of Troy may have had the face that launched a thousand ships, but even the best facial recognition algorithms might have had trouble finding her in a crowd of a million strangers. The first public benchmark test based on 1 million faces has shown how facial recognition algorithms from Google and other research groups around the world still fall well short of perfection.

Facial recognition algorithms that had previously performed with more than 95 percent accuracy on a popular benchmark test involving 13,000 faces saw significant drops in accuracy when taking on the new MegaFace Challenge. The best performer, Google's FaceNet algorithm, dropped from near-perfect accuracy on the five-figure data set to 75 percent on the million-face test. Other top algorithms dropped from above 90 percent to below 60 percent. Some algorithms made the proper identification as seldom as 35 percent of the time. "MegaFace's kevidea is that algorithms

the project's principal investigator. "And we make a number of discoveries that are only possible when evaluating at scale."

> cognition algorithms inevitably fa ch challenges in the real world. Peo creasingly trust these algorithms to ctly identify them in security verifi n scenarios, and law enforcement n so rely on facial recognition to pick s ects out of the hundreds of thousands

ne nost populat benchmark untinow has been the Labeled Faces in the Wild (LFW) test created in 2007. LFW includes 13,000 images of just 5,000 people. Many facial recognition algorithms have been fine-tuned to the point that they scored near-perfect accuracy when picking through the LFW images. Most researchers say that new benchmark challenges have been long overdue.

"The big disadvantage is that [the field] is saturated--that is, there are many, many algorithms that perform above 95 percent on LFW," Kemelmacher-Shlizerman says. "This gives the impression that face recognition is solved and working perfectly." With that in mind, University of Washington researchers raised the bar by cre-

1 million Flickr images of 690,000 unique faces that are publicly available under a Creative Commons license.

The MegaFace Challenge forces facial recognition algorithms to do verification and identification, two separate but related tasks. Verification involves trying to correctly determine whether two faces presented to the facial recognition algorithm belong to the same person. Identification involves trying to find a matching photo of the same person among a million "distractor" faces. Initial results on algorithms developed by Google and four other research groups were presented at the IEEE Conference on Computer Vision and Pattern Recognition on 30 June. (One of MegaFace's developers also heads a computer vision team at Google's Seattle office.)

The results presented were a mix of the intriguing and the expected. Nobody was surprised that the algorithms' performances suffered as the number of distractor faces increased. And the fact that algorithms had trouble identifying the same person at different ages was a known problem. However, the results also showed that algorithms trained on relatively small data sets can compete with those trained on very large ones, such as Google's FaceNet, which was trained on more than 500 million photos of 10 million people.

For example, the FaceN algorithm from Russia's N-TechLab performed well on certain tasks in comparison with FaceNet, despite having trained on 18 million photos of 200,000 people. The SIAT MMLab algorithm, created by a Chinese team under the leadership of Yu Qiao, a professor with Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, also performed well on certain tasks.

Nevertheless, FaceNet has so far performed the best overall. It delivered the most consistent performance across all testing. The huge drops in accuracy when scanning a million faces matter because facial recognition algorithms inevitably face such challenges in the real world. People increasingly trust these algorithms to correctly identify them in security verification scenarios, and law enforcement may also rely on facial recognition to pick suspects out of the hundreds of thousands of faces captured on surveillance cameras. The most popular benchmark until

The effects on the considered applications





How to deal with that?

Intelligence for embedded systems



Intelligence for embedded systems



Intelligent Objects/Devices



Line up to the Unit Layer



Continuously Learning Complex Behaviors



Continuously Learning Complex Behaviors



Designing Intelligent Embedded Systems: from centralized



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Designing Intelligent Embedded Systems :to distributed intelligent systems



Capturing the relationships among the sensors ...







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Distributing Intelligence among the Units



Intelligence or "is this an Al course?"

- The adjective *intelligent*, when associated with a sensing system, can be inflected differently, depending on the reference community
- As such, it may imply:
 - ✓ the ability to make decisions
 - the capability of learning from external stimuli
 - ✓ the promptness in adapting to changes
 - the possibility of executing computationally intelligent algorithms



The theoretical framework: three milestones

- All the above definitions, explicitly or implicitly, rely on a computational paradigm or application which receives and processes incoming acquisitions to accomplish the requested task.
- Under this framework, the literature generally assumes that sensors are fault free, that data are stationary, time invariant, available and ready to be used and that the application is capable of providing outputs and taking decisions.
- Unfortunately, assumptions about the quality and validity of data are so implicitly taken as valid by scholars that, most of the time, even their existence as assumptions is forgotten.

How is the course organized?

- The course presents the intelligent-based methodological and technical aspects making embedded systems and embedded applications able to deal with uncertainties and evolving environments.
- The course addresses the following aspects:
 - From metrology to digital data
 - Uncertainty, information and learning mechanisms
 - Emotional cognitive mechanisms for embedded systems
 - Adaptive mechanisms in embedded systems
 - Learning in nonstationary and evolving environments
 - Cognitive Fault Detection and Diagnosis



Lesson	Schedule
1)	23/01/17
2)	01/02/17
3)	03/02/17
4)	08/02/17
5)	13/02/17
6)	22/02/17
7)	27/02/17
8)	03/03/17

Room Seminari (DEIB) Seminari (DEIB) Seminari (DEIB) Seminari (DEIB) Seminari (DEIB) Conferenze (DEIB) Seminari (DEIB) Seminari (DEIB)

Time

13.15-16.15 13.15-16.15 13.15-16.15 13.15-16.15 13.15-16.15 10.15-13.15 13.15-16.15 09.15-13.15



- Slides provided by the lecturer
- Reference book:
 - "Intelligence for Embedded Systems: A Methodological Approach",
 C. Alippi, Springer, 2014
- Selected papers



MathWorks – MATLAB

- Download from the POLIMI web site
- Servizi On Line -> Servizi ICT -> Software Download -> Matlab
- STMicroelectronics IDE for embedded programming in C language
- Codes and Examples available on the course web page



Project/Thesis

- a) Analysis of the literature
- b) Design of a solution
- c) Development of the designed solution
- d) Experimental Analysis
- Different combinations for a, b, c, d but a+b+c+d= 100%
- Different workloads for Ph.D. and Master Students
- Up to two people
- Knowledge of Matlab and C/C++
- Topics available at the end of the course