Artificial Intelligence, Machine Learning and Sensor Data Fusion

Lyudmila Mihaylova
The University of Sheffield
Sheffield, United Kingdom
l.s.mihaylova@sheffield.ac.uk

Wolfgang Koch
Fraunhofer FKIE
Wachtberg, Germany
w.koch@ieee.org

Recent years witnessed tremendous developments in artificial intelligence (AI), machine learning (ML), computer vision, and autonomous systems. While AI focusses on incorporating human intelligence to machines, ML can be seen as a range of tools aimed to empower computer systems with the ability to "learn". AI is seen as a broader concept compared with ML [1]. Figure 1 shows the relationship between these three related areas.

Considered in the light of sensor data fusion and the International Society of Information Fusion (ISIF), the area of ML has been present with different developments and in various ways–from biologically inspired neural networks to sequential Monte Carlo probabilistic methods for non-linear systems with non-Gaussian distributions. However, it is mainly in recent years, when ML methods became popular and expanded towards trustworthy ML and explainable AI. These are especially linked with the necessity to introduce different levels of autonomy [2], [3] and find the reasons or causality of events which brings the level of explainability. These two are especially linked with sensor data and nowadays data come both from "hard sensors" from different modalities such as radar, acoustic sensors, LiDAR, combined with optical, thermal cameras, and wireless sensor networks but also from soft sensing modalities (Internet of Things, social networks such as Twitter, Facebook, and others). Moreover, data arrives with different time rates and levels of accuracy. Making sense of such multiple heterogeneous data is a challenging task that has been extensively studied, but the provision of reliable solutions for autonomous and semi-autonomous systems is a task that remains only partially solved. Fusion of data from multiple heterogeneous sensors of this type is part of the challenge; even more so when the autonomous decisions have to be performed sequentially and in real-time. This is especially important for safety critical tasks such as with unmanned aerial vehicles (UAVs), aircraft flight control systems, the Future Combat Air System, digital health systems, and many others.

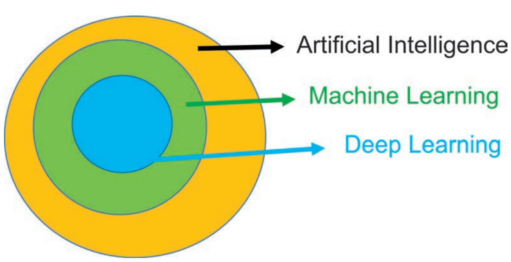

Figure 1
Artificial intelligence, machine learning, and deep learning [1].

ML methods can be subdivided into *model based* and *data-driven*. There is an increasing interest especially in reinforcement learning with many applied areas, one of them is for smart cities [4]. There is a trend towards data driven methods in which mathematical models are not necessarily present. Instead, patterns from data are autonomously learned and captured to represent these patterns and work without mathematical models that have many parameters and are difficult to calculate in short time scales. At the same time, AI methods need to be able to deal not only with big data, but with missing or incomplete data. Representing confidence levels and uncertainty from the integration of heterogeneous large-scale data still remains a challenging task. This leads to the next question about the level of trust in the developed AI methods.

TRUST, TRUSTWORTHY SOLUTIONS, AND EXPLAINABLE AI

ML methods as a branch of AI have been actively developed in the past decades to address the tasks of trustworthiness. We need to know where the strengths of AI methods are and when we can rely on them. AI provides a range of useful tools, but these can work well under certain conditions; for instance, different environmental or methods related constraints. An example of important environmental conditions for ML and computer vision methods are lighting conditions and other weather conditions or intentional adversarial changes (called adversarial attacks aimed to modify the data and to mislead the overall solution, e.g., in image classification and segmentation). Awareness of such challenges, constraints and other limitations needs further theoretical results and their practical validation before having AI algorithms as part of a UAV or an airplane, used without the presence of a human.

TRUST

To answer this question about trustworthiness of the developed solution, the first step is to characterise what we understand by "trust" in this context. The word trust means: "firm belief in the reliability, truth, or ability of someone or something". Being aware of this, the next question is how to characterise it numerically and have it as part of the learning process in AI solutions. The level of trust can be specified by a probabilistic measure, such as a variance of a Gaussian distribution, a score, a fuzzy logic rule, or by other ways. Under a Gaussian assumption about the considered noises, by propagating the mean and the variance could be a way to answer such questions. The variance as a tool of uncertainty quantification has been proven to be very powerful, especially in image classification, segmentation object tracking, and other inference tasks and can be represented within the Gaussian process methods framework and other upper bounds [5].

THE USER'S PERSPECTIVE

The development of methodological foundations during the past decades was linked with areas such as image fusion, time series analysis, reinforcement learning for robotics, transport systems, communications, and many others. The level of trust in the AI solution needs to be communicated quickly and in the best way to the users.

The user needs to trust the AI systems and be able to operate easily with them. The users need to understand what the AI system is offering, how to use it, and its advantages and limitations. However, the user may not necessarily need to know how exactly the AI system is designed and what methods are embedded.

EXPLAINABLE AI

Explainable AI has a big potential to find the main factors and inherent causes of events and occurrences. Explainable, responsible AI are concerned with questions like: "What is happening and what are the consequences of it?". Heat maps can be especially useful to understand where the objects of interest are, how to interpret them in the context of the overall task. and decision making. Heat maps could be seen also as a tool of quantifying uncertainties and understanding where things work and where deficiencies are present. An example is a heat map for the solution from image classification or for localisation with fingerprinting (Gaussian process methods).

Trustworthy, explainable, and resilient AI solutions need to be modular and to afford further development of all their components during the whole cycle of life. These could be achieved with efficient fusion at the different levels of sensor data, information, knowledge, and ontologies. Scalability adds another level of requirement and it is needed not only with respect to data, states (objects of interest), but is linked with communication constraints, especially for real-time tasks.

DEEP LEARNING FOR DATA FUSION

Data fusion methods have received a lot of developments over the past decades. Well-established methods for tracking such as the interacting multiple model filters, multiple hypothesis tracking [6], [7], or other fusion approaches based on the Dempster–Shafer theory have reached a high level of maturity. In the past, mainly high-level fusion algorithms were developed—for decision making, command and control, knowledge fusion, and fusion of ontologies, whereas the past 10 years witnessed the development of low-level fusion methods—such as for centralised, decentralised tracking, navigation, localisation, situation awareness, and related areas gained a momentum.

Current trends include developments of multiple types of sensor data fusion with convolutional neural networks (CNNs), transformers, kernel methods such as Gaussian process regression, and combinations between them, variational inference, to name a few and many others. New results were reported with deep learning methods, reinforcement learning for image classification, image segmentation, and others. ML methods are also core methods for cyber-security and cyber-physical systems.

Still fusion of multiple types of sensor data with deep learning methods for object detection, multiple target tracking, and localisation is an open area of research. How to fuse data from different modalities, such as images with inertial measurement unit data with data from social networks and other data, needs further attention.

CONCLUDING REMARKS

AI and ML methods are capable of providing efficient solutions and these are valuable to support human decisions, e.g., a pilot of an aircraft operating in difficult weather conditions or autonomous landing of a UAV. The development of trustworthy, resilient ML methods for cyber-physical systems is a big area of research that needs further attention and explainable results.

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