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Perspective:

Physical artificial intelligence (PAI): the next-generation artificial intelligence[*]

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Artificial intelligence (AI) has been a driving force for innovation and social progress in various domains (Pan, 2017). However, most of its industrial applications have focused on the signal processing domain, which relies on data generated and collected by different sensors. Recently, some researchers have suggested combining digital AI (DIAI) and physical AI (PAI), which could lead to a significant advancement in the theoretical foundation of AI. In this paper, we explore the concept of PAI and propose two subdomains: integrated PAI (IPAI) and distributed PAI (DPAI). We also discuss the challenges and opportunities for the sustainable development and governance of PAI. Since PAI requires continuous processing of signals from distributed sources across the edge, fog, and Internet of Things (IoT), it can be seen as an extension of the distributed computing continuum system in the field of AI.

1 Introduction

AI has been widely applied in various academic domains and industrial applications, not only in the typical domains of computer science, such as natural language processing (NLP), speech recognition, face detection, and image classification, but also in other disciplines, such as agriculture, biology, and chemistry. The aim of this paper is not to provide a comprehensive review of the history and application of AI, but rather to highlight the existing AI applications related to PAI. Therefore, we will give only a brief overview of the essential aspects of AI.

AI originated from the idea of building a training machine from neurons, a concept proposed by McCulloch and Pitts in 1943 (Zhang L and Zhang, 1999). Since then, various neural network (NN) milestones have been achieved by researchers, such as the backpropagation algorithm in 1988 (Hecht-Nielsen, 1992). LeCun et al. (1998) proposed the convolutional neural network (CNN) with back-propagation, and in 2006, the fast training of the NN was addressed. The rapid development of AI, including NN, began in 2012 (Yadav et al., 2015) with the support of advanced and affordable computing hardware such as graphics processing unit (GPU) cards. NNs are essential for powering AI, but the development of AI domain has also been influenced by other disciplines, such as knowledge modeling. We illustrate the

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relationships among NN, AI, and other related concepts in Fig. 1.

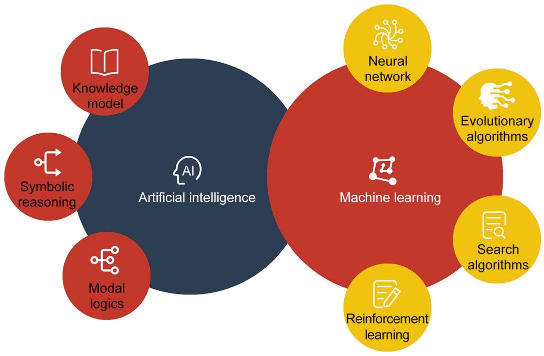

Fig. 1 Disciplines and techniques associated with artificial intelligence

Since NNs are important in the history of AI development, we review the history and successful algorithms of NNs in this section. The success of deep learning stems from deep NNs, especially CNNs applied to image classification (Alom et al., 2018). Most NN algorithms are supervised, such as CNNs and recurrent neural networks (RNNs) (Ma et al., 2022). CNN and its variants are used for classification and recognition tasks, such as image classification and face recognition. RNN is different from CNN because it considers temporal information in the NN.

RNN, including its variant long short-term memory (LSTM), has become popular in speech recognition and language translation applications. Semisupervised learning, such as generative adversarial networks (GANs), is often used in image generation, image enhancement, and video games (Creswell et al., 2018).

Deep learning algorithms can be classified into supervised, semisupervised, unsupervised, and reinforcement learning algorithms based on the level of supervision during the model training phase (Mahesh, 2020). In the early stages of their history, most supervised deep learning algorithms were widely applied in face recognition, text sentiment classification, speech recognition, and other similar tasks. When the training data are not fully labeled, semisupervised learning algorithms are usually preferred. On the other hand, unsupervised learning does not depend on training data labeling but learns from the internal relations derived from the initially defined features, such as auto-encoders (AE), GAN, and restricted Boltzmann machines (RBM). In reinforcement learning, the algorithms can obtain only incremental data instead of all available data in each processing step.

In addition to computer science applications, AI has profoundly and extensively transformed both academia and various industries. For example, it has been used to facilitate the prediction of the process of catalysis utilization (Li et al., 2017). In the financial market, AI has been used in dynamic pricing and fraud detection (Ryman-Tubb et al., 2018). In the energy domain, AI has reduced electricity consumption (Cheng LF and Yu, 2019) and improved solar modeling (Belu, 2013). In agriculture, AI has reformed the detection of fruit ripening (May and Amaran, 2011).

Despite the benefits of AI in various domains of research and industries, AI faces some limitations. Most of the current AI applications are confined to specific tasks. For example, CNN is effective in image classification and text classification, while RNN is effective in machine translation and speech recognition. AI still struggles with handling trivial details and complex business rules, and some of these problems have been the focus of researchers (Xu et al., 2020). Moreover, most AI algorithms rely on binary codes or numbers, because they lack the high-level logical inference and problem-solving skills that humans have, but not every real problem can be translated into pure mathematical problems. For instance, AI may have difficulty in understanding the semantic differences between the sentences “MacBook can be used as a chopping board” and “MacBook is a computer” in the framework of data-information-knowledge-wisdom (DIKW) (Frické, 2019). Furthermore, AI often works like a black box because researchers know only that AI works well, but they do not know the reasons behind its success for any specific problems. Therefore, explainable artificial intelligence (XAI) (Zhang QS and Zhu, 2018; Arrieta et al., 2020) has emerged as a popular research domain that aims to uncover the reasons behind the success of some specific NN algorithms.

2 Concept expansion of PAI

2.1 Reason for concept expansion

As described in the previous section, the concept of AI currently refers to processing data and signals in the computer network. Even the hardware that is related to AI captures only the input data and delivers the output data from the AI system, as shown in Fig. 2. For example, the smart home (Marikyan et al., 2019) supported by Amazon's Alexa speech assistant (Karppi and Granata, 2019) is based on this concept. Miriyev and Kovač (2020) introduced the term DIAI to refer to the current popular data-based and data-processing AI.

Fig. 2 Hardware architecture related to artificial intelligence

In contrast to DIAI, Miriyev and Kovač (2020) proposed the concept of PAI, which refers to nature-inspired robots that are driven by intelligence. Miriyev and Kovač used the bee robot to illustrate the concept of PAI, which is a multidisciplinary field that integrates autonomous robots, materials, structures, and perceptions. PAI requires the balance between software (intelligent system) and hardware (material, mechanics, etc.). As shown in Fig. 3, PAI draws its inspiration from the fields of material science, mechanical engineering, computer science, chemistry, and biology.

In Fig. 3, the initial input data are taken for feature extraction, producing derived values that are designed to be informative and nonredundant, which facilitates subsequent learning and in some cases leads to better results. Classification aims to summarize the rules in the previous data and results and to predict the outcomes for another part of the data. We can use several applications to better understand this process:

1. In medical diagnosis, for example, the inputs can be symptoms, that is, a set of variables that describe a patient's health status (e.g., fever and glucose levels). Human expertise is required to transform raw data into useful features, but it can be complemented by automatic feature extraction methods. The classification and prediction algorithms act as experts and further process and summarize the transformed features

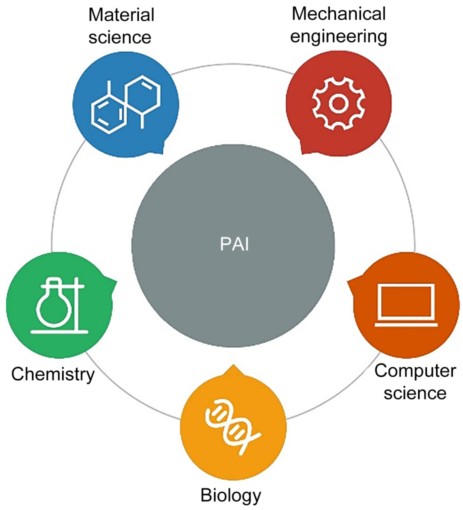

Fig. 3 Multidisciplinary nature of physical artificial intelligence (PAI)

to obtain the output, which in this case is the patient's specific physical condition.

2. Traditionally, new drug development has been expensive, involving the cost of many failed attempts. Therefore, there are strong expectations for the use of distributed computing to improve research and development (R&D) efficiency in AI pharmaceutical approaches. In this case, the inputs can be peptides or protein sequences. Human expertise is required to transform raw data into useful features, but automatic feature extraction methods can also be used. The number of peptides and proteins is now enormous, and the affinity of peptides and protein sequences can be quickly calculated using classification and prediction algorithms rather than human brain operations.

3. When we recognize a dog or a cat, our brain subconsciously extracts and stores features such as differences in face shape, ears, and whiskers. When we see these features again, we identify the animal species by matching the features with those stored in our brain. This process of refining features is known as feature extraction.

The concept of PAI is a restricted concept that is especially limited by the physical space. However, with the development of cloud computing and edge computing, devices connected to the network are more popular than standalone devices. Therefore, we think that it is necessary to extend the concept of PAI to a definition without restrictions, especially physiological restrictions.

2.2 Extended concept

In the concept of PAI (Costeira and Lima, 2020; Miriyev and Kovač, 2020), PAI refers to the typical robot and robot system. Following the notation of PAI, we propose to extend the concept of PAI to all potential applications that are not limited to a specific physical space and processing capability. Here, we use several examples of potential PAI applications to explain the proposed extended concept of PAI with an emphasis on the AI capability:

1. PAI in IoT. IoT is a typical mixed application of the cloud, sensor, software, and data analytics (Srinivasan et al., 2019). The robot integrates the hardware and software in one complete intelligent machine, while IoT can be distributed to either a small space such as a room or a wide area such as a city (Liao and Chen, 2022). Since AI can be used to improve the stability of each node of IoT, such as sensors or central data analytics and prediction, IoT is a typical application domain for PAI. The IoT node used for sensing and control needs the support of science and technologies, materials, chemistry, mechanics, computer science, and even biology.

2. PAI in automobile. The self-driving car can be considered as a variant of the intelligent robot system. The self-driving car has the same essential features as the normal robot: sensor, embedded computing module, mechanical system, new material, and so on. The self-driving car is often connected to the Internet for navigation, and the latter provides the distributed system's feature for the self-driving car.

3. PAI in agriculture. Agriculture is one of the most successful applications of PAI. Sensors, including cameras, temperature meters, and hygrometers, are used to monitor the growth progress of plants and predict the best harvest time. Defects are often detected to alert the potential risk for an intervention.

4. PAI in healthcare. Healthcare, especially healthcare for prevention, is a typical application of PAI. The biological sensors and chemical sensors are used to monitor the elderly and the patients to predict potential risks (de Fazio et al., 2021), such as falling or an unstable situation; the central server is notified by the edge device when the risk occurs. The computation occurs at both the edge sides and the central servers.

5. PAI in logistics. PAI has been extensively used in multiple aspects of logistics. The "last mile" is the expensive and hard problem of the logistics industry that involves parcel and food delivery. Some delivery robots and drones (Janebäck and Kristiansson, 2019) have been used in the delivery market to replace humans. The automatic sorting robot has been used in the sorting center of logistics (Dekhne et al., 2019).

In the above survey, we have shown that the extended concept of PAI has been extensively used in various domains that are outside the robot industry limited to a small physical space. The concept of PAI is based on the interdisciplinary research of five disciplines proposed in Fig. 3 (Miriyev and Kovač, 2020).

3 Trend of PAI

Before 2012, DIAI mimicked the brain's capability of logical thinking and induction to process the data and signals received by human eyes and ears. However, we know that human capabilities are not limited to the brain's logical thinking. The human brain is responsible only for processing signals and transmitting commands to other parts of the body, which are responsible for many functions, such as movement, vision perception, sound perception, and digestion. Therefore, DIAI uncovers only a limited part of the powerful potential of AI, while PAI mimics the whole human body and would greatly extend the application of AI in academia and industry.

PAI has the potential to use deep learning to mimic not only individuals but also the human society. Robots are a typical example of IPAI; they mimic individuals and integrate the perception of the physical world through multiple sensors that collect signals and data, the induction from multiple indices, and the physical response in the physical world. Fig. 4 illustrates the most important modules in IPAI. A robot's perception, computing, and mechanical modules are confined to a limited space, while DPAI distributes the perception, computing, and response modules across a wide space, as shown in Fig. 5, similar to the human society. Industrial IoT systems are a good illustration of DPAI (Cheng JF et al., 2018).

PAI needs to fuse multiple streams of information from multiple sensors, such as materials, temperature, vision, and sound. Therefore, multimodal processing is essential to understand the information in

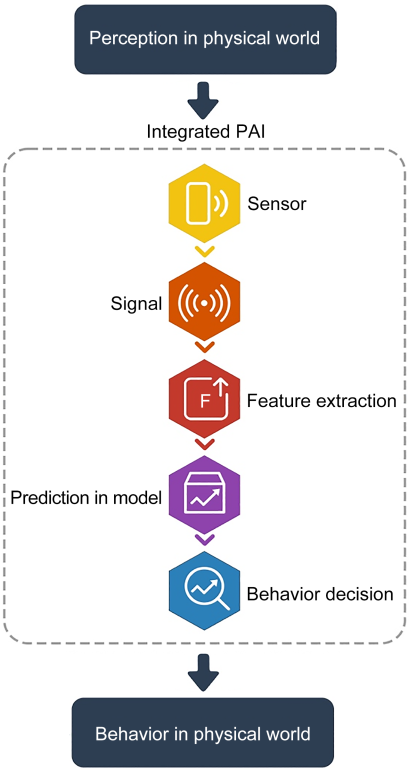

Fig. 4 Integrated physical artificial intelligence (PAI)

PAI. Through the fusion of multimodal information, PAI can use more kinds of information to make better decisions and achieve higher precision (Meyer et al., 2013; Deng, 2016). The data and information sources provide multiple kinds of data to make real-time decisions and predictions, outperforming a single source of data. This is a significant feature of PAI.

We use Fig. 6 to illustrate the components (IPAI and DPAI) and relations of PAI. IPAI will be researched and applied in both home and industry environments. The home environment (Wilson et al., 2019) will receive home service robots such as household robots, while the industry environment will be extensively used in multiple areas of Industry 4.0 (Dalenogare et al., 2018) from automotive to security. DPAI will become increasingly popular when edge computing (Yu et al., 2017) is mature and every device is connected to the network. IoT and edge computing are typical DPAI subdomains. Since it is common for every intelligent system to be online, IPAI and DPAI will have more overlapping areas.

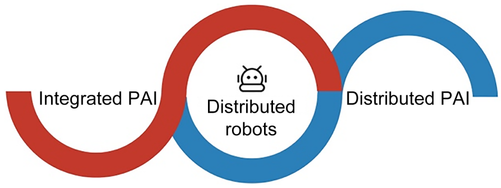

Fig. 6 Integrated physical artificial intelligence (PAI) and distributed PAI

4 PAI governance and sustainable development

DIAI has been facing the challenges of risk and governance problems (Dafoe, 2018). Among the challenges for DIAI, only the most important challenges will be reviewed in this section.

1. The security of DIAI (Gil and Liska, 2019). The training and prediction of AI models require large volumes of data, so the security of data storage is important. Storage security will need both hardware and software predictions. Data masking (Asenjo, 2017) is often used to separate the data from the original source in software- and algorithm-level protection.

2. The fake data of DIAI. Deepfake (Güera and Delp, 2018) attracted much attention when it appeared

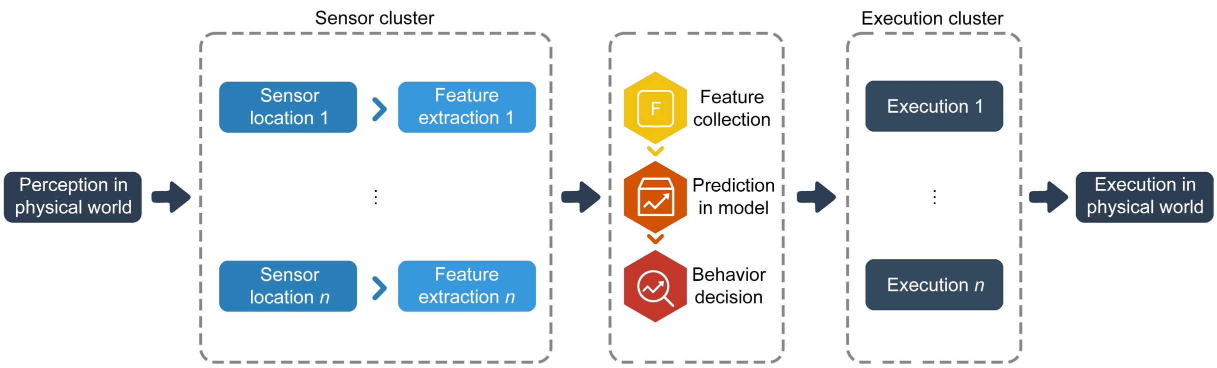

Fig. 5 Distributed physical artificial intelligence (PAI)

on the Internet. Deepfake can convert a human face in a video to the desired face, and in many situations, the converted video looks realistic. The fake image and video challenge the notion of "seeing is believing", which could lead to social and legal problems.

3. The social privacy of DIAI. Face recognition in public spaces has been banned and identified as illegal in many countries (Deb et al., 2018). DIAI has enabled the tracking of our behavior as easily as possible. In addition, DIAI can easily track online data, including social media, and infer the profiles of a person. Therefore, social privacy has been a major focus in recent years.

4. The bias in DIAI. In our society, bias exists even if it is hidden, for example, in the data from the Internet. Most of the training data of DIAI are from web sources, which means that the training model of DIAI naturally contains the property of bias. This bias has been found in the hiring screening AI system (Dattner et al., 2019).

PAI faces more governance problems because of its characteristics of high complexity and ubiquity compared to DIAI:

1. The existence problem. PAI, such as IoT and fog, requires more extensive installation of multiple kinds of sensors. If it is in a limited space like a factory, it does not have much regulation probability. However, if the space is extended to a larger space that is not under the same regulation, PAI will face more problems of privacy regulation and social issues.

2. The information organization problem. As discussed in the previous section, the organization of multiple kinds and multiple layers of data and information will cause the problem of high complexity.

3. Cannikin law. The development of PAI depends on at least five disciplines: material science, mechanical engineering, chemistry, computer science, and biology. The slower development of one discipline will cause the problem of the Cannikin law and hinder the development of PAI.

4. Social acceptance. Similar to the dilemma of DIAI, the ubiquitous application of PAI will cause the worry of society regarding unemployment, privacy, etc.

We illustrate the above problem of PAI in Fig. 7.

As the future form of AI, PAI will be the next popular research topic following DIAI because AI

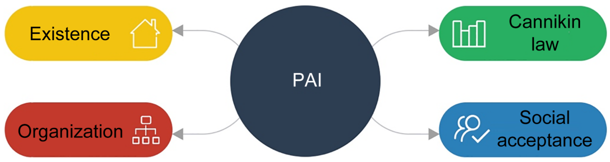

Fig. 7 Physical artificial intelligence (PAI) governance problems

will be increasingly applied in an increasing number of industries. PAI will support the development of mechanics or agriculture because of its hardware characteristics.

5 Discussion and conclusions

The future of PAI functionality and performance will be enhanced not only by hybrid communication and reasoning of multiple modal data and information, but also by responsive adaptation based on precise matching of distributed data/knowledge services and priming of action/response. The challenges of PAI implementation come mainly from the modeling and simulation of the life-cycle form integration and evolution of the material and chemistry disciplines with digital electronic devices.

After briefing the basics of AI, including its history, categories, and popular algorithms, we reviewed the concept of PAI and proposed an extension of PAI, including IPAI and DPAI. We used DIKW and knowledge graph to expand the scope of PAI. We also investigated the governance of PAI and its sustainable development compared to the current popular topics of DIAI governance. We demonstrated the potential development of PAI as the next-generation AI and expected to inspire more research and application of PAI. PAI could become even more complex in the distributed computing continuum system with continuous time and unlimited space and need continuous capabilities of data capturing, data transmission, data processing, and physical manipulation.

Contributors

Yingbo LI and Yucong DUAN designed the research. Anamaria-Beatrice SPULBER drew the figures. Yingbo LI and Zhao LI drafted the paper. Yingbo LI revised and finalized the paper.

Compliance with ethics guidelines

Yingbo LI, Zhao LI, Yucong DUAN, and Anamaria-Beatrice SPULBER declare that they have no conflict of interest.

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