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Editorial

Distributed sensor networks have been widely adopted in the fields of engineering, manufacturing, weather monitoring, and transportation. The data collected can improve the quality of decision-making, but relevant issues such as large volumes, incomplete or incompatible data sets, and noise may present challenges. Machine learning methods have been used as the powerful tools for feature detection/extraction and trend estimation/forecasting in the distributed sensor network applications. Supervised machine learning methods, such as neural network (NN),[1–18] convolutional neural network (CNN),[19–35] and recurrent neural network (RNN),[36–47] can be applied to the prediction and classification, while unsupervised machine learning methods, such as restricted Boltzmann machine (RBM),[48] deep belief network (DBN), deep Boltzmann machine (DBM),[49,50] auto-encoder (AE),[51–56] and denoising auto-encoder (DAE), can be utilized for the data denoising and model generalization. Furthermore, reinforcement learning methods, including generative adversarial networks (GANs)[57–60] and deep Q-networks (DQNs), are widely used in tools for generative networks and discriminative networks to optimize the contesting process in a zero-sum game framework. These methods contribute substantially to improving the prediction and classification in relevant applications, but there remain crucial issues and limitations to be further tackled and investigated.

This Special Collection received a total of eight submissions and three of them were accepted. The 62.5% rejection rate of this Special Collection from the review process is to ensure that high-quality papers with significant results were selected and published. The statistics of this Special Issue are presented as follows:

- Submissions (8)
- Publications (3)
- Rejections (4)
- Withdrawn (1)

Topics covered in this Special Collection include the following three main parts: (I) swarm intelligence, (II) image classification, and (III) voice generation. The topics of the three accepted papers are briefly described below.

Swarm intelligence

The paper presenting a method of swarm intelligence is introduced as follows. Sun et al., the authors of the paper titled “A novel pigeon-inspired optimization with QUasi-Affine TRansformation evolutionary algorithm for DV-Hop in wireless sensor networks,” proposed a novel evolutionary algorithm named QUasi-Affine TRansformation Pigeon-Inspired Optimization (QT-PIO) for improving the update strategy and learning strategy of the particles. The proposed QT-PIO algorithm combines the QUasi-Affine TRansformation Evolutionary (QUATRE) algorithm and Pigeon-Inspired Optimization (PIO) method in that the QUATRE algorithm could be used to optimize the coordinate and speed of all particles for the PIO algorithm. In their experiments, a case study of distance vector-hop (DV-Hop) node localization in wireless sensor networks was selected to evaluate the performance of the proposed QT-PIO method. The results show that the performance of the proposed QT-PIO was higher than that of QUATRE, PIO, and particle swarm optimization (PSO).[61]

Image classification

The paper proposing a method of image classification is introduced as follows. Liu and Qiao, the authors of the paper titled “Mahalanobis distance–based kernel supervised machine learning in spectral dimensionality reduction for hyperspectral imaging remote sensing,” proposed an optimization method based on the Mahalanobis distance multi-kernel learning algorithm with the multiple kernel learning (MKL) algorithm for analyzing a metric matrix and optimizing the weights in models. In their experiments, the Indian Pine data set and the Pavia University data set were adopted to evaluate the proposed optimization method. The practical experimental results show that the performance of the optimization method–based Mahalanobis distance was higher than that of the optimization method based on the Euclidean distance and Kappa coefficient.[62]

Voice generation

The paper developing a method for voice generation is introduced as follows. Kuo et al., the authors of the paper titled “DNAE-GAN: noise-free acoustic signal generator by integrating autoencoder and generative adversarial network,” proposed a denoising auto-encoder with generative adversarial networks (DNAE-GANs) to build a generator and a discriminator for the analyses of original audios and fake audios. The denoising auto-encoder function was applied to extract the denoising features from the audios with noise signals. The adaptive sub-gradient method (AdaGrad) was adopted to minimize the mean square errors. In the experiments, 300 audio samples were used to train the proposed DNAE-GAN, and the feasibility of the proposed DNAE-GAN was proved for the voice generation.[63]

Conclusion and future work

Three main parts, including (I) swarm intelligence, (II) image classification, and (III) voice generation, have been discussed in this Special Collection. These studies utilize and adopt the machine learning and deep learning techniques (e.g. PIO, generative adversarial networks, etc.) to analyze the spatio-temporal features of signals. Several experiments are given to indicate that the performance of the proposed machine learning and deep learning methods could be better than that of the traditional machine learning methods.[61–63]

In the future, the semantic web could be considered to represent the sensing data from distributed sensor networks.[64–67] For improving the performance of machine learning–based distributed sensor network applications, the advanced swarm intelligence techniques[68–70] could be applied. Furthermore, cloud computing and distributed computing techniques[71] could be adopted for improving the effectiveness of distributed sensor network applications.

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