Future Generation Computer Systems 124 (2021) 49–53

Contents lists available at ScienceDirect

Future Generation Computer Systems

journal homepage: www.elsevier.com/locate/fgcs

# Computer-aided intelligent design using deep multi-objective cooperative optimization algorithm

Jingwei Hao *, Senlin Luo, Limin Pan

*School of Information and Electronics, Beijing Institute of Technology, Beijing 100081, China*

ARTICLE INFO

*Article history:*
Received 18 October 2020
Received in revised form 5 May 2021
Accepted 9 May 2021
Available online 11 May 2021

*Keywords:*
Multi-objective decision-making
RBF neural network
Weight-based algorithm

ABSTRACT

Computer-aided product design means using artificial intelligent systems to automatically design multiple industrial products. This technique has been pervasively applied in multiple domains, such as 3D printing and vehicle manufacture. One challenge of computer-aided design is to incorporate deep neural network to optimally fuse multiple decisions. Multi-objective decision encapsulates many decision-making objectives and leverages deep CNNs to evaluate/optimize the fused multiple decisions. Due to the objectives of economic and social benefit, it is necessary to use a variety of criteria to deeply evaluate and optimize schemes. In this paper, we propose a novel quality-guided deep neural network and weighting scheme to achieve multi-objective decision. We leverage RBF neural network to construct objective weight assignment model. Then, a deep CNN is designed to implement the weighting task, each of which corresponds to a single decision. Our deep CNN has five layers and contains multilayerperceptrons, which indicate the fully connected networks. Each neuron in one layer is connected to all neurons in the next layer. The target of our deep weight-based model is that the multi-objective optimization can be formulated as a single-objective optimization by assigning different weights to each objective. Finally, the non-inferior solution of the multi-objective optimization is generated by updating the weights of the deep CNN during fine tuning. In our experiment, we have demonstrated that our method has the potential to facilitate a variety of applications, such as 3D reconstruction and system optimization. We believe that our proposed algorithm can guide the optimization of various intelligent system pipeline.



## 1. Introduction

Multi-objective decision-making method is a decision-making analysis method developed from the mid-1970s. Decision-making analysis is an analysis process of selecting and deciding the best scheme among several alternative schemes in order to solve the current or future problems in the system planning, design and manufacturing stages [1,2]. Multi-objective decision-making is widely used in many fields such as industry, agriculture, commerce, trade, regional planning and so on [3–8]. Compared with single-objective decision, multi-objective decision considers more factors, especially in complex environment. We divide the multi-objective problem into three parts: (1) trade-offs and choices of solutions; (2) goal establishment and achievement; (3) value and utility. In most researches, these three parts are used in combination and have been developed and improved in application. Mathematical analysis and optimization methods are applied to find the optimal solution and maximum value.

In practice, from the analysis of the process and mechanism of rational decision-making under multi-objective conditions, the main theories of multi-objective decision-making are: the analysis and description of multi-objective decision-making process; the theory of conflict decomposition and ideal point transfer; the theory of multi-attribute utility; the theory of demand multiplicity and hierarchy, etc. They are the theoretical basis of the multi-objective decision analysis method. On the premise of meeting the needs of decision-making, the number of objectives should be minimized. Subordinate objectives can be eliminated and similar objectives can be merged into one objective, or those secondary objectives which only need to meet the minimum standard but not to achieve the optimum can be reduced to constraints; and by summing up the same measure, finding the average value or constituting a synthesis function, comprehensive indicators can be used instead of single indicators. The method achieves its purpose. Decide the choice of goals according to their priorities. Therefore, it is necessary to arrange the objectives in an order of importance and to specify the importance coefficient so as to be followed in the selection decision-making. The contradictory objectives should be coordinated on the basis of the general objectives, and strive to take all objectives into consideration and give overall consideration.

* Corresponding author.
*E-mail address:* 3120195386@bit.edu.cn (J. Hao).

https://doi.org/10.1016/j.future.2021.05.014
0167-739X/

In this paper, we leverage a quality-guided RBF neural network and weight-based algorithm to achieve multi-objective decision. We leverage RBF neural network to construct objective weight assignment model and weight-based algorithm assigns weights to each objective.

## 2. Related work

### *2.1. Multi-objective decision-making*

Multi-objective decision-making is a hot research topic in both academic and industry domains [9–15]. Ustun et al. [16] proposed an integrated multi-objective decision-making algorithm with supplier selection. An analytic network process (ANP) was designed and multi-objective mixed integer linear programming (MOMILP) was combined to achieve this task. The green supply chain (GSC) helps most companies improve the environmental performance. The authors leveraged simple and effective scheme to evaluate the performance of using GSC concept. Chang et al. [17] proposed a multi-objective decision-making scheme for Boston sludge disposal problem. To solve this task, cluster analysis, redundancy solutions were utilized. Kennedy et al. [18] leveraged Pareto optimality for multi-objective decision-making. The proposed method can be used in many industrial domains such as logistics Distribution, transportation. Belien et al. [19] proposed a multi-objective decision method for cyclic master surgery scheduling. Fan et al. [20] proposed multi-objective decision-making algorithms based on genetic algorithm (GA). The genetic algorithm was used for decision and optimization. Insua et al. [21] proposed a novel framework for discrete multi-objective decision making. The authors designed a pareto optimal solution, which was applied in multi-objective decision-making.

### *2.2. Visual information quality assessment*

Maffei et al. [19] first realized the difficulty of information quality assessment in 1958. The quality of information is difficult to assess for the following reasons:

(1) Information quality standards are mainly determined by users. The subjective characteristics are hard to be automatically extracted.

(2) Information sources are usually autonomous, unorganized, and lack useful quality metadata. Some sources of information even take measures to prevent information quality assessment.

(3) Large-scale data makes it impossible to evaluate the entire information set without sampling techniques, which reduces the accuracy of the evaluation.

(4) The unorganized nature of information sources makes information vulnerable to sudden changes in content and quality, which is not conducive to information quality assessment.

For the research of information quality assessment, the early focus was mainly on data quality assessment and data quality issues. In 1979, Codd [20] proposed a mechanism for adding data labels to assess data quality, and was adopted by Wang et a. In 1993, data-based attributes were proposed and quality indicators were used to label data quality. Paradice and Fuerst [21] proposed a formula for calculating the storage error rate in 1991. These studies focus on stored data and less on user evaluation and perception of data information. In the research of data quality issues, Klein et al. [3] conducted a series of tests and found that information system users can find data errors in a specific environment. They further clarified that clear error detection targets, management instructions, training, and various incentives can improve the effectiveness of false detections. However, Dasu et al. [4] believed that some data quality dimensions, such as accuracy and completeness, are difficult to find errors or even unevaluable. Strong et al. conducted a data quality project check on three organizations, identified a general pattern of quality issues, and found that data quality issues in one category affected the quality of data in another.

With the comprehensive and in-depth understanding of information quality, the research on information quality assessment has gradually broken through the limitations of data quality. In 2000, Naumann et al. [5] developed a classification method based on evaluation-oriented information quality standards. On the basis of summarizing the classification of information quality standards by predecessors, they summarized three classification methods: semantic-oriented classification, process-oriented classification and goal-oriented classification. On this basis, the classification method of evaluation orientation is proposed, and three standards are established from the three aspects of user, information itself and information acquisition process—subjective standard, objective standard and process standard. Each type of standard has different assessment methods and techniques, including user experience, user sampling, ongoing user evaluation, data cleaning and analysis, and more. The study comprehensively summarizes all aspects of information quality assessment and establishes a mature information quality assessment standard system. YW Lee et al. [6] proposed an information quality assessment method called AIMQ to help organizations assess the quality of their information and monitor the information quality improvement process at any time.

### *2.3. Data quality understanding*

Maffei proposed the difficulty of data quality problems and data quality assessment. Later, with the development of computers, data quality problems have become increasingly prominent. In the research of data quality, it mainly focuses on the quality of structured data in information systems. The research mainly focuses on the definition and dimension of data quality, the solution of data quality problems, and the elimination of "data ambiguity". For data quality problems, most of these studies use technical means, data-oriented, and solve quality problems. Early research believes that data quality is the accuracy of data, and it is divided into two types: correct and wrong. It refers to the quality formed in the data production process. This view captures the essential characteristics of data quality, but it is relatively narrow. Redman [7] defined data quality at three levels—conceptual level, data value level, and formal level. Data quality at the conceptual level includes data details, view consistency, components, robustness, and flexibility. Data value hierarchy includes data accuracy, integrity, generality and consistency. The data form hierarchy includes the suitability, comprehensibility and accessibility of data. This point of view is completely based on the data in the database, with strong pertinence and operability, and relative comprehensiveness, for data quality management laid a theoretical foundation.

Because information is different from data, the focus, level, angle, and means of information quality and data quality research are different. Klein [3] believed that data quality and information quality are a multi-dimensional concept that presents different characteristics depending on the researcher's own point of view. Johannsen [8] believes that the focus of information quality in library and information services research is "quality management"; Levitin [9] believes that the use of "data quality" is primarily related to the accuracy of information products, such as databases. B Zhang [10] et al. pointed out that high-quality data is not necessarily high-quality information, and information users may still not be able to obtain valuable information. Therefore, users should first pay attention to user needs, so that information production forms a complete data producer from information user. Information manager conducts demand-based "applicability" data production quality management approach while the information sharing platform system acts as a "quality agent" for information

## 3. Our proposed method

In our method, the object patches extraction is based on the BING operator [22], which can effectively extracts hundreds of windows that optimally contain each visually/semantically salient objects. The key advantage of BING is the ultra-high speed in object patches extraction and the high generalization ability. After extracting 400∼1000 object patches inside each prostate cancer image, the following features are extracted to represent each object patch.

Spatial feature: Generally speaking, there are a rich set of tissues scattered within each prostate image. Their positions as well as their spatial interactions are important for visual quality modeling. It is observable that the position is fixed for those static object. Such observation inspires us to attend to only on the moving objects while ignoring the complex backgrounds. This will inevitably reduce the computational cost in practice. Traditional bag of features (BOG) based visual quality evaluation methods extracted SIFT features toward the entire image, where the spatial information of image will be dismissed [1]. In order to handle the inherent limitation of BOG, spatial pyramid (SP) model is proposed that calculates the distribution of a set of image features with multiple resolutions, in order to obtain the spatial information of an image. In particular, each image can be divided into multiple evenly-divided grids at each level of the multi-scale pyramid, based on which visual features are derived from each grid and subsequently combined to form a very long feature vector. Spatial pyramid based image feature extraction can be described as: a rich set of grid-nets are leveraged to extract quality-related visual features from multiple image regions. We utilize a three-level spatial pyramid to extract visual features from the prostate cancer image. Both the local and global spatial structure can be well encoded. In order to search the disease tissue inside each prostate, we formulate a three-level spatial pyramid to extract features from each prostate image.

Semantic feature: semi-supervised semantic learning algorithms have a rich set of manually assigned labels to encode image semantic features. Nevertheless, it is infeasible in practice owing to the massive-scale prostate cancer images. To enhance this method, we propose a weakly-supervised learning method to intelligently convert the textual semantic labels into image regions. Particularly, the semantic labels of image are transferred into different regions based on a manifold embedding algorithm. In detail, we first decompose each prostate image into multiple sub-regions based on a superpixel algorithm. We believe that the visual features of sub-regions belonging to the same object should be similar.

### 3.1. Neural network construction

Radial basis function (RBF) was proposed by Powell in 1985. RBF is a radially symmetric scalar function, usually defined as a monotone function of the Euclidean distance from any point $\boldsymbol{X}$ to a central $\boldsymbol{c}_i$ in space. The most common radial basis function is Gaussian kernel function, which is defined as $k_i(\mathbf{x}) = \exp(-|\mathbf{x} - \boldsymbol{c}_i|^2 / 2\sigma^2)$. Where $\boldsymbol{c}_i$ denotes the center of the kernel function. RBF neural network is a kind of neural network designed by RBF with multivariable interpolation. It has been proved that RBF neural network can approximate any non-linear function with arbitrary accuracy and has the characteristics of optimal approximation and global approximation. Its network topology is

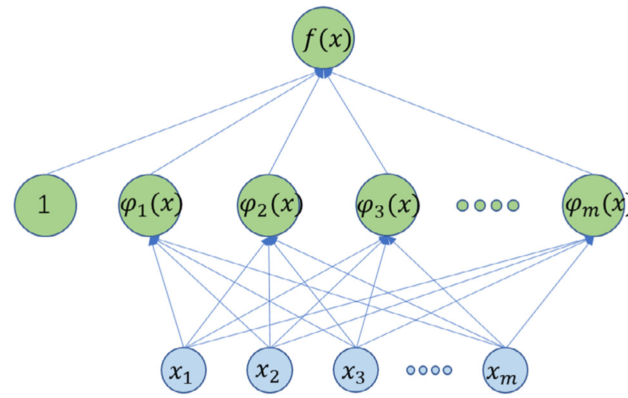


**Fig. 1.** The classical architecture of the three-layer forward network.

a forward network consisting of an implicit layer and a standard fully connected linear output layer. The most commonly used hidden layer is Gauss radial basis function, while the output layer uses linear activation function. Fig. 1 shows the classical architecture of the three-layer forward network.

We define $\{x_1, x_2, x_3, \ldots, x_m\}$ as $m$ input data, and $\{v_1, v_2, v_3, \ldots, v_p\}$ as $p$ hidden node, and $\mathbf{Y}$ is the output node. $w_{1ij}$ denotes a series of weights that connect input layer and hidden layer. $w_{2j}$ denotes a series of weights that connect hidden layer and output layer.

### 3.2. CNN-based decision quality assessment

The decision model for blog video is based on 3D CNN, which consists of nine convolutional layers, three average pooling layers, and an output layer. This part consists of three blocks, each of which including three convolutional layers with kernels in different sizes, 3 × 3 × 3 and 1 × 1 × 1, and an average pooling layer. The first two convolutional layers use 3 × 3 × 3 kernel with padding of 1, making the size of the output the same as the input. The third convolutional layer adopts 1 × 1 × 1 kernel, which is used for the dimension reduction. Leaky rectifier linear unit (LReLU) [23] activation function is used for the three convolution layers, and its formula is defined as follows:

$$LReLU(z) = \begin{cases} z \\ \alpha z \end{cases} \tag{1}$$

where $\alpha$ is called leaky parameter, specifically, LReLU degenerates into ReLU activation function when $\alpha$ equals to 0.

To handle with the overfitting problem probably occurring in 3D CNN architecture, the last layer adopts a fully connected layer based on the dropout strategy. The purpose of the strategy is that each execution of the dropout is equivalent to randomly selecting a smaller network from the original network at a certain probability to update parameters. Therefore, dropout can be regarded as an integrated training of several small networks. Meanwhile, the occupied memory space of parameters and training time does not increase.

The last layer adopts a sigmoid function to predict the segmentation-based video quality score. Since the value range of sigmoid is inconsistent with that of difference average opinion score (DMOS) given in different data sets, it will be normalized in experiments to reduce its range to the interval of [0,1].

### 3.3. Learning algorithm

The learning process of the algorithm consists of forward and backward propagation. In the process of forward propagation, the input information is processed layer by layer from the input layer to the output layer through the hidden node layer, and the state of each layer of neurons affects the state of the next layer of neurons. If the desired output cannot be obtained in the output layer, the error signal will be transferred back to the back propagation, and the error signal will be returned along the original connection path. By modifying the weights of neurons in each layer, the error signal will be minimized and satisfactory weights will be obtained. In network, we leverage formula (1) as the action function between the input node and the output node.

$$f(\mathrm{x}) = \frac{1}{1+e^{-x}} \tag{2}$$

The learning algorithm is described as follows: Firstly, the weights $w_{1ij}(i = 1, \ldots, m; j = 1, \ldots, p)$ and $w_{2j}(\mathrm{j} = 1, \ldots, p)$ is initialized. We calculate the hidden node $V_j$ by

$$V_j = \frac{1}{1+e^{-\sum_i w_{1ij}x_i}} \quad j = 1, 2, \ldots, P \tag{3}$$

and the output node $\hat{Y}$ is calculated by

$$\hat{Y} = \frac{1}{1+e^{-\sum_i w_{2j}V_i}} \tag{4}$$

The weights will be updated based on the difference between the ground-truth and the output node $\hat{Y}$.

$$W_{2j} = W_{2j} + \eta\hat{Y}\left(1-\hat{Y}\right)V_j\sigma_2 \quad j = 1, 2, \ldots, p \tag{5}$$

where $\eta$ denotes the learning rate. The whole learning process is iteration operation. In order to highlight the importance of different component characteristics, we designed a weight-based updating algorithm. Specifically, in each iteration, formula (5) is calculated as:

$$W_{2j} = W_{2j} + \eta w_j\hat{Y}\left(1-\hat{Y}\right)V_j\sigma_2 \quad j = 1, 2, \ldots, p \tag{6}$$

After iterations using our method, the weights will sum to one $\sum_i w_i = 1$. Implicit nodes in the network can determine the $M$ weight allocation needed for solving multi-objective programming. Obviously, adjusting the size of input $u$ can produce different weight distribution. The weight here refers to the $M$ weight allocation needed to solve non-inferior solutions of multi-objective problems.

### 3.4. Multi-view feature fusion

In our application, by leveraging the above shallow/deep features, we adopt the multi-view spectral feature fusion algorithm proposed by Xie et al. [27]. It can simultaneously optimize the fused feature for each view and toward the entire feature channels under a unified framework. For each feature view, the optimization can be formulated as:

$$\operatorname*{argmin}_{z_i^{(j)}} \sum_{i=1}^{K} \left\| z_j^i - z_{jt}^i \right\|^2 (U_j^i). \tag{7}$$

where matrix $\mathrm{U_j^i}$ is a weighting matrix, i.e., the $ij$-th entity denotes the contribution of the $i$th sample to re-build the $j$th sample. Z is a matrix containing the multimodal feature vectors extracted from the entire prostate cancer images.

By simultaneously optimizing all the feature channels, the global optimization toward all the view channels can be formulated as follows:

$$\operatorname*{argmin}_{Z,\gamma} \sum_{i=1}^{K} \gamma_i \cdot \mathrm{trace}(ZW_j^i L_j^i \left(W_j^i\right)^T Z^T), \tag{8}$$

where $\gamma_\mathrm{i} \in [0, 1]$ is the weight of features from the $i$th view.

Herein, a probabilistic Gaussian mixture model (GMM) is trained to calculate the disease level toward each prostate cancer image. Specifically, given a rich set of training normal prostate images, we train a GMM with R components:

$$\mathrm{p}(\mathrm{z}|\eta) = \sum_{i=1}^{R} \rho_i \cdot \mathcal{N}(z|\eta_i), \tag{9}$$

where $\rho_\mathrm{i}$ denotes the non-negative weight to the $i$th GMM component, and $\sum_{i=1}^{R} \rho_i = 1$, and $\eta_\mathrm{i}$ denotes the average and variance of the $i$th Gaussian component.

After the GMM is trained, i.e, parameter $\eta$ is identified, we calculate the disease level of each prostate cancer image as:

$$\mathrm{level} = \mathrm{p}(\mathrm{z}'|\eta), \tag{10}$$

## 4. Experiment and analysis

In our experiment, we analyze some cases to verify the effectiveness of our proposed method. Let $f = \{f_i | i = 1, 2, \ldots, 5\}$ as the objective set, and $X = \{x_j | j = 1, 2, \ldots, 4\}$ as the scheme set. $f_1, f_2$ is the input index, and $f_3, f_4, f_5$ is the output index. The decision of four candidate and five objects is shown as follows:

$$\mathrm{Y} = \begin{matrix} 742 & 1259 & 896 & 4026 \\ 48.5 & 86.3 & 27.1 & 63.2 \\ 622.1 & 564.7 & 446.8 & 656.4 \\ 2067 & 1862 & 2587 & 2842 \\ 234.6 & 133.6 & 213.8 & 168.5 \end{matrix}$$

Then, the decision matrix $Y$ is standardized and reduced to the target matrix:

$$\mathrm{F} = \begin{matrix} 1 & 0.546 & 0.8281 & 0.1843 \\ 0.5588 & 0.314 & 1 & 0.4288 \\ 0.9477 & 0.86 & 0.6807 & 1 \\ 0.7273 & 0.6552 & 0.9103 & 1 \\ 1 & 0.5695 & 0.9113 & 0.7182 \end{matrix}$$

Subsequently, we calculate the entropy value of each object: $E_1 = 1.2514$, $E_2 = 1.2907$, $E_3 = 1.3763$, $E_4 = 1.3356$, $E_5 = 1.3613$. Then we can obtain the weight by normalization $\theta = \{0.250, 0.223, 0.163, 0.191, 0.173\}$. The weight-based algorithm can highlight the importance of each component. Our multi-objective decision-making algorithm can decide the best scheme among several alternative schemes in order to solve the current or future problems in the system planning, design and manufacturing stages.

To validate the effectiveness of the aid of each decision-related text, two ablation model of Bi-LSTM-s2s models, LSTM-forward and LSTM-backward, which only consider the forward and backward procedure respectively, are testified. For the sake of description, six signs of M1 to M6 stand for the six counterparts, Moorthy + LSTM-forward, Mittal+LSTM-forward, Saad+LSTM-forward, Moorthy+LSTM-backward, Mittal + LSTM-backward, Saad + LSTM-backward.

From experimental results of seven models on decision set is shown in Table 1, the proposed segmentation-based video quality evaluation method outperforms the other counterparts on the PLCC and SROSS measurements. The reason lies in that, in addition to effective features within 2D nature images, our method takes advantage of spatial and temporal information within the three-dimensional frame sequence within each video. Moreover, compared with the ablation models with LSTM-forward and backward, Bi-LSTM-s2s utilized bi-directional information within the corresponding text information to achieve better performance. Furthermore, as shown in Fig. 1, we present some segmentation results. As shown, our segmentation algorithm can effective decompose the semantically important objects within each image. This observation can show the performance of our method.

**Table 1**
Comparison of seven decision-based video quality evaluation methods on PLCC and SROCC.

| Method | SROCC | PLCC |
|---|---|---|
| M1 | 0.6271 | 0.6657 |
| M2 | 0.7786 | 0.7921 |
| M3 | 0.7451 | 0.7786 |
| M4 | 0.6547 | 0.6436 |
| M5 | 0.7984 | 0.8002 |
| M6 | 0.7326 | 0.7432 |
| Proposed | 0.8441 | 0.8456 |

## 5. Conclusions

In this paper, we propose RBF neural network and weight-based algorithm to achieve multi-objective decision. More specifically, we leverage RBF neural network to construct objective weight assignment model. The goal of our weight-based algorithm is that the multi-objective optimization problem is formulated as a single-objective optimization problem by assigning certain weights to each objective. Afterward, the non-inferior solution of the multi-objective optimization problem is generated by changing the weights of each sub-task.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgment

This study was supported by the Information Security Software Project 2020 of Ministry of Industry and Information Technology of China (No. CEIEC-2020-ZM02-0134).

## References

[1] M. Zeleny, Optimal system design with multiple criteria: De-novo programming approach, Eng. Costa Prod. Econ. (10) (1986) 89–94.
[2] Y. Shi, Studies on optimum-path ratios in multicriteria De-Novo programming problems, Comput. Math. Appl. 29 (5) (1995) 43–50.
[3] Mingliang Xu, Yunpeng Wu, Yangdong Ye, Illes Farkas, Hao Jiang, Zhigang Deng, Collective crowd formation transform with mutual information-based runtime feedback, Comput. Graph. Forum 34 (1) (2015) 60–73.
[4] Masud Ibn Afjal, Md. Al Mamun, Md. Palash Uddin, Band reordering heuristics for lossless satellite image compression with 3D CALIC and CCSDS, J. Vis. Commun. Image Represent. 59 (2019) 514–526.
[5] Yildiray Anagün, Sahin Isik, Erol Seke, Srlibrary: Comparing different loss function for super-resolution over various convolutional architectures, J. Vis. Commun. Image Represent. 61 (2019) 178–187.
[6] Junwei Han, Xiang Ji, Xintao Hu, Dajiang Zhu, Kaiming Li, Xi Jiang, Guangbin Cui, Lei Guo, Tianming Liu, Representing and retrieving video shots in human-centric brain imaging space, IEEE Trans. Image Process. 22 (7) (2013) 2723–2736.
[7] M. Zhang, Y. Wu, Y. Du, L. Fang, Y. Pang, Saliency detection integrating global and local information, J. Vis. Commun. Image Represent. 53 (2018).
[8] Dingwen Zhang, Deyu Meng, Junwei Han, Co-saliency detection via a self-paced multiple-instance learning framework, IEEE Trans. Pattern Anal. Mach. Intell. 39 (5) (2017) 865–878.
[9] Mingliang Xu, Jiejie Zhu, Pei Lv, Bing Zhou, Marshall Tappen, Rongrong Ji, Learning-based shadow recognition and removal from monochromatic natural images, IEEE Trans. Image Process. 26 (12) (2017) 5811–5824.
[10] Junwei Han, King Ngi Ngan, Mingjing Li, Hong-Jiang Zhang, Unsupervised extraction of visual attention objects in color images, IEEE Trans. Circuits Syst. Video Technol. 16 (1) (2006) 141–145.
[11] D. Nair, P. Sankaran, Color image dehazing using surround filter and dark channel prior, J. Vis. Commun. Image Represent. (2017).
[12] R. Pramanik, S. Bag, Shape decomposition-based handwritten compound character recognition for bangla ocr, J. Vis. Commun. Image Represent. 50 (2018) 123–134.
[13] Mingliang Xu, Mingyuan Li, Weiwei Xu, Zhigang Deng, Yin Yang, Kun Zhou, Interactive mechanism modeling from multi-view images, ACM Trans. Graph. 35 (6) (2016) 236.
[14] Junwei Han, Dingwen Zhang, Gong Cheng, Lei Guo, Jinchang Ren, Object detection in optical remote sensing images based on weakly supervised learning and high-level feature learning, IEEE Trans. Geosci. Remote Sens. 53 (6) (2015) 3325–3337.
[15] Mingliang Xu, Chunxu Li, Pei Lv, Lin Nie, Rui Hou, Bing Zhou, An efficient method of crowd aggregation computation in public areas, IEEE Trans. Circuits Syst. Video Technol. (2017) http://dx.doi.org/10.1109/TCSVT.2017.2731866.
[16] O. Ustun, Ezgi Aktar Demrtas, An integrated multi-objective decision-making process for multi-period lot-sizing with supplier selection, Omega 36 (4) (2008) 509–521.
[17] S.Y. Chang, Multi-objective decision-making in waste disposal planning, J. Environ. Eng. 111 (3) (1985) 373–385.
[18] M.C. Kennedy, E.D. Ford, P. Singleton, M. Finney, J.K. Agee, Informed multi-objective decision-making in environmental management using pareto optimality, J. Appl. Ecol. 45 (1) (2008) 181–192.
[19] Belien, Jeroen, Demeulemeester, ErikCardoen, A multi-objective decision support system for cyclic master surgery scheduling, 2007.
[20] S.C. Fan, J.F. Wang, Multi-objective decision and optimization of process routing based on genetic algorithm (ga), in: Advanced Materials Research, Vol. 457–458, 2012, pp. 1494–1498.
[21] D.R. Insua, S. French, A framework for sensitivity analysis in discrete multi-objective decision-making, European J. Oper. Res. 54 (2) (1991) 176–190.
[22] L.Y.Y. Lu, C.H. Wu, T.C. Kuo, Environmental principles applicable to green supplier evaluation by using multi-objective decision analysis, Int. J. Prod. Res. 45 (22) (2007) 5451.
[23] Z. Li, H. Liao, D.W. Coit, A two-stage approach for multi-objective decision making with applications to system reliability optimization, Reliab. Eng. Syst. Saf. 94 (10) (2009) 1585–1592.

**Jingwei Hao** (1994-) received the B.E. degree from Dalian University of Technology, Dalian, China, in 2017, and the M.S degree from Beijing Institute of Technology, Beijing, China, in 2019. She is currently pursuing the Ph.D. degree with the Information System and Security and Countermeasures Experimental Center, Beijing Institute of Technology. Her current research interests include cyberspace security, machine learning, and data mining.
Email: 3120195386@bit.edu.cn

**Senlin Luo** (1968-) received the B.E. and M.E. degrees from the College of Electrical and Electronic Engineering, Harbin University of Science and Technology, Harbin, China, in 1992 and 1995, respectively, and the Ph.D. degree from the School of Information and Electronics, Beijing Institute of Technology, Beijing, China, in 1998. He is currently the Deputy Director, the Laboratory Director, and a Professor with the Information System and Security and Countermeasures Experimental Center, Beijing Institute of Technology. His current research interests include machine learning, medical data mining, and information security.
Email: luosenlin2012@gmail.com

**Limin Pan** (1968-) received the B.E. and M.E. degrees from the College of Electrical and Electronic Engineering, Harbin University of Science and Technology, Harbin, China. She is currently with the Information System and Security Countermeasures Experimental Center, Beijing Institute of Technology. Her current research interests include machine learning, medical data mining, and information security.
Email: panlimin2016@gmail.com