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A knowledge matching approach based on multi-classification radial basis function neural network for knowledge push system

Key words: Product design; Knowledge push system; Augment training set; Multi-classification neural network; Knowledge matching

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Motivation

- Knowledge matching is the most important part of knowledge push. It is required to select the correct design knowledge relevant to the design tasks or the designers' demands.
- An applicable probability classifier needs to match the design knowledge with the design content one by one, resulting in long response time of knowledge matching, which will impair the user experience during the human-computer interaction (Zhang SY et al., 2018).
- To improve the accuracy, the limited training set in practical operations needs to be augmented in knowledge matching.

Main idea

- To shorten the response time, we completely replace the knowledge matching mode with artificial neural networks (ANNs). The neurons in the output layer represent the design knowledge, and the input is the original design content vector. We propose some key enhancements to the ANNs to boost the performance of knowledge matching.
- We investigate two methods to augment the training set, namely, oscillating the feature weight and revising the case feature in the case feature vectors.

Method

1. Augment the training set

- Oscillating the feature weight
- Revising the case feature

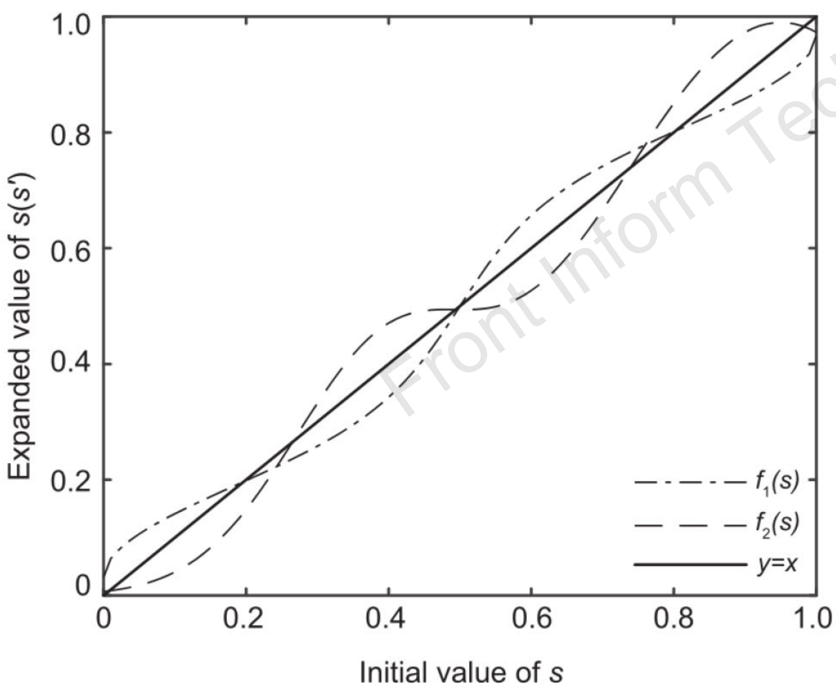


Fig. 4 Two oscillatory function curves

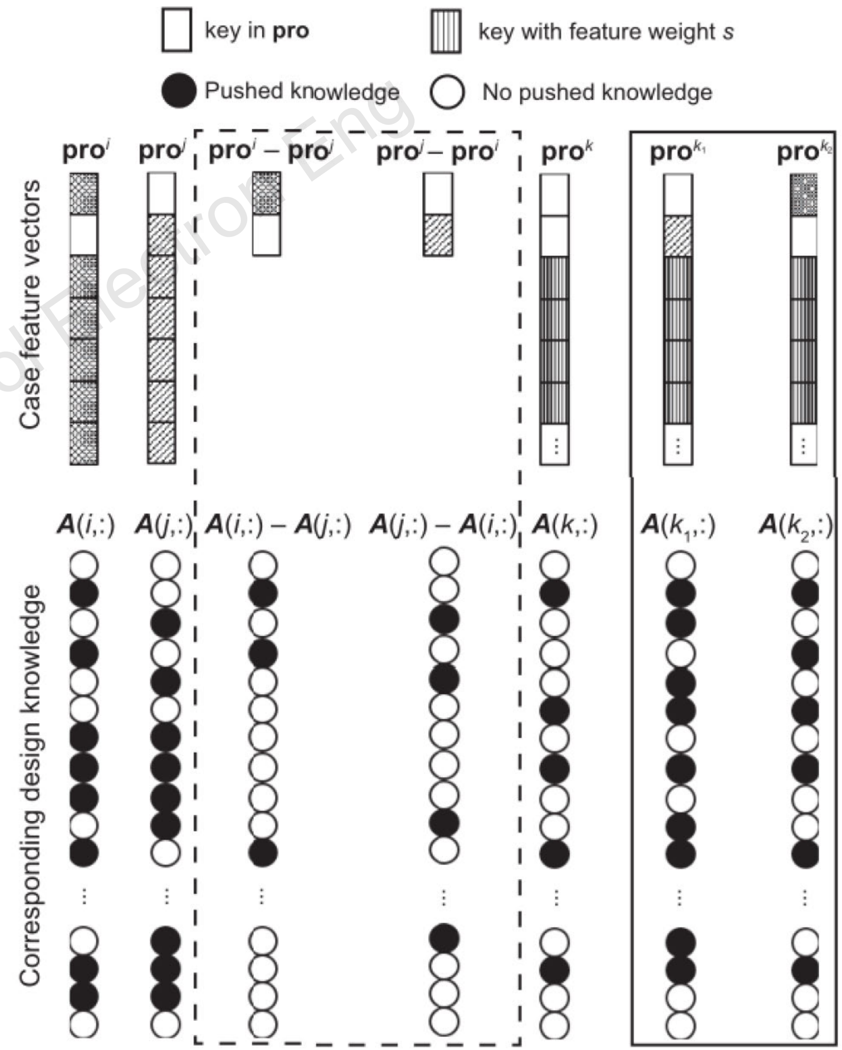


Fig. 5 Revision of the case feature key

Method

2. Multi-classification radial basis function (RBF) neural network

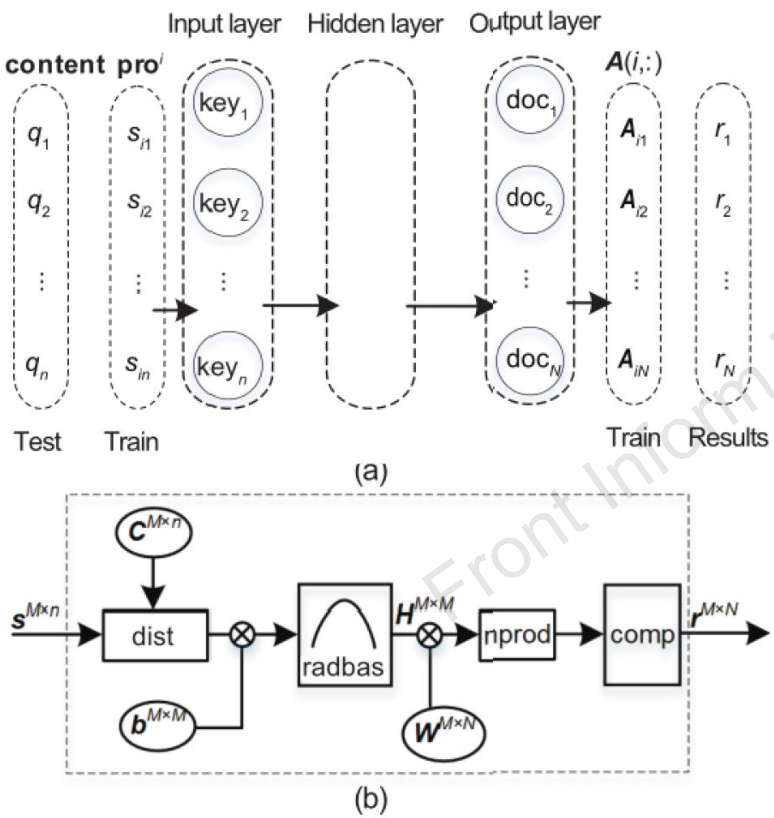


Fig. 6 The proposed neural network for knowledge matching: (a) input and output layers; (b) hidden layer

We enhance RBF in two parts: “nprod” and “comp,” for the characteristics in knowledge matching.

$$\mathrm{dist}_{i,j} = \|\boldsymbol{s}^i - \boldsymbol{C}^j\| = \sqrt{\sum_{m=1}^{n}(s_{i,m} - C_{j,m})^2}, \quad (3)$$

$$H_{i,j} = \mathrm{radbas}(\mathrm{dist}_{i,j} \times b_{i,j}) = \mathrm{e}^{-(\mathrm{dist}_{i,j} \times b_{i,j})^2}, \quad (4)$$

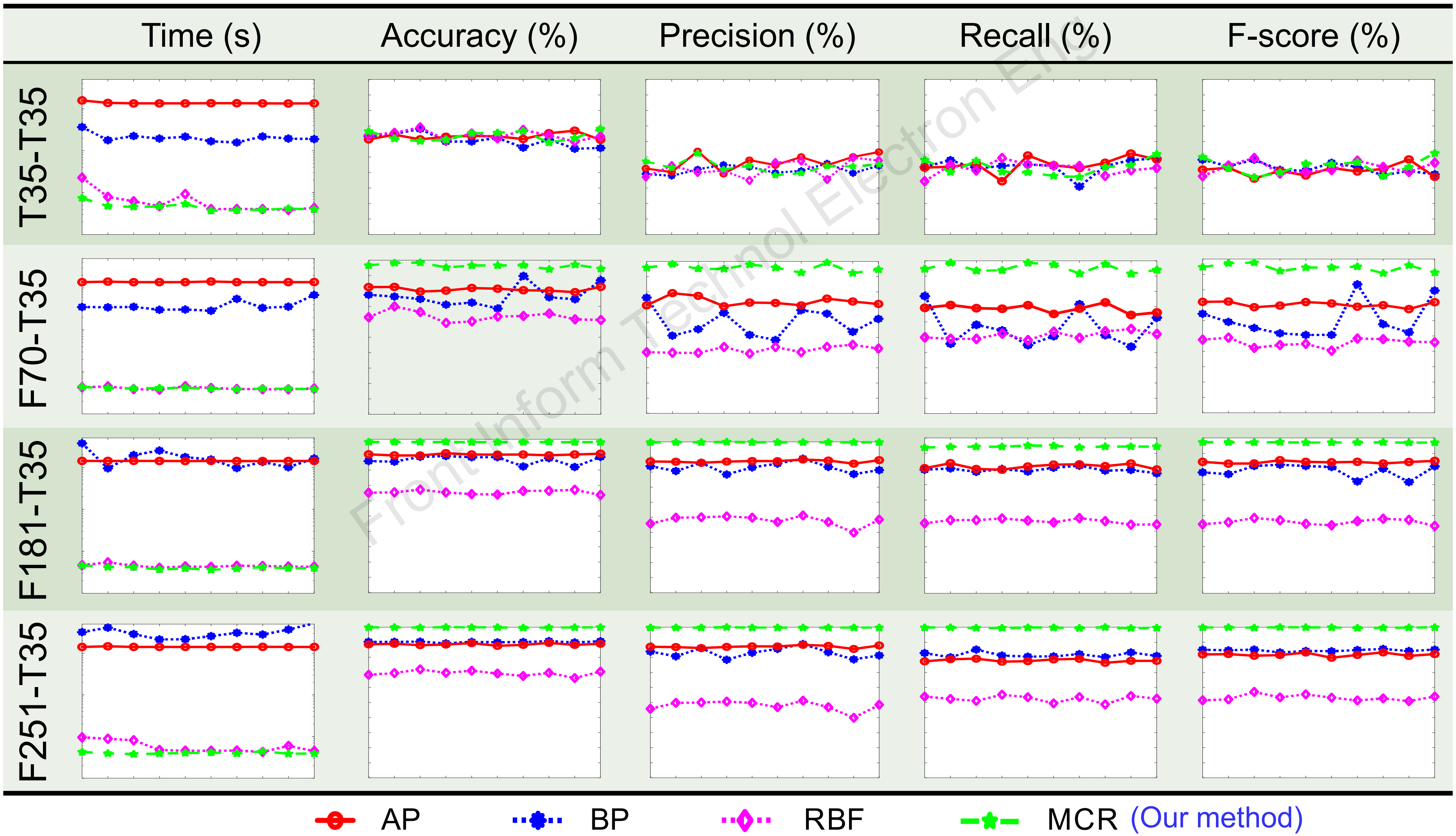
$$\mathrm{nprod}_{i,j} = \mathrm{norm}(\boldsymbol{H} \times \boldsymbol{W}) \quad (5)$$

$$= \frac{\sum_{k=1}^{M} H_{i,k} \times W_{k,j} - \min_{l}\left(\sum_{k=1}^{M} H_{i,k} \times W_{k,l}\right)}{\max_{l}\left(\sum_{k=1}^{M} H_{i,k} \times W_{k,l}\right) - \min_{l}\left(\sum_{k=1}^{M} H_{i,k} \times W_{k,l}\right)},$$

$$r_{i,j} = \mathrm{comp}(\mathrm{nprod}_{i,j}) = \begin{cases} 1, & \mathrm{nprod}_{i,j} > \alpha, \\ 0, & \mathrm{nprod}_{i,j} \leq \alpha, \end{cases} \quad (6)$$

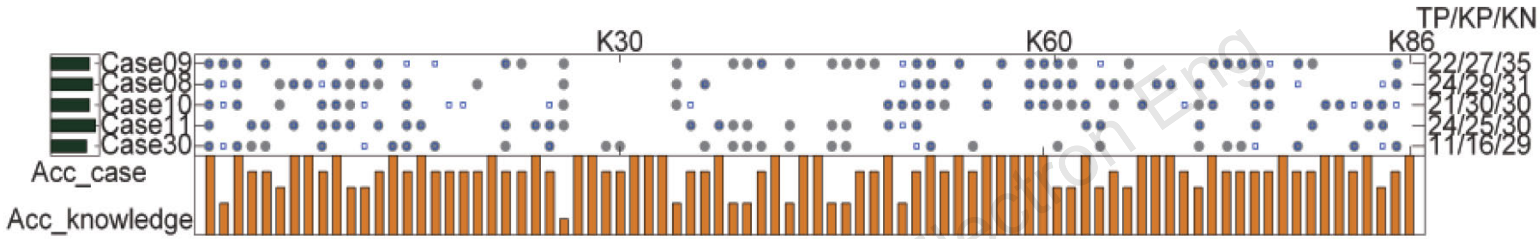
Major results

Evaluations for different matching approaches in different datasets

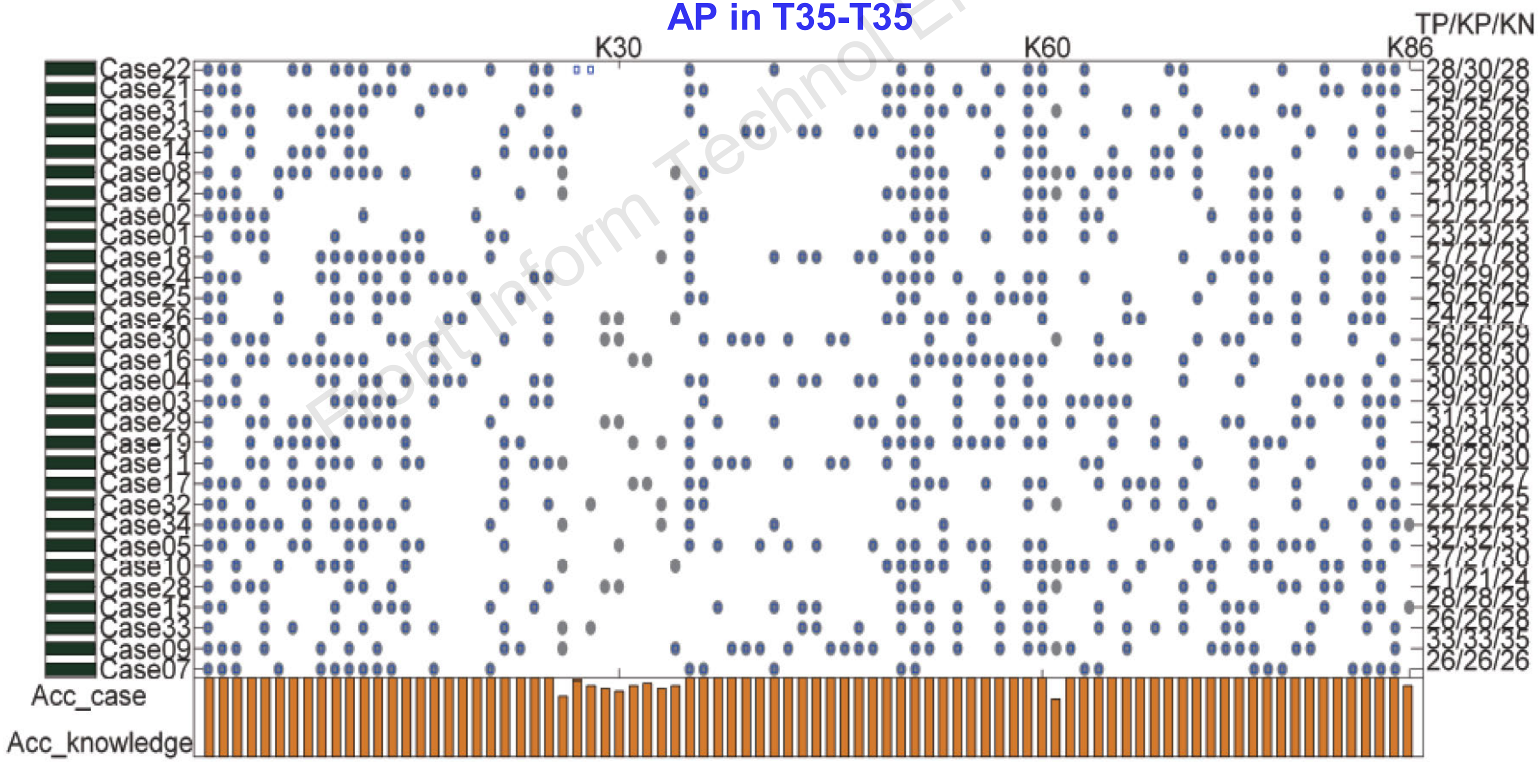


Major results

Detailed knowledge matching results



AP in T35-T35



MCR in F181-T35

Conclusions

- We proposed two methods to augment the training set. Augmenting the training set is positive when using artificial intelligence algorithms in industrial and production engineering.
- We proposed a new knowledge matching approach called MCR based on the traditional RBF. We enhanced the neural network in two parts, i.e., “nprod” and “comp,” to adapt to the multi-classification problem of knowledge matching.
- We compared the performances of different approaches in different datasets about the design of guides.