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Battle damage assessment based on an improved Kullback-Leibler divergence sparse autoencoder

Key words: Battle damage assessment; Improved Kullback-Leibler divergence sparse autoencoder; Structural optimization; Feature selection

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Motivation

- Battle damage assessment (BDA), which provides real-time diagnoses for emergency repair on the battlefield, is a vital premise of battlefield repair , and data-driven methods, instead of complex battle damage models, are playing increasingly important roles in BDA research.
- The nodes number of the hidden layer in a deep learning network is quite difficult to determine in traditional methods.

Main idea

- The improved KL-SAE regression model is an un-supervised learning model, which gains hidden high-level feature representations. The regression layer attached to the KL-SAE is a supervised learning method that estimates the output values.

- The hidden representation of the KL-SAE will be regarded as the input for the regression layer. The hid-den layer of the KL-SAE is a high-level feature representation of raw input data that can be used as the pre-extracted features for other machine learning algorithms. The regression layer outputs final estimation values of each input.

Method

1. Introduce the algorithm of traditional KL-SAE.
2. Based on the traditional KL-SAE, an algorithm of the improved KL-SAE regression model is introduced.
3. Based on the improved KL-SAE, improved KL-SAE regression model which is summarized in algorith is introduced .
4. Propose a novel regression approach to quantitatively calculate the exact value of the battle damage based on the improved KL-SAE regression model, which can optimize the structure of the network through feature selection.

Major results

- The improved KL-SAE regression model is superior in important feature selection and prediction when compared to the reference methods.

Parameter	Value		
	SVR	KL-SAE +SVR	Improved KL-SAE +SVR
Dimension of features	11	11	10
Training time (s)	2.32	2.25	2.05
Prediction time of one sample (μs)	74.26	82.88	62.86
RMSE	0.19	0.21	0.18
MAE	0.16	0.18	0.15

Conclusions

- A novel regression approach is proposed based on an improved KL-SAE regression model, which remedies the disadvantages in structural optimization and feature selection of traditional deep learning networks.
- The improved KL-SAE regression model can extract sparse features in hidden layers through a sparse constraint, and the features obtained can be used to improve the performance of the autoencoder.
- Imroved KL-SAE regression model keeps the features that are effective and important for data reconstruction, and abandons the invalid features.