ABSTRACT

Contour preserving classification technique can enhance the robustness and fault tolerance of the feed-forward neural network. Its major idea derives from the assumption that there exists linearly separable problems when forcing the neural network to perform nonlinear classification can enhance the robustness and fault tolerance of the network. The technique augments a set of training vectors with a set of synthesized vectors, called outpost vectors, generated from the training vectors of two classes of data. These outpost vectors are placed at the boundary between two classes of data to preserve their contour to assist the neural network to classify a linearly separable problem nonlinearly. As a result, the learning process is indirectly biased towards distributing classification workload around the set of hidden neurons, thereby forcing the network to perform nonlinear classification. Three problems have been found in this technique. First, the technique was presented to support only two-class data. It should support multi-class data to be applicable with real-world problems. Second, there is no classification performance evaluation to know the effect of injecting outpost vectors into the training set. Third, a large number of outpost vectors placed deep inside their class do not help preserve the contour of problem. They should be removed without affecting the ability to preserve the contour of the problem to reduce the amount of resource usage.

This research presents an augmentation of the original technique to support multi-class data. It also presents three reduction methods, named FF-AA, FA-AF and FAF-AFA reduction, to reduce the number of multi-class outpost vectors (MCOVs) by selecting only MCOVs located at the boundary between consecutive classes of MCOVs. The experimental results on a four-class synthetic-problem and six real-world problems indicated that the FF-AA reduction method could reduce the number of MCOVs most effectively but this yielded the highest misclassification rate. The FA-AF reduction method could reduce the number of MCOVs least effectively but this yielded the lowest misclassification rate. The FAF-AFA reduction methods reduction and misclassification rates lied between the rates of the FF-AA reduction method and FA-AF reduction method. For real-world problems, only three out of the six real-world problems could benefit from the injection of MCOVs or reduced MCOVs. Hence, there is an uncertainty in what type of real-world problems can benefit from MCOVs or reduced MCOVs. For real-world problems where the injection of MCOVs or reduced MCOVs cannot improve the levels of accuracy of the classification, the levels of accuracy of the classification is not adversely affected.