Intelligent Threshold Prediction for Hybrid Mesh Segmentation Through Artificial Neural Network

Vaibhav J. Hase, Yogesh J. Bhalerao, G. J. Vikhe Patil and Mahesh P. Nagarkar

Abstract Accurate and reliable Area deviation factor (threshold) is one of the decisive factors in hybrid mesh segmentation. Inadequate threshold leads to under-segmentation or over-segmentation. Setting the optimal threshold is a difficult task for a layman. This proposed method, automatically predicts the threshold using artificial neural networks (ANN). ANN predicts the threshold by considering mesh quality of Computer-Aided Design (CAD) mesh model as input feature vectors. Extensive testing on benchmark test cases validates ANN prediction model, and based on Levenberg-Marquardt back propagation (LM-BP) improves the accuracy and stability of prediction. The efficacy of the approach is quantified by measuring coverage. The ANN predicts the threshold elegantly using LM-BP algorithm with coverage for hybrid mesh segmentation greater than 95%. The novelty of the proposed method lies in the "mesh quality"-based threshold prediction through ANN. The predicted threshold finds application in automatic feature recognition from CAD mesh model using hybrid mesh segmentation.

Keywords Artificial neural network · CAD mesh model · Feature recognition · Hybrid mesh segmentation · Threshold prediction

1 Introduction

CAD mesh models are generated by exporting B-rep models using Computer-Aided Design (CAD) software into Standard Triangulated Language (STL). Almost all commercial CAD/CAM systems support STL which makes STL a platform-independent CAD data exchange format [1]. STL has been used in 3D printing, computer graphics,

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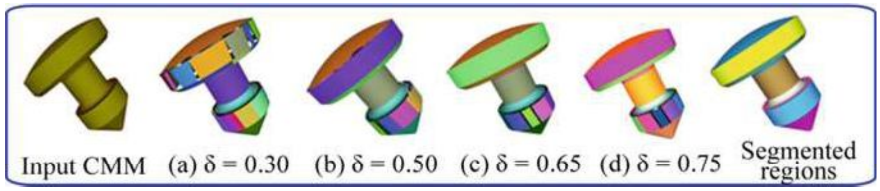


Fig. 1 Sensitivity of the threshold (δ) **a** δ = 0.30, **b** δ = 0.50, **c** δ = 0.65, **d** δ = 0.75 [7]

Computer-Aided Manufacturing (CAM), and Computer-Aided Engineering (CAE) applications [2].

Feature recognition (FR) recreates the feature in the target system. The commercial FR tool works on B-rep models. However, innovative 3D design and manufacturing methods are mesh-based [3]. A need exists to develop FR tool for CAD mesh model (CMM), which will be a novel data translator utility in CAD/CAM and CAE applications [1].

The most favored approach for extracting features from CMM is segmentation [4]. Mesh segmentation partitions CMM into distinct, mathematically analyzable regions [5]. Hase et al. [6] have implemented a hybrid mesh segmentation to extract volumetric features from CMM. Hybrid mesh segmentation heavily depends on Area Deviation Factor (threshold δ). Figure 1 illustrates the effect of varying threshold from 0.30 to 0.75 on segmentation quality. For a layman, it is difficult to set the appropriate threshold.

The above observations inspire the research work reported in this paper. In this research paper, an elegant threshold prediction for hybrid mesh segmentation through Artificial Neural Network (ANN) has been proposed. ANN makes hybrid mesh segmentation automatic. LM-BP have been proposed to predict thresholds with two input feature vectors, viz., standard deviation of "ratio of area to max side" and "ratio of inradius to circumradius" of a CAD mesh model in predicting threshold for hybrid mesh segmentation.

1.1 Contributions

The following are our significant contributions:

- Establish a method for threshold prediction using ANN.
- ANN efficiently predicts the threshold for hybrid mesh segmentation.
- Successfully applied ANN for predicting threshold based on mesh quality.
- Automatic intelligent threshold prediction for automated hybrid mesh segmentation.

1.2 Outline

The outline of the paper is as follows: Sect. 2 discusses the literature findings related to threshold prediction through ANN. Section 3 depicts the framework of the proposed methodology. ANN for threshold prediction is presented in Sect. 4. Results and discussion are illustrated in Sect. 5. Section 6 presents conclusions and future scope.

2 Literature Findings

ANN is one of the most frequently used computing methods for prediction. It finds applications in the optimization of decision, prediction, enhancing process control, signal processing, pattern recognition, parallel computing, etc.

According to Ye and Kim [8], 90% of neural network (NN) applications were based on Back propagation (BP) algorithm. The ANN has been used in the prediction of rainfall [9], rail wheel wear [10], strength properties of carbon fiber-reinforced concrete [11], heat transfer coefficient [12], electricity consumption in a building [13], groundwater level [14], thermal resistance of knitted fabrics [15], Tool life [16], air pollution [17], etc.

Hase et al. [7] have attempted to predict the threshold for hybrid mesh segmentation using KNN classifiers. However, the performance of threshold prediction significantly depends on the value of K (nearest neighbor).

From the literature review, it is evident that most of the researchers have used a trial and error approach for a setting threshold, which is laborious [18]. To the best of our knowledge, threshold prediction for the computer graphics domain has not been addressed so far. The need exists to develop an elegant approach to predict the threshold for hybrid mesh segmentation.

3 Methodology

The proposed methodology involves two phases, viz., Levenberg-Marquardt back propagation (LM-BP) based threshold prediction and hybrid mesh segmentation. Figure 2 illustrates the overall framework for threshold prediction using ANN for hybrid mesh segmentation. The MATLAB™ neural network Toolbox is used for implementations and simulations.

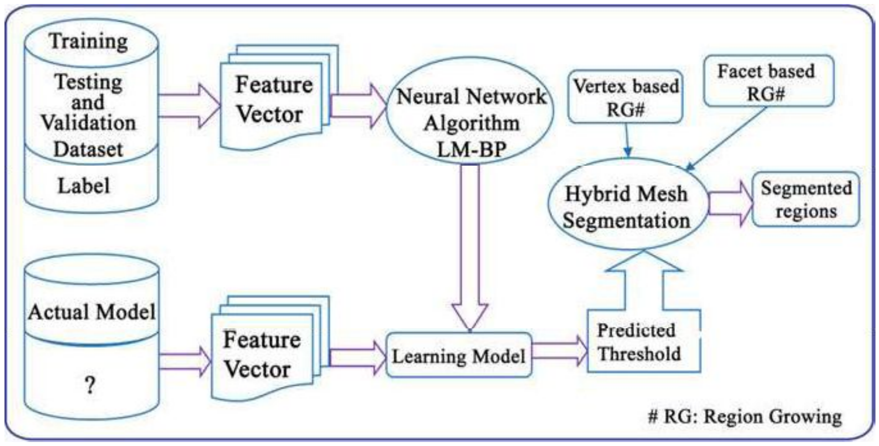


Fig. 2 The framework for threshold prediction using ANN

3.1 LM-BP Neural Network for Threshold Prediction

In the present study, 2-250-1 supervised learning, a multilayer neural network (NN) is built for threshold prediction. A detailed description of LM-BP functional module is discussed in Sect. 4.

3.2 Hybrid Mesh Segmentation

Hybrid mesh segmentation partitions CMM into basic primitives like a plane, sphere, cylinder, cone, and tori. Hybrid mesh segmentation uses "Facet Area" property to cluster facets together, using a combination of vertex-based and facet-based region growing algorithms [6]. After segmentation, each cluster is subjected to several conformal tests, to identify the type of analytical surface it might be representing.

The Hybrid mesh segmentation leads to over-segmentation or under-segmentation based on input threshold. The over-segmented regions are merged with the similar adjacent region by iterative region merging technique. Region merging results in small cracks at the region boundaries [19]. These cracks are filled by the reclamation process. Iterative region merging and reclamation make a watertight segmented model with distinct regions. Figure 3 illustrates examples of the cylindrical regions generated by the hybrid mesh segmentation. Figure 3a is the input mesh models, Fig. 3b illustrates the segmentation results (12 planes and 523 cylindrical patches), Fig. 3c shows the results of the iterative region merging process, Fig. 3d demonstrates the reclamation results and Fig. 3e illustrates the final region merging after reclamation (12 planes and 50 cylinders). Hase et al. [6] have reported a detailed description of hybrid mesh segmentation.

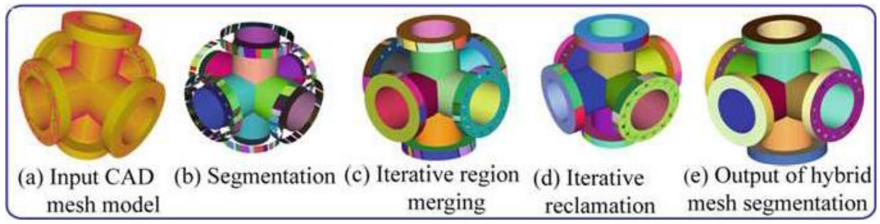


Fig. 3 Hybrid mesh segmentation process

4 LM-BP Neural Network for Threshold Prediction

LM-BP is used to predict the threshold. The artificial network model is designed with 2-250-1 configuration with back propagation; see Fig. 4. The network has two neurons fed to the network representing feature vectors of CAD mesh model in the input layer: 250 hidden neurons in the hidden layer and one neuron for the threshold prediction for hybrid mesh segmentation in an output layer. Table 1 shows the parameters of ANN MATLAB^{TM} implementation.

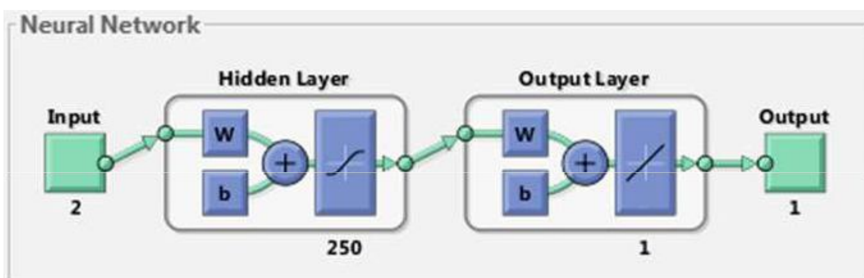


Fig. 4 Model of the multilayer feedforward LM-BP algorithm

Table 1 Parameters for neural network

Parameter	Description
NN training method	Leverberg-Marquardt (trainlm)
NN performance criteria	Mean Square Error (MSE)
NN transfer function	Hyperbolic tangent sigmoid (tansig)
NN type	Feedforward backpropagation
NN learning function	Learn Gradient Descent with Momentum (learngdm)
NN hidden layer	1
NN neurons	250
NN maximum epoch	100

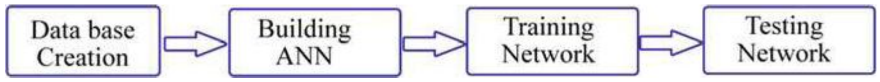


Fig. 5 A systematic procedure ANN model

A systematic procedure for threshold prediction through ANN is illustrated in Fig. 5.

4.1 Datasets Used for Experiments

To predict the threshold value for the test case is a cumbersome task. There is no universal way of finding the correct threshold. A trial and error approach has been used to identify a threshold value for each CAD model [18]. Until now, there has been no accepted benchmark for 3D CAD models [20]. In this research work proposed, a new 3D CAD model database as the training dataset has been created. CAD models are used for creating dataset are taken from NIST [21]. A training dataset is created for CAD mesh models, based on the accuracy of feature extracted and percentage of coverage.

The dataset was created using 400 real CAD models. Dataset consists of 400 number of records and six classes. All the records of the dataset have the same number of attributes. For each CAD model, we compute per face quality according to the triangle shape and aspect ratio. Each CAD model has three attributes in the dataset: standard deviation of "ratio of area to max side"; the standard deviation of "ratio of inradius to circumradius", and the threshold value.

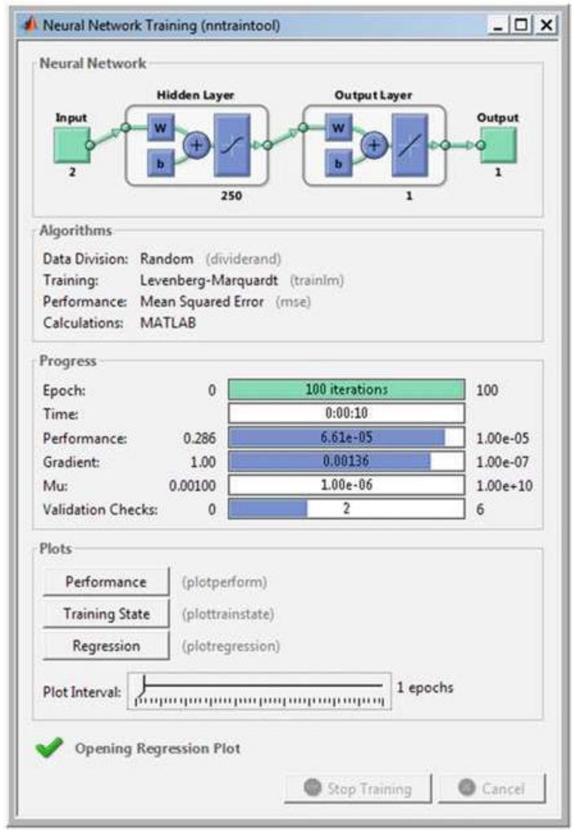
4.2 Building ANN

The ANN has been designed with 2-250-1 configuration with backpropagation. ANN is implemented with one hidden layer feedforward NN trained with LM-BP. To formulate an NN, the datasets are randomly divided into training, testing, and validation with 70%, 15%, and 15%, respectively.

4.3 Training Network

The training data is used to create the NN. It is used to adjust weights. The validation data validates the NN. The training of the NN is stopped based on validation data. The training is stopped when the mean square error (MSE) of the validation dataset

Fig. 6 ANN training state: MATLAB^{TM} implementation



stops improving. The testing data is independently used by created NN to check the performance of the created NN. Figure 6 shows the ANN training state.

4.4 Testing Network

The MSE is the squared difference between targets (simulation values) and output (i.e., ANN output values). The ANN model is tested for unseen data and Mean Square Error (MSE) is evaluated for measuring performance. Lower values of MSE means better trained model.

5 Results and Discussion

Figure 7 shows the regression plot for an ANN trained using training data. It shows correlation coefficients (R) values for validation data and testing data. A very good fit is observed having R values as 0.99392, 0.99367, 0.97794 for training, validation and testing data, respectively.

Figure 8 shows the MSE variation concerning epoch for training, validation, and testing. Performance after training has MSE 6.61×10^{-5} at 98 epoch, and best validation performance is 7.8917×10^{-5} at 98 epochs.

The percentage coverage has been used to measure of success indicator for a hybrid mesh segmentation algorithm. It is a ratio of a number of features recognized to the number of features present in a CAD mesh model. The comparison has been

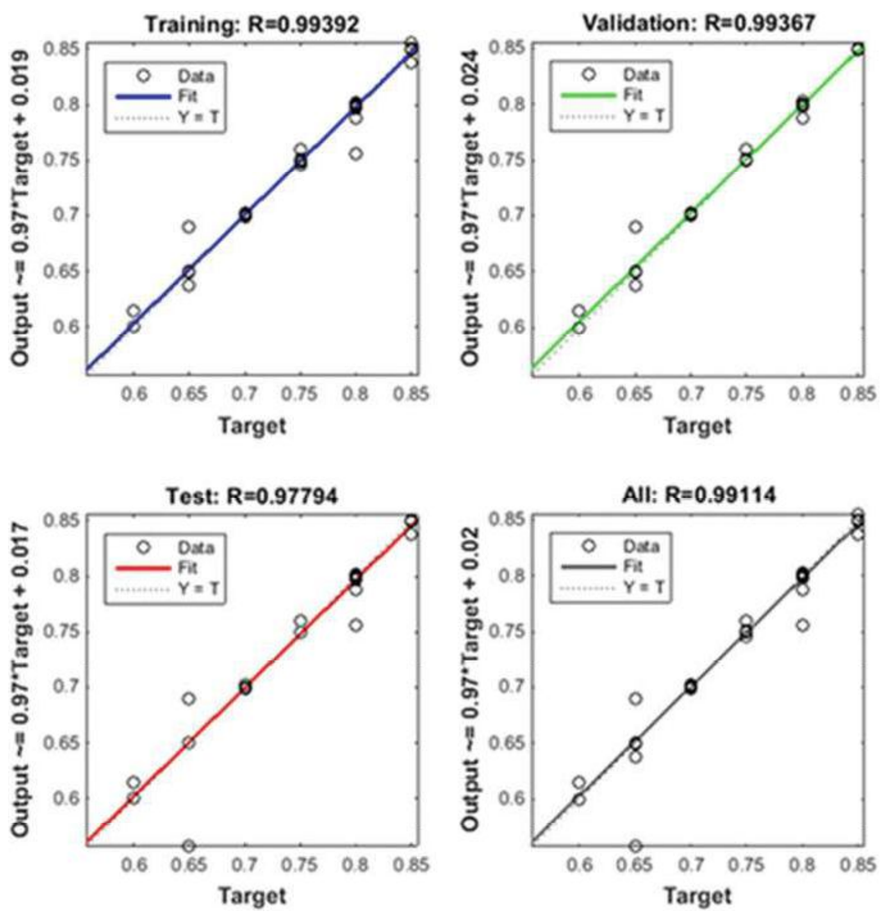


Fig. 7 Regression plots for training, testing and validation phase of ANN

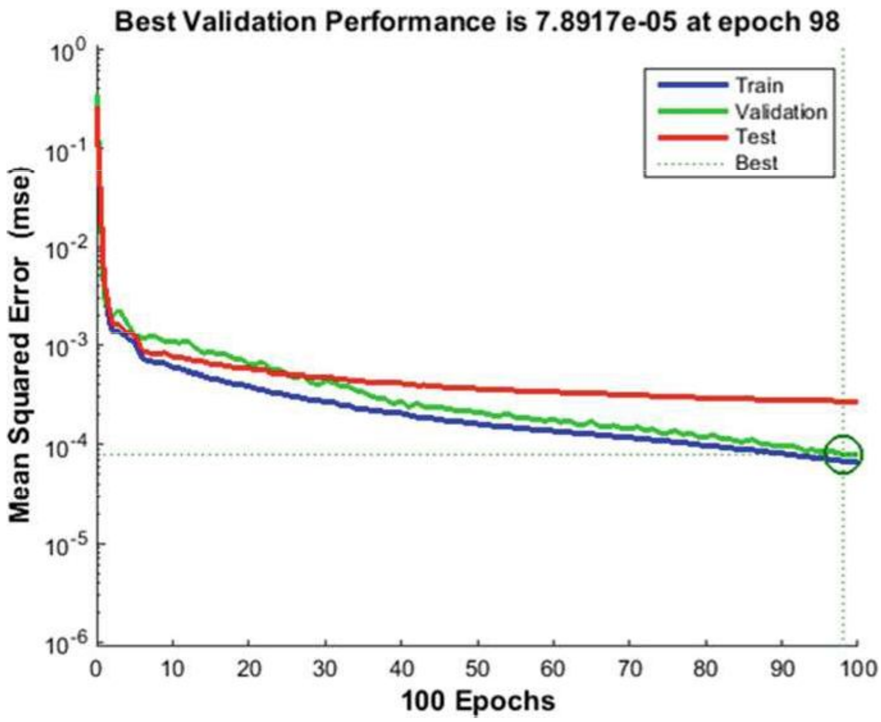


Fig. 8 MSE variation with respect to Epochs–MATLAB

carried out between thresholds predicated from ANN and the actual threshold set by trial and error. It is observed that predicted results have very good agreements with the manual threshold set results in excellent coverage for test cases. Figure 9 shows a performance measure of ANN threshold prediction for hybrid mesh segmentation. Table 2 compares the predicted result by ANN model with experimentation.

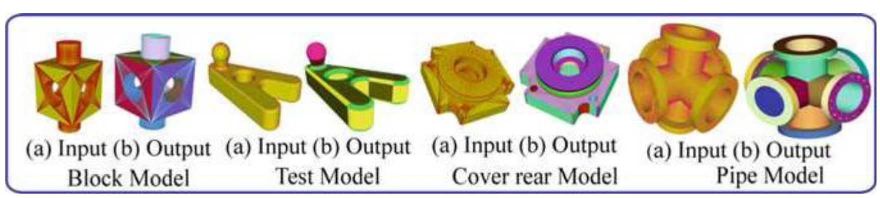


Fig. 9 A performance measure of ANN threshold prediction for hybrid mesh segmentation

Table 2 Threshold comparison by experimentation and predicted by ANN

Model name	Input parameter		Threshold by		N_P	Coverage (%)
	Std. Dev1	Std. Dev2	Exp.	ANN		
Block	0.025786	0.043585	0.60	0.599979375415	14	100
Test case	0.147086	0.232507	0.70	0.699797156838	32	100
Cover rear	0.205617	0.312793	0.75	0.750079261828	45	100
Pipe	0.088974	0.145293	0.80	0.800233768031	62	100

Wherein
N_P: Number of primitives extracted
Exp: Experimentation
Std. Dev1: Standard deviation of "ratio of area to max side"
Std. Dev2: Standard deviation of "ratio of inradius to circumradius"

6 Conclusion

This paper demonstrated a novel approach for threshold prediction for hybrid mesh segmentation through ANN. In this research work, LM-BP algorithm with 2-250-1 configuration has been adopted. The results revealed that R-value (the correlation coefficients) 0.97794 (minimum value), shows the excellent correlation. The performance after training has MSE 6.61×10^{-5} at 98 epoch, and best validation performance is 7.8917×10^{-5} at 98 epochs.

Comparing predicted results with actual experimentation for unseen input data shows ANN outperforms favorably and found to be robust and consistent. ANN can be used as a reliable and efficient threshold predictor for hybrid mesh segmentation.

Future work involves threshold predicting using deep learning and compares the results of ANN with deep learning.

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