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A Novel Dynamic Classifier Selection for Transmission Line Fault Location

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Abstract: Transmission line is an important part of smart grid, so it very significant to accurately and quickly detect the occurrence of the fault location once the fault occurs in transmission line. Currently, there are many artificial intelligence methods for fault location, but most of them use a single classifier, such as SVM, RBFNN, BPNN and so on. Many scholars have demonstrated Multiple Classifier Systems (MCSs) are more accurate than the single classification system in many application areas. In this study, we will propose a classifier selection method which depends on member classifier's relative error rate and sensitivity. In this method, we will try to find the nearest the training sample of the unseen sample, then attempt to select a most suitable member classifier for the testing sample according to the base classifier's testing error for the nearest training sample and the sensitivity of the classifiers for the unseen sample and the training sample. At last, we will use the selected classifier predict the unseen sample. In this paper, five kinds of smart grid fault location problem data set will be used for our experiment and we will illustrate the comparative of our proposed classifier selection method.

Key words: Multiple classifier selection, error rate, sensitivity, smart grid, transmission line, fault location

INTRODUCTION

In recent years, along with the continuous development of world economy, the continual growing of energy demand, people requirement of power grid is become higher and higher, so power grid is now facing an unprecedented challenge and opportunity (Jiang *et al*., 2011). Transmission line is an important part of smart grid, which bears with very important conveying task between the generator and the user (Shahid *et al*., 2012; Hagh *et al*., 2007). However, it's susceptible to all kinds of interference and malfunction since the vast majority of transmission line routes exposed to the outside environment are complex (Silva *et al*., 2006; Samantaray *et al*., 2006). When fault occurs on a transmission line, to detect rapidly and accurately the occurrence of the fault, determine the type of fault and find the fault location is the current research hotspot in smart grid area. As a key transmission line protection, transmission line fault location has got great attention from the power industry all the time. With the continuous development of the power system and the deepening of the concept of smart grid in research and architecture progress, high pressure, more and more long-distance transmission lines worked. In order to reduce the workload of the line inspections, shorten recovery time of the lines, reduce manpower, material waste and improve power system operating management level, it's urgent to introduce a highly efficient, accurately and quickly transmission line fault location algorithm (Samantaray *et al*., 2007).

Multiple Classifier Systems (MCSs) are a popular research topic recently Yeung and Chan (2009). Many studies show that it's effective way to improve performance of the classifier system by MCSs (Woods *et al*., 1997). It combine the decisions of a set of classifiers, which have certain complementary functions in reducing classification error (Kittler *et al*., 1998). In the literature Kittler *et al*. (1998), the author proposed a dynamic fusion method using Dynamic Voting (DV). However, if there are many unsuitable base classifiers for a new testing sample, the unsuitable classifiers will affect the performance of the suitable base classifiers.

In this study, we propose a classifier selection method, which select a most suitable classifier based on the testing sample's nearest training sample and the base classifier's error rate on the training sample. At the same time, it will take the sensitive of the base classifiers on

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data change. That is we will taking into account the comprehensive sensitivity and error rate to choose the best classifier to classify the test samples.

The rest of this study is organized as follows. In Section 2, it introduces the classifier selection aspect; the relative technology and formula will be introduced in Section 3; the proposed method is described in Section 4; In Section 5, it gives experimental result and the conclusion is discussed in Section 6.

CLASSIFIER SELECTION METHODS

As we know, it need to train some classifiers as base classifier for Dynamic Multiple Classifier Systems (DMCSs), then dynamically select some opportune classifiers for the testing sample based on the deferent function of the base classifiers.

So, how to choose the classifier is a critical step for good DMCSs, because that some members of the base classifiers have average classification performance but they may be not the best for a certain testing sample. e.g., the average error rate of SVM and K nearest classifiers is lower than BPNN and RBFNN classifiers and is not that sensitive as them but is less accurate than theirs on some difficult testing sample. If we can dynamically select the most accurate base classifier according to the testing sample, it will greatly improve the accuracy of multiple classification system, especially when the classifier systems are used to predict problems. In this paper, we want to solve the problems about transmission line fault location, in which, in order to improve the repair speed of the fault, it needs more accurately find the position of the fault with fewer manual interventions.

Some classifier algorithms, such as SVM, RBFNN, MLPNN are localized learning machine, they will more accurate for the testing samples closer to the training samples (Yeung *et al*., 2007). The authors produced raw classification effective local accuracy decision region for every testing sample and selected deferent classifiers combinations based on the region in (Fang, 2006). The authors in Yeung *et al*. (2007) selected the better neurons using L-GEM and authors in Yeung and Chan (2009) made multiple classifier fusion using L-GEM. However, they all believe that there are some relativity between the base classifiers and the testing samples. For a same testing sample, some classifiers perform well, the others will perform badly and so, if we can elect a better performed base classifier for each sample to be predicted as the output of the multiple classifier systems, we will obtain a better classifier performance for our problems.

RELATED WORK

Similarity between samples: Many researchers adopt the euclidean distance to compute the distance of two samples, e.g., K-mean, K-nearest algorithms etc. There is no exception in this paper. We also use the Euclidean Distance to calculate similarity between two samples. It's a key phase to compute similarity between the samples to find the most similar training sample to the unseen testing sample. As we know, the larger the Euclidean Distance the farther the training sample will be from the testing sample, they will be more dissimilar and the less probability they are in the same class.

In this study, we calculate the similarity between two samples using Euclidean Distance. Suppose X_i, X_j are two samples, the similarity between them are represented as similarity (X_i, X_j), we define it as:

$$\text{Similarity}(X_i, X_j) = \frac{1}{\sqrt{(x_{i1}-x_{j1})^2 + (x_{i2}-x_{j2})^2 + ... + (x_{in}-x_{jn})^2}} \quad (1)$$

where, is tth feature value of sample X_i, is tth feature value of sample X_j.

Absolute error of a classifier: Error rate here is not opposite to accurate rate of the universal significance, it is the absolute error between the actual output of a sample and the output of the classifier for the sample. For any sample X (x,y), x is the input, *y* is the actual output, we call h_i (x) as the output of the classifier on the sample X. We define the absolute error of the base classifiers for the sample X as:

$$e_i(X) = |h_i(x) - y| \quad (2)$$

Sensitivity of a classifier: Deferent learning algorithm has deferent sensitivity on the same input data, that tells that their sensitive level vary for the samples. Some algorithms are obtuse for the little change in the sample, but the other algorithms will have tremendous change of output for only little change in the input of the sample. In this paper, we want to find the testing sample's most similar training sample and decide the most suitable classifier base on the performance of the base classifiers to classify the most similar training sample. We believe that the less sensitive the better for a classifier, so we hope to find a base classifier like this, the absolute difference between the output of it for the testing sample and the most similar training sample. We define the absolute difference as the output sensitivity for classifier h_i between the two samples, which is defined as follows:

$$\text{Sentitive}(h_i, X, X_0) = |h_i(x) - h_i(x_0)| \quad (3)$$

Where, X is the new coming testing sample, X_0 is the most similar training sample of the testing sample, x is the input of X, x_0 is the input of X_0.

Combination of Absolute error and sensitivity: In classifier selection methods, we always want to find the most conducive member classifier for the current unseen sample. The member classifier is a classifier whose absolute error is lowest in all the base classifiers. So, what kind of member classifiers is able to achieve such a goal? In this study, we believe the classifier with little absolute error on the most similar training sample can more accurately classify the testing sample. After all, it is not the absolute of test sample and deferent classifier have deferent sensitivity on the same input data, some classifier have tremendous change of output for only little change in the input of the sample. So, it maybe not the best classifier for the testing sample if only considers the absolute error. Therefore, we will take into account the sensitivity of the output sensitivity for classifiers and absolute error of the base classifiers.

Suppose $X = (x, y)$ is the new testing sample and $X_0 = (x_0, y_0)$ is the most similar training sample $H = \{h_i, i = 1, 2, 3...\}$ is the base classifier poor which contain all the member classifiers. $h_i (x)$ and $h_i (x_0)$ are the outputs of classifier h_i for the testing sampleand training sample X_0. So, the sensitivity of h_i for the two samples are sensitive (h, X, X_0) and the absolute error of the h_i for the training sample X_0 is $e_i (X_0) = |h_i (x_0)-y_0$.

In this study, to get better classifier selection criteria, we will make linear combination of the two aspects. We call it relativity between the testing samples and the base classifiers and define the relativity as:

$$\text{Relativity } (h_i, x) = \alpha e_i(x)+(1-\alpha) \text{ sensitive } (h_i, x, x_0) \quad (4)$$

where, α is combination of factors, which represent the weight of the absolute error in the combination, so the weight of sensitivity is $1-\alpha$◦

PROPOSED METHOD

First, train a lot of base classifiers, each base classifier has an output for a new testing sample and then select a relatively optimal classifier based on a pre-established selection criteria from all the base classifiers. At last take the output of the selected classifier as the result of the multiple classifier system.

As stated in section II, it should train many base classifiers and every base classifier has an output for every testing sample, then selects a best classifier for this testing sample based on the pre-defined selection policies and use the output of the selected classifier as the entire multi-classifier output.

In this algorithm, we fully take into account the specificity of the test sample and sensitivity between training samples and this testing sample. Specific steps are divided into two steps.

Training phase: Division of the training set is the first phase of the MCSs, then to train effective base classifiers based on the divisions and ensure their accuracy and diversity is the second step. After that, it can satisfy deferent testing tasks. In this study, we train deferent base classifiers using deferent algorithms and put them into the base classifier poor for the testing phase.

The training phase will be divided in two steps:

- Train the ith base classifier H_i using training set $(i = 1, 2, ..., m)$;
- Generate the base classifier pool H using the H_i $(i = 1, 2, ..., m)$ as $H = \{H_1, H_2,..., H_m\}$.

Testing phase: The testing samples are handled one by one in testing phase. For the new sample $X = (x, y)$, we will firstly find the most similar training sample $X_0 = (x_0, y_0)$ from the training set based on the similarity between two samples. And x and x_0 is the input, y and y_0 is the output. Secondly, on the one side, we calculate the testing error of every base classifier on X_0, the testing error of a member classifier h_i on X_0 defined as follows:

$$e_i (X_0) = |h_i(x_0)-y_0| \quad (5)$$

On the other side, we should calculate the sensitive of every member classifiers from the testing sample X to the most similar training sample X_0. We define the sensitivity of classifier h_i as follows:

$$\text{Sensitivity } (h_i, x, x_0) = |h_i (x)-h_i (x_0)|$$

Thirdly, we will combine the testing error rate of classifier h_i on X_0 and the sensitivity of the classifier h_i from X-X_0:

$$\text{Relativity } (h_i, x) = \alpha e_i (x)+(1-\alpha) \text{ sensitivity } (h_i, x, x_0) \quad (6)$$

At last, we will find the most suitable member classifier based on every their e_sensitivity. The selection criterion is defined as follows:

$$\min_{h_i} \text{relativity}(h_i, x) \quad (7)$$

H is the base classifier pool, which contains all the member classifiers. We will use the selected classifier's output as the label of the new testing sample.

EXPERIMENT AND THE RESULTS

Experiment design: This study, firstly we built a 200-kilometer-long, 735-kv-ultra-high voltage double side power transmission line model using Matlab\Simulink power module to simulate the 11 most common types of short-circuit fault occurs in transmission line and obtain the three-phase voltage, three-phase current and zero sequence current from both ends of the transmission line. Secondly we analyzed the 11 most common types of short-circuit fault and then divided them into five major categories, (1) Single phase-to-earth fault (1PEF), (2) Two phase fault (2PF), (3) Two phase-to-earth fault (2PEF), (4) Three phase fault (3PF), (5) Three phase-to-earth fault (3PEF).

At the same time, we made detailed analysis and comparison between different classifiers such as K Nearest Neighbor (KNN), back propagation (BPNN), radial basis neural network (RBFNN), Support Vector Machine (SVM) combined with wavelet energy entropy feature extraction technology respectively based on single side features and two end features. And use the four types of classifiers as base classifiers of our proposed MCSs and made comparison of the 4 base classifiers and our MCSs on the data set of five fault location.

To make more convincing experiment results, we did 10 times experiments for every data set by randomly selection with replacement. For every random set, the 50% is selected as training set randomly; the rest 50% is selected testing set. We use the mean absolute error rate as the evaluation criteria. In these experiments, we made comparison between the single classifiers and our Multiple Classifier Selection method(MCS).

In every figure, the blue line represent the result of KNN classifier; the red line represent the result of BP classifier; the green line represent the result of RBF classifier; the purple line represent the result of SVM classifiers; the black line represent the result of our multiple classifier selection system. The number i in the horizontal axis stands for the experiment result in ith experiment. And MRE in the vertical axis stands for mean relative error rate.

Results and analyses: Figure 1 shows the 10 times experiment results of the single phase-to-earth fault(1PEF) data set. The experimental results clearly show that the accuracies of our method have lower relative error rate than the other single classifiers in the 1PEF data set.

Figure 2 shows the 10 times experiment results of the two phase fault (2PF) data set. The experimental results

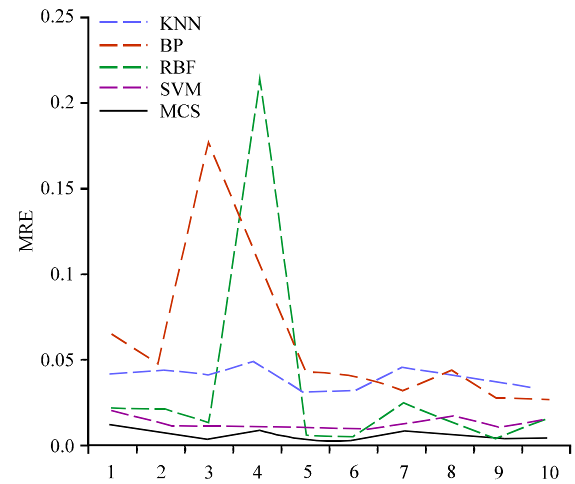

Fig. 1: Results on single phase-to-earth fault

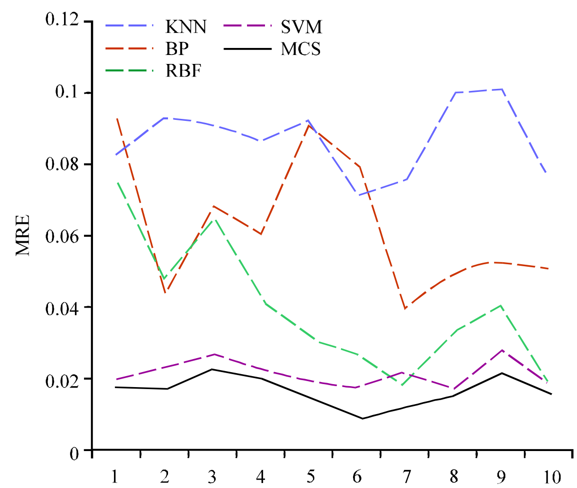

Fig. 2: Results on two phase fault

clearly show that the accuracies of our methods have lower relative error rate than the other single classifiers in the 2PF data set.

Figure 3 shows the 10 times experiment results of the two phase-to-earth fault (2PEF) data set. The experimental results clearly show that the accuracies of our method have lower relative error rate than the other single classifiers in the 2PEF data set.

Figure 4 shows the 10 times experiment results of the three phase fault (3PF) data set. The experimental results clearly show that in the most time, the accuracies of our method have lower relative error rate than the other single classifiers in the 3PF data set. The error rate is a little higher than SVM classifier only in the third experiment.

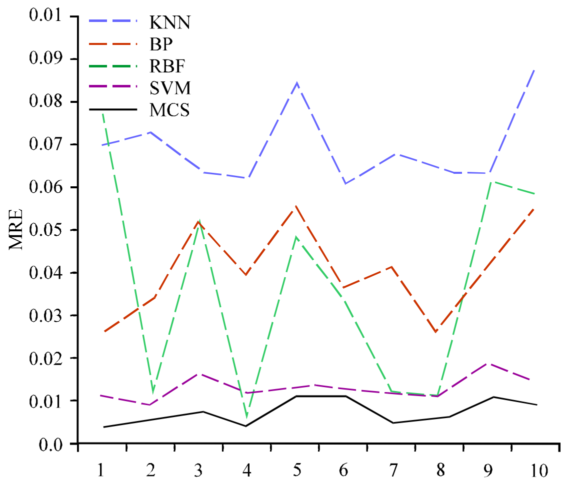

Fig. 3: Results on two phase-to-earth fault

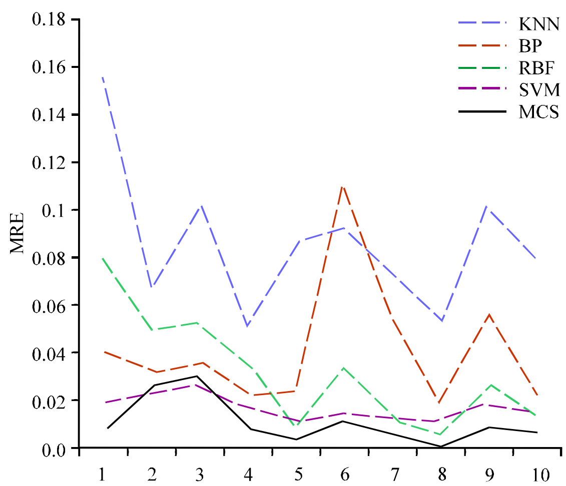

Fig. 4: Results on three phase fault

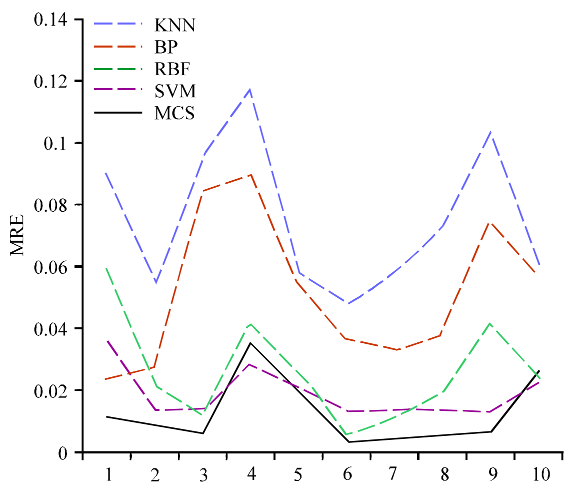

Fig. 5: Results on three phase-to-earth fault

Figure 5 shows the 10 times experiment results of the three phase-to-earth fault (3PEF) data set. The experimental results clearly show that in the most time, the accuracies of our method have lower relative error rate than the other single classifiers in the 3PEF data set. The error rate is a little higher then SVM classifier only in the fourth experiment.

CONCLUSION

In this study, a novel dynamic selection method in MCSs for improving the fault location accuracy is proposed. In the method, we select the most suitable classifier with the most similar training sample for the unseen sample and take into account the absolute accurate and sensitivity of the base classifiers. And use the new method to make experiment with the 5 grid fault location problems. And the experiment result clearly show that the proposed method will better than all the single classifiers. And the relative error rates are all decrease in the 5 fault location data sets.

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REFERENCES

Fang, M., 2006. Study of integration method for multiple classifiers on ensemble learning. Syst. Engin. Electron., 28: 1759-1763.

Hagh, M.T., K. Razi and H. Taghizadeh, 2007. Fault classification and location of power transmission lines using artificial neural network. Proceedings of the International Power Engineering Conference, December 3-6, 2007, Singapore, pp: 1109-1114.

Jiang, J.A., C.L. Chuang, Y.C. Wang, C.H. Hung, J.Y. Wang, C.H. Lee and Y.T. Hsiao, 2011. A hybrid framework for fault detection, classification and location-Part I: Concept, structure and methodology. IEEE Trans. Power Delivery, 26: 1988-1998.

Kittler, J., M. Hatef, R.P.W. Duin and J. Matas, 1998. On combining classifiers. IEEE Trans. Pattern Anal. Mach. Intell., 20: 226-239.

Samantaray, S.R., P.K. Dash and G. Panda, 2006. Fault classification and location using HS-transform and radial basis function neural network. Elect. Power Syst. Res., 76: 897-905.

Samantaray, S.R., P.K. Dash and G. Panda, 2007. Distance relaying for transmission line using support vector machine and radial basis function neural network. Elect. Power Energy Syst., 29: 551-556.

Shahid, N., S.A. Aleem and I.H. Naqvi, 2012. Support vector machine based fault detection & classification in smart grids. Proceedings of the Globecom Workshops, December 3-6, 2012, Anaheim, CA., pp: 1526-1531.

Silva, K.M., B.A. Souza and N.S.D. Brito, 2006. Fault detection and classification in transmission lines based on wavelet transform and ANN. IEEE Trans. Power Delivery, 21: 2058-2063.

Woods, K., W.P. Kegelmeyer Jr. and K. Bowyer, 1997. Combination of multiple classifiers using local accuracy estimates. IEEE Trans. Patt. Anal. Mach. Intelli., 19: 405-410.

Yeung, D.S. and P.P.K. Chan, 2009. A novel dynamic fusion method using localized generalization error model. Proceedings of the International Conference on Systems, Man and Cybernetics , October 11-14, 2009, San Antonio, pp: 623-628.

Yeung, D.S., W.W.Y. Ng and D. Wang, 2007. Localized generalization error model and its application to architecture selection for radial basis function neural network. IEEE Trans. Neural Network, 18: 1294-1305.