A Method For Dynamic Ensemble Selection Based on a Filter and an Adaptive Distance to Improve the Quality of the Regions of Competence

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Abstract—Dynamic classifier selection systems aim to select a group of classifiers that is most adequate for a specific query pattern. This is done by defining a region around the query pattern and analyzing the competence of the classifiers in this region. However, the regions are often surrounded by noise which can difficult the classifier selection. This fact makes the performance of most dynamic selection systems no better than static selections. In this paper we demonstrate that the performance of dynamic selection systems end up limited by the quality of the regions extracted. Thereafter, we propose a new dynamic classifier selection system that improves the regions of competence in order to achieve higher recognition rates. Results obtained from several classification databases show the proposed method not only significantly increase the recognition performance, but also decreases the computational cost.

I. INTRODUCTION

Multiple Classifier Systems/Ensemble of Classifiers have been widely studied in the past years as an alternative to increase efficiency and accuracy in pattern recognition problems [1], [2]. The main motivation for using combination of classifiers derives from the observation that different classifiers usually commits errors in different patterns. The advantages of the individual (base) classifiers are combined into a final solution. This leads to a system that presents more accurate results. There are many examples in the literature that show the efficiency of ensemble of classifiers in many tasks, such as, handwritten recognition [3], [4], [5], signature verification [6] and image labeling [7].

There are two basic approaches for combination of multiple classifiers: selection and fusion. In the classifier fusion techniques [1], [8], [9], [10], every classifier in the ensemble is used and the outputs are aggregated using a function (e.g. product rule, majority vote). Furthermore, another different classifier can be used to fuse the outputs [10], [11], [3], [4]. In classifier selection the idea is to define a region of competence and search for the most competent or a subset with the most competent classifiers in the region. The selected classifier(s) is(are) used to give the final answer [12], [13], [14]. In some case it is possible to use a combination of selection and fusion [15]. These methods can also be static (the same combination for every pattern) or dynamic (the combination depends on the query pattern).

The problem examined in this paper relies on dynamic classifier selection (DCS). The classical dynamic classifier selection procedure is divided into three levels [16]: (1) Classifier generation which defines how the base classifiers are generated, (2) Region of competence that is how to define the region in which the search for the best classifier is performed and (3) Dynamic selection that defines the rule that selects the classifier(s), generated on the first level, based on the information extracted from the regions defined on the second level. The classifier(s) selected on the third level is(are) used to classify the query pattern. Figure 1 shows an overview of a dynamic classifier selection system.

![Figure 1. Overview of dynamic classifier selection systems](image)

Fig. 1. Overview of dynamic classifier selection systems

Many studies have been conducted on the first and on the third level. On the first level the most used algorithms are bagging [17], boosting [18] and random subspaces [19]. Duin [20] presented different ways to generate ensemble of classifiers and rank the methods according to its success.

On the third level, Woods et al. [12] proposed the DCS-LA (Dynamic Classifier Selection by Local Accuracy). In this technique, the accuracy of each classifier in the neighborhood of the test pattern is computed and the classifier with the best result is selected. The classifier rank [14] approach is similar to the DCS-LA, but the selected classifier is the one that correctly classified more consecutive patterns in
the neighborhood. Giancinto and Roli [21] proposed the Multiple Classifier Behavior algorithm which is a mixture of the DCS-LA with the behavior-knowledge space (BKS) [5]. In this algorithm the local region is measured based on the behavior of the classifiers. Kuncheva [22] used the overall local accuracy on previously defined regions. During the test phase, the classifier with the highest accuracy in the desired region is selected.

However, given the fact that selecting only one classifier is very error prone, some researchers decided to select a subset of classifiers. Ko et al. [13] proposed an approach that aims to imitate the Oracle concept. The Oracle is the upper limit of the ensemble performance [23]. The KNORA-E (K Nearest ORAcles - Eliminate) which eliminates a classifier of the ensemble if the classifier misclassify any pattern of the neighbors. There is also a weighted version KNORA-E-W that weights the outputs of the selected classifiers according to the distance between the query pattern and the neighbors. This work also introduces two fusion algorithms: KNORA-U (K Nearest ORAcles - Union) and its weighted version KNORA-U-W. Soares et al. [24] select the \( N \) most accurate classifier, based on a defined region of competence, and the \( J \) most diverse classifiers to create the ensemble. The values of \( N \) and \( J \) were defined by the authors. These techniques are called dynamic ensemble selection (DES) as they can select more than one classifier.

However, not much attention have been given to the second level (region of competence) in how the quality of this region influences the final result. The rule defined for selecting the classifiers (third level) depends on the quality of the information obtained from the region of competence. The dynamic selection should probably fail if there are many noisy patterns in the region of competence.

The focus of this paper is on the second level. First we show the performance of dynamic classifier selection is limited by the quality of the region of competence (how it is defined). A practical example is used to illustrate cases when the dynamic classifier/ensemble selection systems fail because of noises in the region of competence. Also we compare the recognition performance of the techniques with the algorithm that defines the region of competence and show that the results are really close. In some cases the dynamic classifier selection results are even slightly inferior.

Based on this analysis, we propose a new dynamic ensemble selection technique that achieve more accurate results by improving the quality of the regions of competence. This is performed using two strategies: One is a filter that removes samples that are considered noise, creating soft decision boundaries. The other is an adaptive version of the k-Nearest Neighbor algorithm that uses weights to indicate whether a pattern is close to patterns of different classes or not. The objective is to eliminate noisy patterns before the execution of the classifier selection (third level). Thus, improving the overall system performance.

In order to demonstrate the efficiency of the proposed approach, we conducted experiments using nine classification problems. We show that the performance of previous techniques becomes limited by the performance of the algorithm that creates the region of competence. Thereafter, we show the proposed technique not only increases the recognition rate but also can decrease the computational time as it becomes easier for the system to select the best classifiers.

This paper is organized as follow. An analysis of how the regions of competence influences the classifier selection is shown in Section II. Section III describes the proposed system. The experiments are presented in Section IV and the conclusion is shown in Section V.

II. ANALYSIS OF THE INFLUENCE OF THE REGION OF COMPETENCE

The influence of the region of competence in DCS system is analyzed in this section. In order to do so, first we explain the KNORA-ELIMINATE algorithm [13]. The KNORA-E was selected because it performs slight better than the other dynamic selection schemes [13]. Thereafter, we perform an analysis of the influence of the quality of the region of competence using a practical example.

A. KNORA-ELIMINATE

This approach explores the oracle concept to dynamically select the classifiers. Let \( X_i, i = 1, \ldots, k \) be the \( k \) nearest neighbors of the query pattern \( X \) and an ensemble of \( L \) classifiers \( C_j, j = 1, \ldots, L \), the dynamic ensemble \( E^* \) is composed of the classifiers \( C_j \) that correctly classifies every neighbor \( X_i \). Classifiers that misclassify any of the \( k \) neighbors are eliminated. If none classifier can correctly classify every neighbor, the value of \( k \) is decreased and the rule continues the search until at least one classifier correctly classifies all the neighbors.

One advantage of this method is that the number of neighbors is not fixed, although it can only decrease. However, the cost of reducing the neighborhood and recalculate the method is computationally expensive. Like the other dynamic techniques, this rule is very dependent on the quality of the neighborhood.

B. Analysis

To demonstrate the problem that the dynamic classifier/ensemble selection techniques have with the quality of the region of competence, we performed an experiment using an ensemble of 10 Perceptrons generated using the bagging algorithm. A neighborhood of \( k = 7 \) is used. Figure 2 shows the misclassifications obtained by the KNORA-E for the Banana dataset. Figure 2(a) shows the form of the Banana dataset. Figure 2(b) shows the errors obtained in this dataset (in red) and the validation set (in blue). The validation dataset is used to compute the region of competence. Figure 2(c) shows some patterns of the class * (in red) that although they are closer to its class mean, they were misclassified because there is a pattern from the other class + among them. This pattern is closer to the other class mean * than its own class mean +. Thus it can be considered a noise.
The current dynamic ensemble selection systems fail when situations like this happens. The current systems end up selecting the wrong classifiers when there are noisy patterns near the query pattern as the classifier that can recognize those noise patterns and therefore achieve the highest accuracy in the neighborhood probably have overfitted in the region. That explain why the dynamic selection methods become limited to the performance of the algorithm that defines the region of competence. Thus, if we improve the quality of the neighborhood, the performance of the dynamic classifier/ensemble selection method will also improve. This is an important point in the recognition rate of the system that did not receive much attention. In the experiments section we demonstrate the limitation imposed by the performance of the algorithm that defines the region of competence using empirical results.

III. The Proposed Approach: DES-FA

In this section the proposed ideas to improve the quality of the neighborhood and consequently the dynamic selection are shown. Two techniques were used. First, a noise reduction filter is applied to the validation dataset (dataset where the regions of competence are computed) to remove noisy patterns. This step is done during the training procedure. Thereafter, a variation of the k-Nearest Neighbor algorithm is proposed in order to improve the quality of the computed neighbors. Figure 3 shows an overview of the proposed system. $T$ is the training set, $V$ the validation dataset and $G$ the test dataset (generalization). During the training stage, the ensemble $E = \{C_1, \cdots, C_L\}$ is generated using the dataset $T$. The Edited Nearest Neighbor (ENN) filter [25] is applied to the validation dataset $V$ generating the dataset $V', |V'| \leq |V|$. The ENN filter works eliminating noise on the decision boundaries. Thus the algorithm produces soft decision boundaries.

In the test phase, the local region is computed using the adaptive k-NN algorithm [26] using the patterns of the filtered dataset $V'$. The adaptive k-NN is a variation of the traditional k-NN that uses weights to indicate how close a training pattern is from patterns of different classes. The weight is used in order to have a higher probability of selecting patterns that are distant from the border. Thus, patterns with higher probability of being noise are less likely to be chosen. On the third stage (classifier selection) we use the KNORA-Eliminate rule [13] to select the dynamic ensemble $E^*$ using the region of competence defined by the adaptive k-NN algorithm. We call the proposed system DES-
FA (Dynamic Ensemble Selection by Filter + Adaptive Distance). The ENN filter and the Adaptive k-NN are described in the next sections.

A. Edited Nearest Neighbor Filter

The edited nearest neighbor rule [25] works as a noise reduction filter to create smoother class boundaries. The central points of the classes are preserved. Figure 4 and Algorithm 1 show the steps of the ENN algorithm. The algorithm works as follow: Let $T$ be the training set, and $S$ the filtered set, the algorithm perform the nearest neighbor classification for each $X_i \in T$ using $T$ as reference. If $X_i$ is misclassified using the k-NN algorithm, it is considered a noise and removed from the final set $S$.

**Algorithm 1** The Edited Nearest Neighbor Algorithm

**Input**: Training Set $T$

1: $S = T$
2: **for** each $X_i \in T$ **do**
3:  **if** class($X_i$) $\neq$ class(kNN($X_i$, $T$)) **then**
4:   $S = S - \{X_i\}$
5:  **end if**
6: **end for**
7: **return** $S$

Figure 5 shows an example of the application of the ENN filter. The data was constructed using two Gaussian distributions generated with $\mu_1 = [0.0, 0.0]$, $\mu_2 = [3.5, 0.0]$ and $\sigma_1^2 = \sigma_2^2 = 1$. Figure 5(a) shows the original distribution. Figures 5(b), (c) and (d) present the result after the execution of the ENN algorithm with $k = 1, 3$ and 5 respectively.
B. K-Nearest Neighbor with Adaptive Distance

The adaptive distance [26] calculates, for each training sample $X_i$, the largest sphere centered on $X_i$, $i = 1, \cdots, N$ that excludes every training pattern of different classes $X_j$, $j = 1, \cdots, N$. This is performed by computing the minimum distance (sphere radius) $R_i$ between the training pattern $X_i$ and the training samples of different classes (Equation 1).

With the radius $R_i$, the adaptive distance between the test pattern $X_{test}$ and $X_i$ is defined by equation 2. The distance $d(X_{test}, X_i)$ can be any distance, such as, the Euclidean or the Manhattan distance.

\[
R_i = \min d(X_i, X_j), c_i \neq c_j 
\]

\[
D_{\text{adap}}(X_{test}, X_i) = \frac{d(X_{test}, X_i)}{R_i} 
\]

Using this method, samples closer to its class mean have bigger radius ($R_i$) than samples that are near the class boundaries. Thus, samples that are closer to the class boundaries become more distant to the query pattern while the ones next to the class means becomes closer. Therefore, the probability of selecting a noise as neighbors is lower.

The idea behind using the ENN filter and the adaptive k-NN techniques comes from the fact that they reduce the number of undesirable patterns in the region of competence. However, it is not guaranteed that the ENN will eliminate every undesirable pattern. The adaptive k-NN works in a way that pattern closer to the decision boundaries and therefore more probable of being noise have less chance of being selected. Therefore even if an undesirable pattern was not eliminated using the ENN, the probability of selecting this pattern using the adaptive k-NN is lower. Thus, it is interesting to use both techniques as one can overcome the limitation of the other.

IV. EXPERIMENTS

To ensure the efficiency of the proposed DES-FA, the experiments were conducted using nine databases, seven from the UCI machine learning repository\(^1\) and two artificially generated using the Matlab PRTOOLS toolbox\(^2\). The key features of the databases are shown in Table I. The ensemble is generated using the bagging technique which is described below.

A. Bagging

Bagging is an acronym for Bootstrap AGGregatING [17]. The idea behind bagging is to simply build a diverse set

\(^1\)http://archive.ics.uci.edu/ml
\(^2\)www.prtools.org
of classifiers by selecting different subsets of the training set to train the base classifiers. The subsets are generated randomly. The diversity among the classifiers is achieved by the use of different training sets. One important point using this technique is the fact that the base classifiers should be unstable. A classifier is considered unstable if small perturbations in the training set results in large changes in the constructed predictor [27]. In general, classifiers that presents high variance such as Neural Networks and Decision Trees are unstable. Linear Discriminant and k-Nearest neighbor are considered stable classifiers. Also it is known that bagging presents good results when used with weak classifiers [27]. Algorithm 2 summarizes the steps of the bagging algorithm.

Algorithm 2 The Bagging Algorithm

**Input**: Training Set $T$

1: for $i = 1$ to $L$ do
2: Take a bootstrap $T*$ from $T$
3: Train $C_i$ with $T*$
4: $E = E \cup C_i$
5: end for
6: return $E$

B. Results

A total of 20 iterations using different divisions between training/test were used for each dataset. The datasets were divided into 50% for the training set and 50% for the test set. The only exceptions were the Optical Digits and the Image segmentation datasets as the training and test set have been defined by the UCI repository. The training set was divided into 75% for training and 25% for validation. The validation dataset is used to compute the regions of competence. The ensemble is composed of 10 Perceptron and the number of neighbors is empirically set to 7. The Perceptron classifier was selected because it is unstable and a weak model. Therefore it is suitable to be used with Bagging. Majority Vote rule [1] was selected as combination rule.

First, we show a comparison of the KNORA-E with the performance of the k-NN algorithm using the leave-one-out methodology [28] to demonstrate that the current dynamic classifier selection systems are limited by the performance of the region of competence algorithm. This methodology uses only one pattern as the test and the remaining as the training data. This is repeated until every pattern of training data is used as test. Thus, using this test, we have the percentage of patterns that have a "bad" neighborhood. They are the patterns that the dynamic selection techniques mostly presents error.

The comparison is shown in Table II. It can be observed that the performance of the KNORA-E is close to the results of the leave-one-out on the datasets and in some cases, the results are even slightly inferior. The result of the KNORA-E is even lower than the best classifier of the ensemble (Single Best) or the static ensemble for some datasets. This demonstrates that the dynamic selection methods are being limited to the performance of the local region algorithm. The classifier selection does not produces accurate results if the results extracted from the region of competence is not accurate enough. These results show how important the definition of region of competence is and the importance of putting efforts in the design of a better region of competence.

| Database     | Leave-One-Out | KNORA-E | Static Ensemble | Oracle |
|--------------|---------------|---------|-----------------|--------|
| Pima         | 73.05         | 73.16   | 73.28           | 95.10  |
| Liver Disorders | 65.80     | 63.86   | 62.76           | 90.07  |
| WDBC         | 97.91         | 96.93   | 96.35           | 99.13  |
| Optical Digits | 85.97     | 79.32   | 81.47           | 91.81  |
| Image Segmentation | 85.72     | 59.09   | 65.27           | 89.97  |
| Banana       | 90.27         | 88.83   | 81.43           | 94.75  |
| Vehicle      | 78.35         | 81.19   | 82.18           | 96.80  |
| Lithuanian Classes | 91.92     | 85.83   | 82.33           | 98.75  |
| Blood transfusion | 74.74     | 74.59   | 75.24           | 94.20  |

The comparison of the KNORA-E with the proposed DES-FA is shown in Table III. The number inside parenthesis is the value of the parameter $k$ used in the ENN filter ($k = 1, 3$ and 5). The KNORA-E is compared with the version using only the adaptive k-NN and with the DES-FA. The ENN was evaluated with $k = 1, 3$ and 5. The performance of the single best classifier, static ensemble and the Oracle are also shown for comparison.

Only one out of nine datasets the KNORA-E algorithm presented the best result (Vehicle dataset). In most cases the DES-FA presented the best results. It is also important to observe that the adaptive k-NN improved the result upon the standard algorithm in eight datasets. For the Optical digits and the WDBC the adaptive k-NN alone presented better results than the DES-FA (although the DES-FA still improves upon the KNORA-E). The ENN filter probably removed some important patterns in these datasets. A paired t-test with 95% confidence was performed to better compare the performance of the methods. The results of the DES-FA over the Pima, Liver Disorders, Image Segmentation, Banana and Lithuanian datasets showed statistically better than the KNORA-E technique. For the other datasets the difference between the DES-FA and the KNORA-E is not statistically different. However, the mean accuracy obtained by the DES-FA is higher.

It is important to mention that one of the problems of the KNORA-E algorithm is the computational cost of reducing
that turns patterns that are more probable of being noise more difficult to be selected. These techniques are used together in order to enhance the quality of the extracted region of competence.

Experiments were conducted over nine different datasets. Results show the proposed technique improves the recognition rates for eight of the nine datasets. We believe this idea can be used to improve recognition rates for any other dynamic classifier selection method. It is important to mention that the use of these techniques not only improves the recognition rate but also can decrease the computational cost. Even for the methods that have a fixed neighborhood size and therefore does not need to re-compute, the use of the algorithms can still reduce the computational cost because the ENN eliminates some training patterns. Therefore it reduces the cost of computing the nearest neighbor rule which can be high in some cases.

In this paper the problem of dynamic classifier selection is discussed. The paper is focused in how the regions of competence influences the performance of the system and two strategies are proposed in order to achieve better results. We demonstrate that the performance of the ensemble selection methods is very dependent to the performance of the algorithm that defines the regions of competence. Based on that two techniques for improving this information is shown. One that works as a filter eliminating undesirable patterns and the other is a variation of the nearest neighbor algorithm

| Database          | DES-FA (1) | DES-FA (3) | DES-FA (5) | A-k-NN + KNORA-E | KNORA-E | Static Ensemble | Oracle |
|-------------------|------------|------------|------------|-------------------|---------|----------------|--------|
| Pima              | 74.89(1.63) | 75.35(1.37) | 76.04(1.61) | 74.02(1.57)       | 73.16(1.86) | 73.28(2.08)   | 95.10(1.19) |
| Liver Disorders   | 65.72(3.81) | 65.49(3.39) | 65.23(4.07) | 63.98(3.148)      | 63.86(3.284) | 62.76(4.81)   | 90.07(2.41) |
| WDBC              | 96.77(1.11) | 96.40(0.95) | 96.46(1.13) | 97.18(1.13)       | 96.93(1.10) | 96.35(1.14)   | 99.13(0.52) |
| Optical Digits    | 83.65(2.63) | 84.73(3.51) | 82.84(3.40) | 86.78(3.20)       | 79.32(3.47) | 81.47(4.67)   | 91.84(2.03) |
| Blood Transfusion | 77.35(0.97) | 78.17(1.56) | 76.42(1.16) | 75.27(1.10)       | 74.59(2.62) | 75.24(1.62)   | 94.20(2.08) |
| Image Segmentation| 88.74(0.70) | 86.88(6.62) | 80.45(5.25) | 66.16(5.47)       | 59.09(11.32) | 65.27(3.32)   | 89.97(3.46) |
| Banana            | 90.16(3.18) | 89.16(2.25) | 89.57(2.65) | 89.93(2.87)       | 88.83(1.67) | 81.43(3.92)   | 94.75(2.09) |
| Vehicle           | 71.74(1.11) | 80.00(2.21) | 80.20(4.05) | 80.29(1.45)       | 81.19(1.54) | 82.18(1.31)   | 96.80(0.94) |
| Lithuanian Classes| 92.16(2.64) | 92.23(2.46) | 91.65(2.37) | 92.16(2.73)       | 88.83(2.50) | 82.33(4.81)   | 98.35(0.57) |

V. Conclusion

In this paper the problem of dynamic classifier selection is discussed. The paper is focused in how the regions of competence influences the performance of the system and two strategies are proposed in order to achieve better results. We demonstrate that the performance of the ensemble selection methods is very dependent to the performance of the algorithm that defines the regions of competence. Based on that two techniques for improving this information is shown. One that works as a filter eliminating undesirable patterns and the other is a variation of the nearest neighbor algorithm

| Database          | DES-FA (k) | KNORA-E |
|-------------------|------------|---------|
| Pima              | 91.71      | 177.00  |
| Liver             | 75.82      | 103.52  |
| Breast            | 48.94      | 64.66   |
| Optical Digits    | 599.09     | 1609.00 |
| Blood Transfusion | 78.59      | 222.30  |
| Segmentation      | 696.83     | 288.03  |
| Banana            | 58.95      | 100.59  |
| Vehicle           | 122.03     | 150.97  |
| Lithuanian Classes| 61.60      | 82.55   |

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