Towards a Line-Crawling Robot Obstacle Classification System: A Rough Set Approach

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Abstract. The basic contribution of this paper is the presentation of two methods that can be used to design a practical robot obstacle classification system based on data mining methods from rough set theory. These methods incorporate recent advances in rough set theory related to coping with the uncertainty in making obstacle classification decisions either during the operation of a mobile robot. Obstacle classification is based on the evaluation of data acquired by proximity sensors connected to a line-crawling robot useful in inspecting power transmission lines. A fairly large proximity sensor data set has been used as means of benchmarking the proposed classification methods, and also to facilitate comparison with other published studies of the same data set. Using 10-fold cross validated paired t-test, this paper compares the rough set classification learning method with the Waikato Environment for Knowledge Analysis (WEKA) classification learning method.

1 Introduction

This paper presents sensor data change classification learning based on proximity sensor measurements using data mining methods from rough set theory [1, 6,7,8,9]. In the context of obstacle classification, the term *data mining* refers to knowledge-discovery methods used to find relationships among proximity sensor data sets and the extraction of rules useful in identifying obstacles encounter by a mobile robot. The derivation of rules that can be used by a robot in navigation planning and in mapping the environment of a robot. The focus of this paper is an introduction to an approach to solving this problem based on recent findings in rough set theory and the availability of a number of complete rough set toolsets. It has been shown rough sets work well in coping with the uncertainty in various classification systems [7], and the design of rough-set based classification systems [7]. This paper also compares the two rough set classification learning schemes with Waikato Environment for Knowledge Analysis (WEKA) classification learning [10,11]. The contribution of this paper is the presentation of two models for obstacle classification based on rough sets.

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2 LCR Navigation Problem

Basic features of the line-crawling robot (LCR) navigation problem are described in this section. A principal task of the LCR control system is to guide the movements of the robot so that it maintains a safe distance from overhead conductors and any objects such as insulators attached to conductor wires or towers used to hold conductors above the ground. To move along a conductor, the LCR must continuously measure distances between itself and other objects around it, detect and maneuver to avoid collision with obstacles. Let a1, a2, a3, a4 denote proximity sensors (e.g., ultrasonic sensors as in Fig. 1).

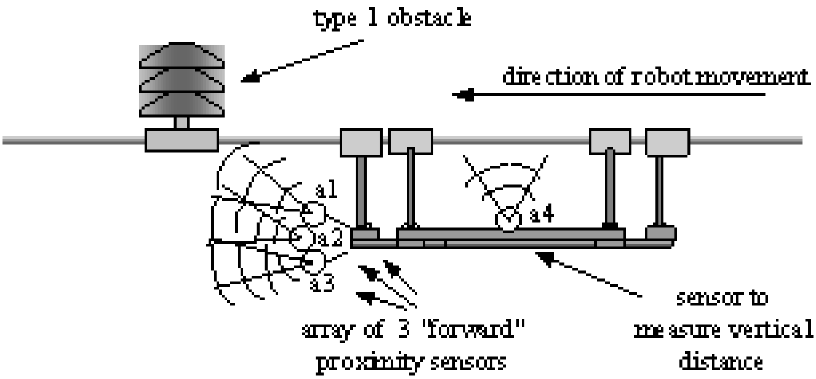


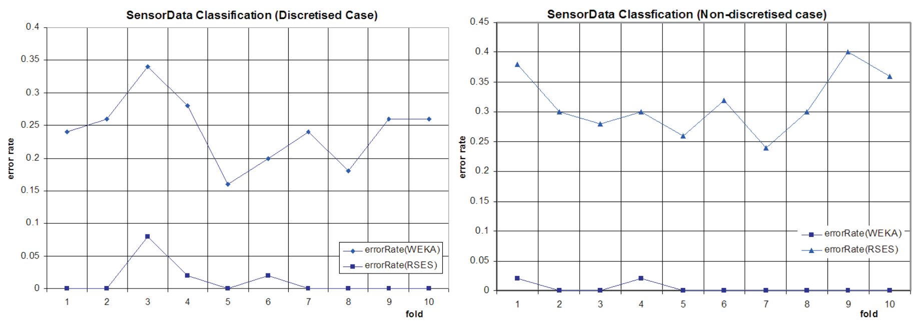
Fig. 1. Sample proximity Sensors of LCR

We want to obtain a classifier so that the LCR can make a decision about which type of movement it can safely make based on readings from its sensors. Table 1 gives some sample navigation decisions based on aggregate information from fusion of various sensors. Let d denote a decision class. Sensor measurements are separated in collections (a form of sensor fusion) used to construct convex sets. Each convex set contains sensor measurements (often with some noise) either close to a preset threshold or significantly greater than {less than} the threshold. In effect, this form of convex set represents what is known as an upper approximation in rough set theory. In addition, each convex set is associated with a LCR navigation decision that initiates a set of many movements of the robot parts to carry a LCR maneuver.

3 Comparison of Classification Learning Algorithms

A comparison of the Rough Set Exploration System (RSES 2.0, cf. [9]) and WEKA classification learning algorithms in terms of the error rate is given in this section. Variations of error and a comparison of pairs of differences in error rates for the RSES and WEKA using the 10-fold cross-validated paired t-test are given in this section.

This section gives a brief discussion of the variations in error rates using 10-fold cross validation with RSES and WEKA. The variations in the error rates across the 10 folds for the sensor data with respect to the discretized case is shown in Fig. 2a. The plots show that the error-rate is consistently lower in the discretized case for RSES 2.0 whereas the error-rate is lower using WEKA in the non-discretized case (see Fig. 2b). With the k-fold cross-validated paired t-test we want to test the hypothesis that mean difference between the two classification learning algorithms used by RSES and WEKA is zero. Let μ_d denote the mean difference in the error rates during a 10-fold classification of sensor data. Let H_0 denote the hypothesis to be tested (i.e., $H_0 : \mu_d = 0$). This is our null hypothesis. The paired difference t-test is used to test this hypothesis and its alternative hypothesis ($H_A : \mu_d \neq 0$). We start with pairs $(\varepsilon_{11}, \varepsilon_{21}), \ldots, (\varepsilon_{1n}, \varepsilon_{2n})$, where ε_{1i}, ε_{2i} are the i^{th} error rates resulting from the application of the RSES and WEKA classification learning algorithms, respectively, and $i = 1, \ldots, n$. Let $d_i = \varepsilon_{1i} - \varepsilon_{2i}$. Underlying the null hypothesis H_0 is the assumption that the d_i values are normally and independently distributed with mean μ_d and variance σ_d^2. Let $\bar{d}, S_d^2$ denote the mean difference and variance in the error rates of a random sample of size n from a normal distribution $N(\mu_d, \sigma_d^2)$, where μ_d and σ_d^2 are both unknown.



a) b)

Fig. 2. ε-variations: a) Discretized case; b) Non-discretized case.

The t statistic used to test the null hypothesis is as follows:

$$\mathrm{t} = \frac{\bar{d} - \mu_d}{S_d/\sqrt{n}} = \frac{\bar{d} - 0}{S_d/\sqrt{n}} = \frac{\bar{d}\sqrt{n}}{S_d}$$

where t has a Student's t-distribution with $n-1$ degrees of freedom [3]. The shape of the t distribution depends on the sample size $n-1$ (number of degrees of freedom). In our case, $n-1 = 9$ relative to 10 sample error rates. The significance level α of the test of the null hypothesis H_0 is the probability of rejecting H_0 when H_0 is true. Let $t_{n-1,\alpha/2}$ denote a t-value to right of which lies $\alpha/2$ of the area under the curve of the t-distribution that has $n-1$ degrees of freedom. Next, formulate the following decision rule:

***Decision Rule*:** Reject $H_0(\mu_d = 0)$ at significance level α iff $|t| > t_{n-1,\alpha/2}$

Pr-values for $t_{n-1,\alpha/2}$ can obtained from a t-distribution table [2]. In what follows, $\alpha = 0.10$, and $n-1 = 9$. Consider, for example, the paired t-test applied to the error rates obtained from the use of RSES and WEKA in classifying the metric data from VME subsystem 1 (discretized case). With 9 degrees of freedom, we find that $\Pr(|t| < 1.833) = 0.95$ where $t_{n-1,\alpha/2} = t_{9,0.05} = 1.833$. It was found that the null hypothesis H_0 can be rejected, since $|t| = |-19.56| > 1.833$ (non-discretized) and $|t| = |18.06| > 1.833$ (discretized case) at the 10% significance level.

In both the discretized and non-discretized cases, $|t| > t_{9,0.05}$. Hence, the null hypothesis is rejected (in effect, $\mu_d \neq 0$) at the 10% significance level. The average error rates for WEKA and RSES differ quite significantly in both cases. It is noteworthy that RSES does better than WEKA for the discretized case in classifying the proximity sensor data. This is significant since sensor data is real-valued.

4 Conclusion

Two rough set methods for deriving obstacle rules useful mobile robot navigation. A rough set classification learning algorithm provided by RSES has been compared with WEKA classification learning algorithm using the 10-fold, cross-validated paired t-test. In both the non-discretized and discretized cases, the results of the paired t-test reveal that the WEKA and RSES 2.0 classification algorithms are different. In classifying sensor data sets in the non-discretized case, the WEKA wrapper method outperforms the exhaustive method in RSES in classifying the obstacles. By contrast, RSES error rates are significantly lower than the WEKA error rates across the ten folds in the discretized case. The non-discretization method is more suitable for making obstacle decisions in a uniform, unchanging environment. However, rules derived using non-discretized data lack generality. The discretization method results in a set of obstacle classification rules cover more cases than rules produced using the non-discretization method. Based on the results of the study reported in this paper, the rough set methodology offers a promising basis in designing a navigation planner and environment mapper for a mobile robot that lives in a changing environment.

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References

1. Bazan J., Szczuka M., Wróblewski J., A new version of the rough set exploration system. In Proceedings of RSCTC'02, LNAI **2475**. Springer-Verlag, Berlin, 2002, 397–404.
2. Beyer, W.H. Handbook of Tables for Probability and Statistics. CRC Press, Ohio, 1968.
3. Hogg R.V., Tanis E.A. Probability and Statistical Inference. Macmillan Publishing Co., New York, 1997.
4. Hussein, A., Dietterich, T.G. Efficient algorithms for identifying relevant features. Proc. of the 9^{th} Canadian Conf. on AI, Vancouver, B.C., 1992, 38–45.
5. Mitchell, T.M. Machine Learning. McGraw-Hill, NY, 1997.
6. Pawlak, Z. Rough Sets: Theoretical Aspects of Reasoning About Data. Kluwer Academic Publishers, Boston, 1991.
7. Peters, J.F., Skowron, A., Suraj, Z., Pedrycz, W., Pizzi, N., Ramanna, S. Classification of meteorological volumetric radar data using rough set methods. *Pattern Recognition Letters* 24(6), 2002, 911–920.
8. Rosetta 1999. `http://www.idi.ntnu.no/~aleks/rosetta/`
9. RSES 2002. `http://logic.mimuw.edu.pl/~rses/`
10. WEKA 2002. `http://www.cs.waikato.ac.nz/ml/weka`
11. Witten, I.H., Frank, E. Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations, Morgan Kauffman, San Francisco, 2000.