Classification based Symbolic Indoor Positioning over the Miskolc IIS Dataset

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Performance analysis of classification based symbolic indoor positioning methods are presented in this paper. Symbolic positioning can be considered as a classification task, where the classes are the positions, and the attributes are the measured values. The ILONA (Indoor Localization and Navigation) system was used to record a hybrid indoor positioning dataset that was used for the evaluation of the tested methods. The goal of this performance analysis is to determine the most accurate classification based symbolic indoor positioning method for the ILONA system. The results can be used to improve the currently used positioning algorithm of the ILONA system.

Hybrid indoor positioning systems simultaneously use various sensors and technologies [1]. Hybrid systems were designed to overcome the limitation of the standard indoor positioning systems that are based on a single technology, such as Bluetooth [2, 3], GSM [4], WLAN [5], Magnetometer [6], RFID [7], infrared [8] and ultrasonic [9]. Hybrid systems can be based on the fingerprinting [5] approach, which is popular among indoor positioning systems [10]. Data mining algorithms are often used in fingerprinting based solutions. The usage of multiple sensor data could increase the accuracy of the used data mining algorithm. Hybrid systems can achieve higher performance than the standard solutions because they use multiple technologies.

Miskolc IIS Hybrid Indoor Positioning System Dataset [11] was used to evaluate the selected indoor positioning methods. The dataset contains more than 1500 measurements about a 3-story building. Bluetooth, WiFi RSSI and Magnetometer sensors were used to create the dataset. Absolute and symbolic position is given for each measurement in the dataset. Symbolic position can be considered as a class label, so the positioning task can be converted into a classification problem. This paper focuses on the performance of the standard classification methods, such as k–NN, Naive Bayes, Decision Tree and Rule induction. Rapid Miner was used to evaluate the performance of these methods for symbolic indoor positioning. This dataset allows the evaluation and comparison of various indoor positioning methods.

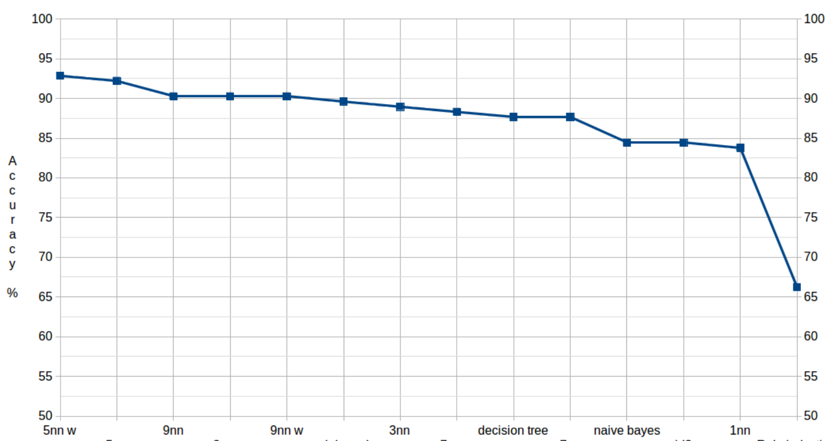

Figure 1: Performances of the tested methods

Experimental results show that the k–NN classifiers are superior than the other tested methods as seen in Figure 1. The $kNN\ w$ denotes the k-NN algorithm with weighted vote based on the distance. The $nb\ kernel$ stands for the Naive Bayes kernel algorithm, where each attribute considered as individual attribute. The highest achieved accuracy was 93% by the weighted k–NN algorithm, where the k parameter was 5. The performance of the k–NN algorithm was depended on the k parameter. The k–NN algorithm had the lowest performance when the k parameter was chosen to 1. The usage of kernel function in the case of Naive Bayes classifier has increased the accuracy with approximately 5%. The performance of the decision tree depended on the building algorithm. The Rule induction achieved the lowest performance in this test. The gradient of the lines denotes the degree of the accuracy decay. Based on the experimental results, the implementation of the k–NN and weighted k–NN algorithms in the ILONA system is suggested.

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