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Computer Aided Systems Theory

EXTENDED ABSTRACTS

12th International Workshop on computer Aided Systems Theory
Las Palmas de Gran Canaria, Spain, February 2009

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Mobile and Autonomous Systems: Robots and Cars

Vision-based vehicle detection for rear-end collision mitigation systems

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Abstract. This paper describes a vision-based system that detects vehicles approaching from the rear in order to anticipate possible rear-end collisions. A camera mounted on the rear of the vehicle provides images which are analysed by means of computer vision techniques. The detection of candidates is carried out using the top-hat transform in combination with intensity and edge-based symmetries. The candidates are classified by using SVM with HOG features. Finally, the position of each vehicle is tracked using a Kalman Filter and template matching techniques.

1 Introduction

The rear-end collisions are one of the most common types of automobile accidents. A rear facing camera mounted on the rear of the vehicle can provide an important number of driving assistance functions such as collision warning systems that will alert the driver of an impending collision or pre-crash systems (seat belt pretensioning, intelligent headrest, etc.). Accordingly, the work presented in this paper is directly related with the automotive industry.

2 System Description and Results

Vehicle detection is carried out in three main stages. In a first stage, the region of interest is reduced thanks to the Lane Departure Warning (LDW) system developed by the authors [1]. Candidates are then selected using the top-hat transform in combination with intensity and edge-based symmetries. Perspective constraints and non-maximum suppression are applied to reduce the number of candidates per frame In a second stage, the selected candidates are classified by means of a SVM classifier with HOG features [2]. All candidates are resized to a fixed size of 64x64 pixels to facilitate the features extraction process. The SVM classifier is trained with 2000 samples (1/1 positive/negative ratio). In the last stage, the position of the vehicles in the image is tracked by using a Kalman Filter. Once a vehicle is detected and tracked during a consecutive number of frames, classification is stopped and a grid-based matching technique is used until the vehicle disappears from the scene. Thus, a considerable reduction in the computational cost is achieved.

The algorithm was implemented on a PC onboard a real automobile. Different test sequences have been recorded in real traffic conditions with a total duration of 240sec and a traffic density of 1.5 vehicles/frame on average. The system achieved a detection rate of 92.2%. The output of the system in a real experiment is depicted on the left side of Figure 1. The distance of each rear-vehicle with regard to the camera is showed on the upper-right corner of the bounding boxes. On the right side of Figure 1 the measurement of the y-position in pixel coordinates and its corresponding filtered value for the car located in the middle lane are provided.

At present, the output of the rear-vehicle detection system is being used in combination with Blind Spot Detection (BSD) system developed by the authors [3], resulting in the the so-called Panoramic BSD.

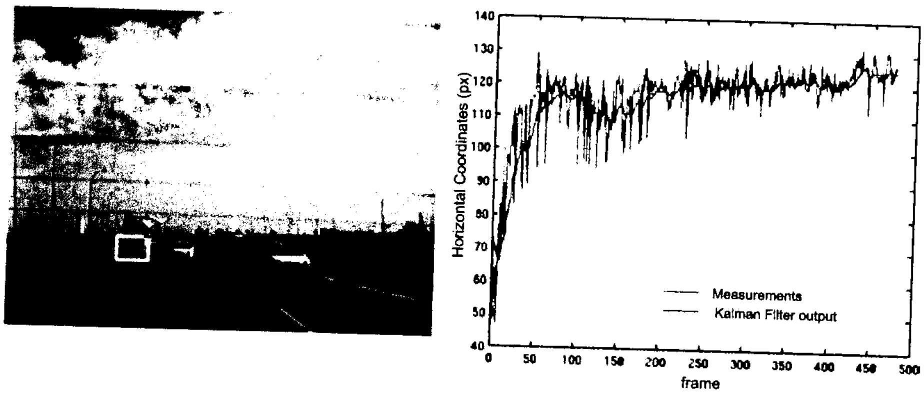

Fig. 1. Left: detected vehicles on a test sequence. Right: filtered y-position of the car located in the middle lane.

References

1. Sotelo, M.A., Nuevo, J., Bergasa, L.M., Ocaña, M., Parra, I., Fernández, D.: Road Vehicle Recognition in Monocular Images. In. Proceedings of IEEE ISIE, 1471-1476 (2005).
2. Dalal, N., Triggs, B.: Histograms of Oriented Gradients for Human Detection. In. Proceedings of IEEE CVPR, 886-893 (2005).
3. Sotelo, M.A., Barriga, J., Fernández, D., Parra, I., Naranjo, J.E., Marrón, M., Álvarez, S., Gavilán, M.: Vision-Based Blind Spot Detection Using Optical Flow. EUROCAST 2007. Lecture Notes in Computer Science 4739, 1113-1118 (2007).

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WiFi Localization System based on Fuzzy Classification

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Abstract. The framework of this paper is robot localization inside buildings using WiFi signal strength measure. This localization is usually made up of two phases: training and estimation stages. In the former the WiFi signal strength of all visible Access Points (APs) are collected and stored in a database or Wifi map, while in the latter the signal strengths received from all APs at a certain position are compared with the WiFi map to estimate the robot location. This work proposes the use of Fuzzy Classification in order to obtain the robot position during the estimation stage, after a short training stage where only a few significant WiFi measures are needed. As a result, the proposed method is easily adaptable to new environments where triangulation algorithms can not be applied since the AP physical location is unknown. It has been tested in a real environment using our own robotic platform. Experimental results are better than those achieved by other classical methods.

1 Introduction

In the literature, we can find multiples systems proposed and successfully deployed to find the pose of a robot from its physical sensors. These systems are based on: infrared sensors, computer vision, ultrasonic sensors, laser or radio frequency (RF) [1]. Within the last group we can find localization systems that use WiFi signal strength measure. These WiFi systems are attractive for indoor environments where traditional techniques, such as Global Positioning System (GPS) [2], fail. One of the main advantages of these systems is that they do not need to add any extra hardware in the environment.

The signal strength depends on the distance and obstacles between APs and the robot. Unfortunately, in indoor environments, the WiFi channel is very noisy and the RF signal can suffer from reflection, diffraction and multipath effect, which makes the signal strength a complex function of distance [1]. To solve this problem, it can be used a priori WiFi map, which represents the signal strength of each AP at certain points in the area of interest [3] [4].

These systems work in two phases: training and estimation of the position. During the first phase, a WiFi map is built while in the estimation phase, the vector of samples received from each access point is compared with the WiFi map and the nearest match is returned as the estimated robot location.

Fuzzy Logic (FL) introduced by Zadeh [5] is acknowledged for both its well-known ability for linguistic concept modeling and its use in system identification. The semantic expressivity of fuzzy logic, using linguistic variables [6] and linguistic rules [7], is quite close to expert natural language. In addition, being universal approximators [8], fuzzy inference systems (FIS) are able to perform non-linear mappings between inputs and output. FL is especially useful to handle problems where the available information is vague. This is the typical situation regarding WiFi localization where measures normally yield incomplete or distorted data.

In this paper we use Fuzzy Classification in the estimation stage to obtain the estimated robot position. Such classification obtains several benefits over the classical methods. The most significant advantages are: (1) The robustness of the built systems which are able to deal with the intrinsic uncertainty of indoor environments; and (2) the adaptability to new environments where AP location is indeterminate.

The rest of the paper is organized as follows: Section 2 provides a description of the proposed Fuzzy Classification system. Section 3 shows the implementation and some experimental results, as well as a description of the used test bed. Finally, the conclusions and future work are described in Section 4.

2 Description of the Fuzzy Classification system

In this section we provide a brief description of the Fuzzy Classification system. It was designed and built using KBCT (Knowledge Base Configuration Tool) a free software tool which implements the HILK methodology [9]. This new methodology focuses on building interpretable fuzzy classifiers, i.e., classifiers easily understandable by human beings.

In classical logic only two crisp values are admissible (0/1, false/true, etc). This is a strong limitation in order to deal with real-world complex problems where there are many important details which are usually vague. Working with FL everything has a membership degree. Rules are of form **If** *condition* **Then** *conclusion*, where both condition and conclusion use linguistic terms. For instance, **If** *Signal received from APi is High* **and** *Signal received from APj is Low* **Then** *The robot is close to Position k*.

Regarding the rule generation from data, we have chosen Fuzzy Decision Tree (FDT) [10], a fuzzy version of the popular decision trees defined by Quinlan [11]. Notice that our implementation of FDT is able to build quite general rules with the partitions previously defined. Then, a simplification procedure is carried out on the whole fuzzy knowledge base with the aim of removing redundancies and even getting more compact and understandable systems.

Finally, the output of the fuzzy classifier will be one position along with an activation degree computed as the result of a fuzzy inference that takes into account all defined inputs and rules. Such activation degree can be understood as a degree of confidence on the system output.

3 Implementation and Results

The robot used in the experimentation (Sancho3) was developed in the European Centre for Soft Computing (ECSC) and it is based on a modular architecture whose first version was designed in the Technical University of Madrid (UPM). The Test-Bed environment was established in the main corridor of the ECSC premises. It was discretized into 16 nodes, and Sancho3 was placed at each node collecting 1000 signal strength samples from each AP (six APs are available at the whole environment).

For each position, we computed the mean and the deviation of the corresponding signal (S) and noise (N) values for each AP. Then, we constructed two tables, one for training and the other for testing. These tables contain tuples of the form: $(\overline{S_{AP1}}, \sigma_{S_{AP1}}, \overline{N_{AP1}}, \sigma_{N_{AP1}}, ..., \overline{S_{APi}}, \sigma_{S_{APi}}, \overline{N_{APi}}, \sigma_{N_{APi}}, pos)$, where pos is the environment position and i is the number of APs. The training data were used to automatically generate the Fuzzy Classification system (FC). In addition, the same data were used to compare our method with the classical localization method called Nearest Neighbour (NN) [1]. Both methods have been tested using different number of samples. The best classification rate was 60.16% for the NN method and 99.2% for FC, these were obtained with 60 samples in the training and test stages.

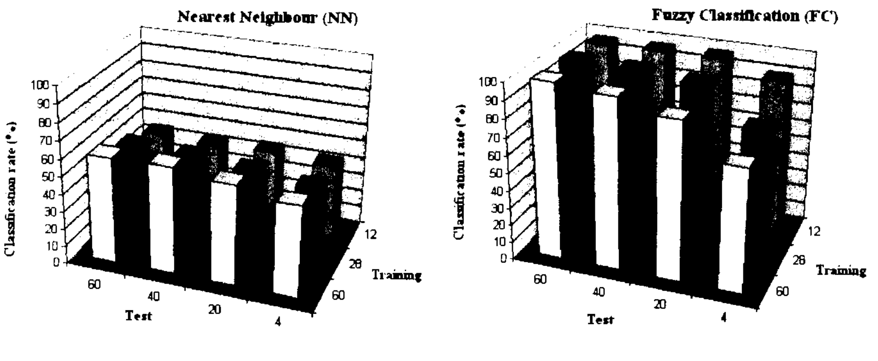

Fig. 1. Comparison of classification rates

Also, we have tested the classification rate when the samples taken in the training and test stage were different. It is important to note that the maximum acquisition frequency of the WiFi interface is 4Hz, then to take 60 samples it is needed to spend 15 seconds at the same place. We have reduced the samples from 60 to 4 with the aim of checking the classification rate of both methods, Figure 1 shows these results. As it can be seen in this figure, the FC (on the right picture of the figure) maintains a good classification rate even when the samples taken are 12 and 4 in the training and test stages. As a result, the FC yields robust and simple solutions. In the worst case, the classification rate is around 70% for a FC trained with groups of 60 samples when it is tested regarding

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groups made up of only 4 samples (the robot only spends 1 second to capture them). In addition, the best classification rate achieved by NN method (on the left picture of the figure) is lower than the worst one obtained by FC.

4 Conclusions and future works

In this work we have presented a WiFi localization system based on Fuzzy Classification. We demonstrate that it is useful and robust to localize the robot in real conditions. The classification rate of our method improves the ratings of other classical methods like Nearest Neighbour. In the near future, we have the intention of using this system in other environments to test the applicability of the method.

Acknowledgment This work has been funded by grant S-0505/DPI/000176 (Robocity2030 Project) from the Science Department of Community of Madrid, TRA2005-08529-C02-01 (MOVICOM Project) and TIN2008-06890-C02-01 (CW-PIE Project) both from the Spanish Ministry of Science and Technology (MCyT).

References

1. Bahl, P., Padmanabhan, V.: Radar: A, in-building rf-based user location and tracking system. In: Proc. of the IEEE Infocom. (2000) 775–784
2. Enge, P., Misra, P.: Special issue on gps: The global positioning system. In: Proc. of the IEEE. Volume 87. (1999) 3–172
3. Youssef, M., Agrawala, A., Shankar, A.: Wlan location determination via clustering and probability distributions. In: Proc. of the IEEE PerCom 2003. (2003)
4. Sotelo, M.A., Ocaña, M., Bergasa, L.M., Flores, R., Marrón, M., García, M.A.: Low level controller for a pomdp based on wifi observations. Robot. Auton. Syst. **55**(2) (2007) 132–145
5. Zadeh, L.A.: Fuzzy sets. Information and Control **8** (1965) 338–353
6. Zadeh, L.A.: The concept of a linguistic variable and its application to approximate reasoning. Parts I, II, and III. Information Sciences **8, 8, 9** (1975) 199–249, 301–357, 43–80
7. Mamdani, E.H.: Application of fuzzy logic to approximate reasoning using linguistic systems. IEEE Transactions on Computers **26(12)** (1977) 1182–1191
8. Wang, L.X.: Fuzzy systems are universal approximators. In: First IEEE Conference on Fuzzy Systems, San Diego (1992) 1163–1169
9. Alonso, J.M., Magdalena, L., Guillaume, S.: HILK: A new methodology for designing highly interpretable linguistic knowledge bases using the fuzzy logic formalism. International Journal of Intelligent Systems **23** (2008) 761–794
10. Ichihashi, H., Shirai, T., Nagasaka, K., Miyoshi, T.: Neuro-fuzzy ID3: A method of inducing fuzzy decision trees with linear programming for maximizing entropy and an algebraic method for incremental learning. Fuzzy Sets and Systems **81** (1996) 157–167
11. Quinlan, J.R.: Induction of decision trees. Machine Learning **1** (1986) 81–106