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동적 도시 환경에서 의미론적 시각적 장소 인식

Semantic Visual Place Recognition in Dynamic Urban Environment

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Abstract: In visual simultaneous localization and mapping (vSLAM), the correct recognition of a place benefits in relocalization and improved map accuracy. However, its performance is significantly affected by the environmental conditions such as variation in light, viewpoints, seasons, and presence of dynamic objects. This research addresses the problem of feature occlusion caused by interference of dynamic objects leading to the poor performance of visual place recognition algorithm. To overcome the aforementioned problem, this research analyzes the role of scene semantics in correct detection of a place in challenging environments and presents a semantics aided visual place recognition method. Semantics being invariant to viewpoint changes and dynamic environment can improve the overall performance of the place matching method. The proposed method is evaluated on the two benchmark datasets with dynamic environment and seasonal changes. Experimental results show the improved performance of the visual place recognition method for vSLAM.

Keywords: Semantics, Simultaneous Localization and Mapping, Visual Place Recognition

1. Introduction

SLAM enables the mobile robots to move autonomously in an unknown environment by generating map along the trajectory and correctly identifying the already visited places. This recognition of places is performed by the loop closure detection system, one of the components of SLAM, which performs visual place recognition to support robot’s relocalization in the environment map and reduction in map drift which may occur during robot motion.

The traditional handcrafted features-based visual place recognition methods have shown good performance in large-scale localization, however they lack resilience to severe appearance changes[1]. Also, image matching using these features is often a bottleneck for mobile robot operation in real-time scenarios. While, the appearance-based approaches such as sequence searching[2], appearance prediction[3], shadow removal[4] and illumination invariance[5] are robust to conditional variations yet their performance suffers from viewpoint dependency and velocity sensitivity. Recently, with the advancements in deep learning, numerous deep neural networks have been trained and used for image representation and place matching and detection tasks[6,7]. The features extracted from convolutional networks are deeper and more abstract, hence being comparatively more robust to environmental conditions[8,9]. A very little attention has been paid to semantics-aware loop closure detection. The use of semantics for place recognition have shown improvement in overall performance[10-12].

This paper specifically addresses the problem of visual place recognition in the presence of dynamic objects in an urban

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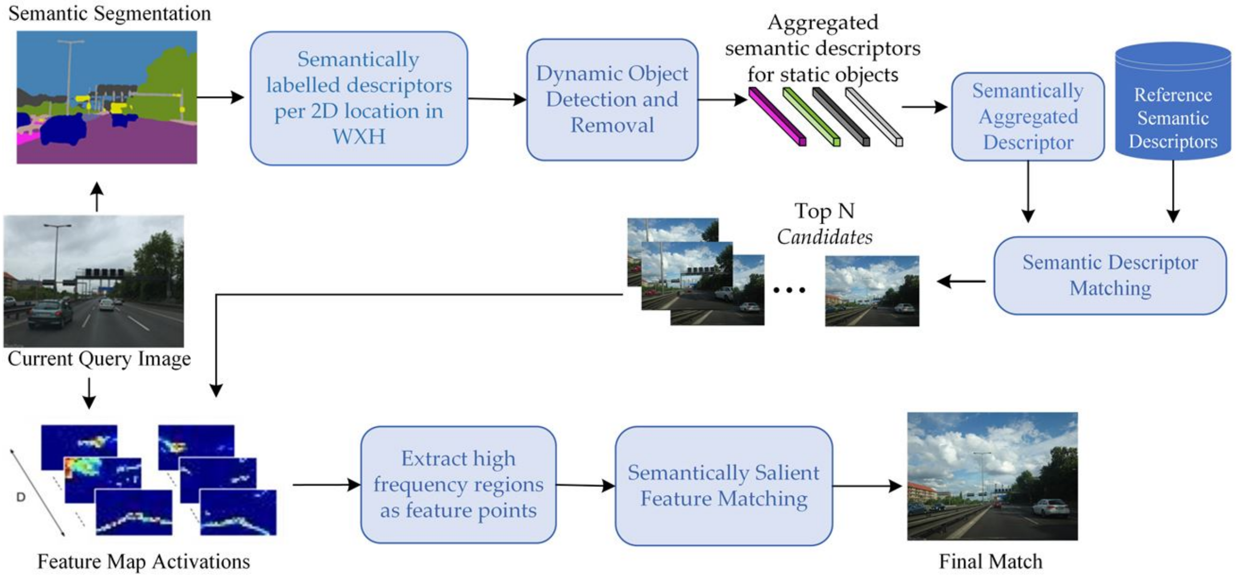

Semantic Segmentation
Semantically labelled descriptors per 2D location in WXH
Dynamic Object Detection and Removal
Aggregated semantic descriptors for static objects
Semantically Aggregated Descriptor
Reference Semantic Descriptors
Top N Candidates
Semantic Descriptor Matching
Current Query Image
D
Feature Map Activations
Extract high frequency regions as feature points
Semantically Salient Feature Matching
Final Match

[Fig. 1] Semantic visual place recognition pipeline

environment. In[13] moving objects have been considered as occlusions, however, the dynamic objects may not necessarily be always moving. Mostly, the dynamic objects might be temporarily static such as parked vehicle, people sitting somewhere and pedestrians standing on traffic signals etc. These dynamic objects that are in temporarily static state may not be present at the same location when robot revisits the same place later leading to the false correspondences because a temporarily static mobile object might appear at different locations. Also, the detection of moving objects from one scene to other overburdens the processor as it stores visual information of multiple scenes in memory.

Recent works applying semantic labels extracted through semantic segmentation networks have shown improved performance in drastic appearance changes[14,15]. Garg et al.[14] proposed a local semantic tensor descriptor and fused pixel-wise semantic labels with deep features building for robust place matching under extreme illumination and viewpoint changes i.e., 180-degree. However, it is typical developed for place recognition in opposing viewpoints while focusing only three semantic class labels i.e., building, road and vegetation. Due to the selected semantic labels, the performance degrades in the environment with semantically similar scenes. A subsequent study[15] proposed a two nearest neighbour local sensor tensor based on TNNVLAD. Thus, instead of relying on a single nearest neighbour match, the algorithm improves the overall accuracy by comparing with the second nearest neighbour descriptor. Similarly,[16] used the LoST in combination with semantic edge features extracted from semantic segmentation mask to achieve loop closure detection. Some researchers have used pixelwise semantic labels for building the topological connectivity graph of semantic objects in a scene to extract the spatial information[17,18]. This topological graph is fused with handcrafted features-based BoW model to achieve robustness in drastic appearance changes.

2. Semantic Visual Place Recognition

[Fig. 1] illustrates the working pipeline of hierarchical visual place recognition method. The proposed method uses a hierarchical approach where top matching candidates are selected based on the global semantic similarity between image pairs and then CNN feature based visual-semantic verification is performed to find the best match.

Initially the semantic information is extracted through pixelwise semantics segmentation using RefineNet[19] trained on cityscapes dataset. The semantic segmentation produces the semantic label scores of 1/4th of the input image size in width and height while depth corresponds to the number of semantic classes. Each pixel is associated with the semantic label based on the probability score. Aggregating the semantic label scores for each static objects available in an image while removing the dynamic object semantics, a semantic descriptor is computed as done in[14]. In a dynamic environment, the feature occlusion occurs due to the moving objects such as person, car, leading to the reduces robustness. Including those semantic objects for place matching causes low accuracy as they will increase non-overlap contents between the image pairs. Thus, we keep only static object to construct the semantic image descriptor vector V. V is obtained through concatenation of L2-normalized semantic descriptors for the class labels given as V = {$V_{road} + V_{building} + V_{vegetation} + V_{pole} + V_{traffic\_light}$}. The semantic descriptor of the reference dataset is extracted as an offline step. The semantic descriptor of each query image is compared with the reference database through cosine similarity δ as given in Eq. (1). Higher the cosine similarity value, higher will be the semantic similarity between the image pairs.

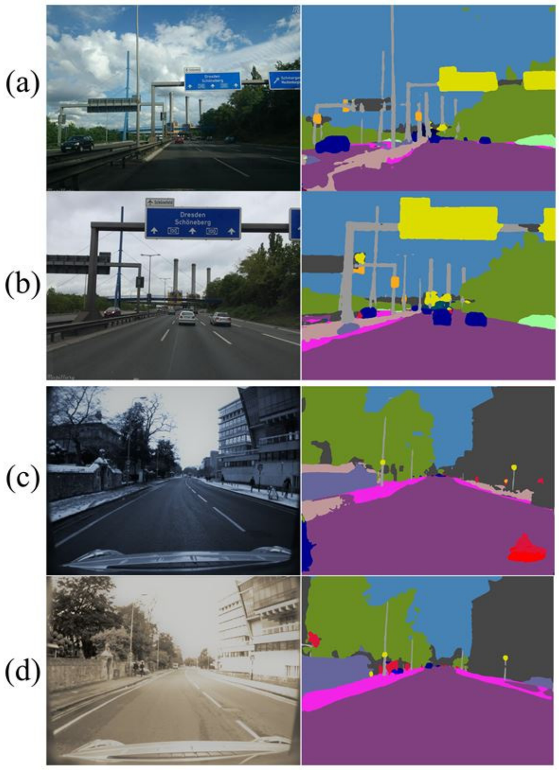
$$\cos(m,n) = 1 - \frac{m \cdot n}{|m| * |n|} \tag{1}$$

After the global scene similarity computation, top 10 reference images with the highest similarity score are selected as candidate images for further processing to obtain the final match.

In the second phase, the feature map activations of the query image are obtained as keypoints. Each keypoint is associated with the semantic labels. Similar to[14] the activations of the query image are compared with those of candidate images. Instead of matching the feature points of all the semantic class labels, the proposed method excludes the feature points from the dynamic objects while only matching the features from the static objects. This greatly enhances the place matching performance while reducing the number of feature correspondences resulting in lower computational cost.

3. Experiments and Results

This section presents the qualitative and quantitative results. The evaluation is performed on the publicly available benchmark datasets captured in different environments with challenging environmental conditions i.e., Berlin A100 and Oxford Robotcar summer vs. winter. Both of the datasets comprise of images captured in dyna mic urban environment with many confusing objects i.e., pedestrians, vehicles etc. These dynamic objects cause dynamic interference making them challenging datasets. Furthermore, the Berlin A100 dataset exhibits strong viewpoint changes while Oxford RobotCar dataset extreme seasonal changes and illumination changes with slight viewpoint variation. The semantic segmentation results obtained from the RefineNet are shown in [Fig. 2]. It can be observed that segmentation network is able to generate fine pixelwise segmentation results. Images of [Fig. 2(a)-(b)] presents the same place in Berlin A100 while with large appearance changes. Similarly, [Fig. 2(c)-(d)] present images from the same place taken in winter and summer seasons. Though the appearance change causes the feature-based method to fail in place recognition however the semantics remains the same. Thus, utilizing useful semantics can significantly improve the overall performance of visual place recognition method even in such challenging environments.



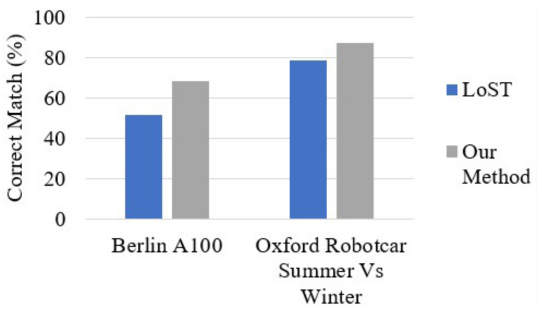
[Fig. 2] Sample images for pixelwise semantic segmentation using RefineNet for benchmark datasets i.e., (a) Berlin A100 Traverse 1; (b) Berlin A100 Traverse 2; (c) Oxford RobotCar Winter Season and (d) Oxford RobotCar Summer Season

The semantic class labels generated by the RefineNet for static objects includes road, building, vegetation, pole, traffic_ light, traffic_sign, terrain, wall and fence. Here, we analyse the significance of each class labels for correct detection of a place. Using the semantic labels, the global semantic descriptors are generated $V_1 \cdots V_6$, as given below.

· V_1 = {road, building, vegetation}
· V_2 = {road, building, vegetation, pole}
· V_3 = {road, building, vegetation, pole, traffic_light}
· V_4 = {road, building, vegetation, pole, traffic_light, traffic_sign}

[Table 1] F1-Score obtained using semantic descriptors on Berlin A100 and Oxford RobotCar dataset

Global Semantic Descriptor Vectors	Berlin A100	Oxford Robotcar Summer Vs. Winter
V_1	0.68	0.88
V_2	0.71	0.89
V_3	0.77	0.94
V_4	0.75	0.89
V_5	0.69	0.92
V_6	0.71	0.91



[Fig. 3] The performance comparison of the percentage of correctly matched places by the baseline method and our algorithm for the benchmark datasets

- V_5 = {road, building, vegetation, pole, traffic_light, traffic_sign, terrain}
- V_6 = {road, building, vegetation, pole, traffic_light, traffic_sign, terrain, wall, fence}

The F1-score obtained using each of the global semantic vector is given in [Table 1]. It can be observed that semantics included in V_3 are significant for scene understanding in an urban environment. The correct place detection performance of the proposed method is compared with the baseline method[14], as shown in [Fig. 3]. Utilizing useful semantics for the specific environment helps improve the place recognition performance of the proposed method while outperforming the[14].

4. Conclusion

This research proposes a hierarchical visual place recognition for visual SLAM based systems. The proposed method analyzes the scene semantics to attain the scene understanding and local and global level to improve the overall performance of the semantic visual place recognition method. The semantics being invariant to the dynamic environment and viewpoint changes helps to improve the overall performance of the system in challenging environmental conditions.

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