Improving Condition- and Environment-Invariant Place Recognition with Semantic Place Categorization

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Abstract— **The problem of place recognition actually comprises two distinct subproblems; "traditional" place recognition which is recognizing a specific location in the world, and place "categorization", which involves recognizing the type of place. Both components of place recognition are competencies for robotic navigation systems and hence have each in isolation received significant attention in the robotics and computer vision community. In this paper, we leverage the powerful complementary nature of the place recognition and place categorization processes to create a new state-of-the-art traditional place recognition system that uses place context to inform place recognition. We show that semantic place categorization creates a more informative natural segmenting of physical space than the blindly applied fixed segmentation used in algorithms such as SeqSLAM, which enables significantly better place recognition performance. In particular, where existing condition-invariant algorithms enable robustness to globally consistent change (such as day to night cycles), this new semantically informed approach adds robustness to significant changes within the environment, such as transitioning from indoor to outdoor environments. We perform a number of experiments using benchmark and new datasets and show that semantically-informed place recognition outperforms the previous state-of-the-art systems. Like it does for object recognition [1], we believe that semantics can play a key role in boosting conventional place recognition and navigation performance for robotic systems.**

I. INTRODUCTION

The problem of traditional place recognition typically focuses on recognizing specific locations in the world stored within a database of "places". This form of place recognition is very powerful, enabling localization on very large scales [2] and during difficult day and night traverses of an environment [3]. The problem of place categorization is similar to the place recognition problem, where environments are evaluated to determine the type of place from a database of place types.

We see the problem of place categorization as an extension to the place recognition problem, where it is possible to use similar frameworks to solve both problems. We highlight the main differences in application between the two approaches, noting that within place recognition frameworks, the goal is to identify and utilize differences between locations within the dataset to enable unique localization. Place categorization algorithms highlight the similarity between intra-class samples to create a comprehensive representation of a particular place type and are expected to be able to generalize class labels to classify and extend to unseen environments. The place categorization framework typically utilizes less "labels" than place recognition and more training examples of what represents a particular place category whereas place recognition has a "label" within a database representing every location in the environment.

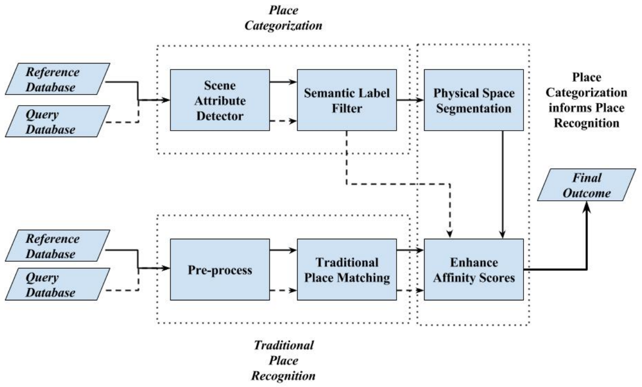

Fig. 1. A block diagram showing the flow of semantic information from the place categorization module to the place recognition module for better performance.

In this work, we combine the two frameworks of place recognition and place categorization to improve place recognition localization performance. Our primary contribution is the development of a novel framework to incorporate semantic labels and place categorization results to inform and improve place recognition place estimates (as seen in Fig. 1). Once a place is categorized, we leverage the SeqSLAM framework to perform place recognition, implementing a novel dynamic weighting scheme, biasing place matches with similar place characteristics and place categorization results.

We evaluate our proposed approach within the two real world datasets, the Campus Dataset and the CTA-Rail Dataset. The Campus Dataset utilizes a single camera traversing indoor and outdoor campus environments and the CTA-Rail Dataset consists of a single camera mounted on a train traversing scenes with subway station platforms, subway tunnels and railroad tracks. The proposed approach, incorporating place categorization information, outperforms a standalone state-of-the-art place recognition system in both the environments.

The paper proceeds as follows. In Section 2, we review literature with a focus on place recognition and place categorization. Section 3 presents our approach describing the implementation of our CNN place categorization framework, outlines our place recognition framework and the proposed

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technique for combining the two frameworks to produce superior place recognition results. We present the experimental setup in Section 4, and results of multiple levels of evaluation in Section 5. Section 6 discusses the significance of the research and areas of future work.

II. Related Work

In this section, we review current research in the areas of place categorization and place recognition. We specifically focus on place recognition, semantic mapping and place categorization frameworks.

A. Place Recognition

Visual place recognition leverages a visual map of the environment and compares visual information, typically from a camera sensor, with the map data to determine the current location of the camera within the map. There are many techniques which have been proposed to solve this problem of determining where an image has been taken within an environment. Typically, these approaches leverage single frame matching to determine the location of the camera in the environment. The key goal of place recognition frameworks is to separate places in the environment and highlight the unique attributes or features which uniquely describe individual locations in the environment [2], [4].

There have been many attempts to improve performance of place recognition systems. This has included the inclusion of temporal information, fusing multiple sensory modalities and implementing unique preprocessing steps to improve localization capabilities like shadow removal techniques.

Temporal information has been incorporated into the place recognition framework with the introduction of the SeqSLAM framework [3], integrating place hypotheses over small distances to accrue evidence and improve place recognition performance.

Multi-sensor fusion has been investigated in a number of works [5], [6], attempting to introduce unique sensory modalities which have different failure modes to produce robust place estimates.

Furthermore, the introduction of unique sensor preprocessing techniques to improve sensor data for place recognition has also been explored. Frameworks utilizing techniques for shadow removal [7] or the introduction of illumination invariant color spaces [8] to remove temporal or environmental changes from images to improve localization.

The work presented in place categorization attempts to develop the generic capability to identify types of places in the world, potentially enabling improvements in place recognition capabilities.

B. Place Categorization

Place categorization systems are an extension of the place recognition problem and attempt to attach semantic meaning to particular places in an environment; attempting to utilize labels from a training set like indoor, outdoors, kitchen, office and bedroom to categorize the location within which an image was taken. These frameworks are powerful as they facilitate generalization of room labels to different environments, for example identifying a bedroom within an unexplored house, potentially enabling robotic platforms to perform generic tasks in unknown environments by recognizing the type of place [9].

There have been a number of works which attempt to imbue traditional SLAM architectures with the ability to semantically label locations in an environment[1], [10]. These types of frameworks utilize the place categorization labels to provide information about a space, for example a location is mostly likely a kitchen, but these labels are not utilized in the process of generating the map or performing place recognition or localization.

In a recent work [11], authors develop a method to generate different categories of environments from a large available reference database for place recognition in order to reduce the search space for matching places. They basically segment the overall physical space into categories of similar environments within the place recognition system and do not use any semantic place categorization.

Place categorization systems have been leveraged in previous work to improve object detection and classification, enabling reduction of the object search space and improvement in object recognition performance [12].

However, there has been no prior work utilizing place categorization information to improve place recognition place estimates.

III. Proposed Method

The proposed approach has three main components: place categorization, physical space segmentation and place recognition as depicted in Fig. 1, with semantic information flowing from the former to the latter to generate the final place match estimate. Our core contribution is the development of a technique to utilize place categorization information to improve place recognition performance. In order to achieve this, we use the semantic labels to divide the physical space into different regions based on its appearance, that is, semantic scene attributes. These segmented regions are then used in the place recognition module for biasing place matches that lie in a paritcular semantic region. We use CNN model VGG16-places365 [13] pre-trained on the Places365 database [14] for labeling reference and query database frames with most probable scene attributes [15]. We use SeqSLAM [3] for showing improved place recognition using semantic information by appropriately enhancing the image matching scores.

A. Place Categorization

The pre-trained CNN model classifies an image with probabilities associated with each of the 365 place categories. It is also made to predict the most probable scene attributes (out of 102 attributes trained on the SUN database [15]) using one of its fully-connected layers (‘fc7’). We use these scene attributes and their associated probabilities to post-process the image labels for semantic segmentation of datasets. The predicted scene attributes for some of the images from

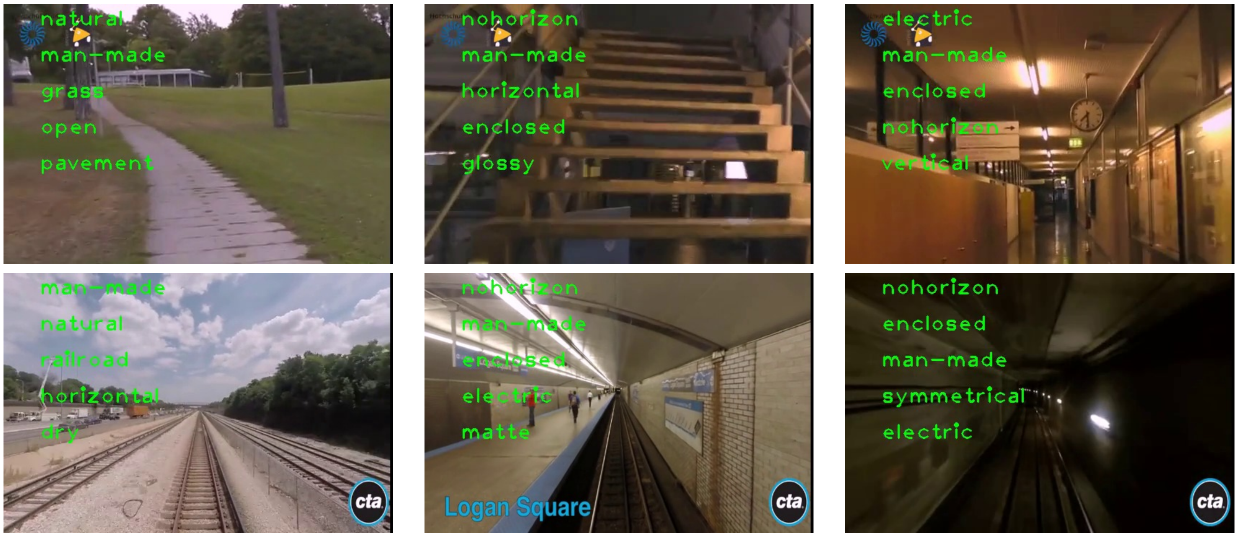


Fig. 2. Images from reference database with top-5 most probable semantic labels out of 102 scene attributes for Campus Dataset (top) and CTA Rail Dataset (bottom).

datasets used in this paper are shown in Fig. 2. The classification is performed only on the reference database. The semantic labels as obtained are used to temporally divide the reference image sequence into different segments.

B. *Physical Space Segmentation*

The place categorization module provides semantic labels for each reference image ranked according to the probabilities associated with those labels. In order to segment the reference database, a unique label corresponding to each image is required while taking into consideration the temporal nature of the input and avoiding any transient errors produced by place categorization module. This is achieved using a Hidden Markov Model (HMM) ((**cite**), where we estimate the model parameters and the hidden state corresponding to each image in the reference image sequence using the semantic label probabilities as the observed variable for that image.

The sequence of semantic labels feature vector corresponding to the reference database having T number of images is represented as a random variable $X = (x_1, x_2 \dots x_T)$ and the hidden variables are denoted as a random variable $Z = (z_1, z_2 \dots z_T)$, where z_t at a given time instant t can belong to one of the N hidden states. It is assumed that given the z_{t-1}, z_t is independent of previous hidden variables and current observation x_t only depends on current hidden state z_t. Hence, the state transition probability matrix, represented as A and initial state distribution π_i is given as:

$$A = \{a_{ij}\} = p(z_t = j | z_{t-1} = i) \qquad \forall i, j \in [1, N] \tag{1}$$

$$\pi_i = p(z_1 = i) \tag{2}$$

The probability of an observation at time t for being in state i is defined as:

$$b_i(x(t)) = p(x(t) | z_t = i) \tag{3}$$

Our objective is to find the hidden state sequence of the model, that is, the desired unique labels for the reference image sequence. This is given by the posterior probability of the state sequence:

$$p(Z|X, \theta) = \frac{p(X, Z|\theta)}{P(X|\theta)} \tag{4}$$

where $\theta = (A, b_i(x(t)), \pi)$ are the parameters of the model and

$$p(X, Z|\theta) = \pi_{z_1} \prod_{t=1}^{T-1} a_{z_t z_{t+1}} \prod_{t=1}^{T} b_{z_t}(x(t)) \tag{5}$$

$$P(X|\theta) = \sum_Z p(X, Z|\theta) \tag{6}$$

The final labels for the reference images, represented as L_t, are obtained after estimating the parameters θ of the model:

$$L_t = \arg\max_i Z_t(i) \qquad \forall i \in [1, N] \tag{7}$$

The input feature vector, that is, the observation $x(t)$, is the output response vector of the place categorization module with size 1x102, where 102 dimensions represent the probability associated with each of the scene attributes. The feature vector is normalized to the range $[0, 1]$ before feeding into the HMM. The parameters θ of the model are determined using Baum-Welch algorithm (**cite**) and the most likely hidden state sequence is obtained. The implementation of HMM used for this work is available here (**cite**). The number of hidden states, that is, N is empirically determined for the datasets used in the paper, though there are ways to determine N using cross-validation (**cite**) or by using Infinite HMM (**cite**), and is not the focus of our work.Fig. 3 shows the images and their semantic labels at the segmentation transition points for one of the datasets used in this paper.

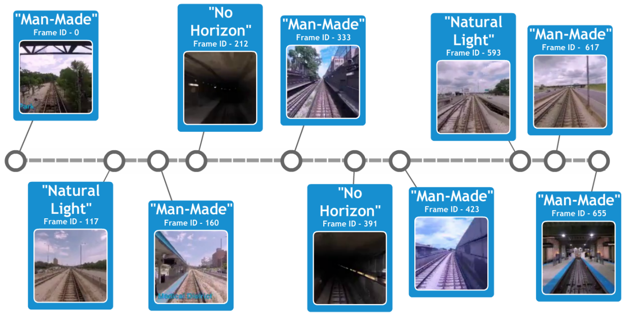


Fig. 3. The time-line of CTA-Rail dataset with semantically labeled images at the transition points of segmented reference database. (Time-line created using [16])

C. Place Recognition

In general, a place recognition system comprises of a pre-processing stage, then a method to calculate affinity scores between database places and the query, and finally a decision module for generating the best matching pairs, as seen in Fig. 1.

1) Sequence-based place matching: In addition to the above mentioned place recognition pipeline, a sequence-based recognition method exploits the temporal information inherent in this problem. Therefore, searching for a matching sequence of places is a better approach than deciding a match based only on single matching template from reference imagery. SeqSLAM [3] is a sequence-based place recognition method developed on similar principle. Moreover, it is known to work remarkably well in challenging environmental conditions and is able to recognize places despite seasonal, weather or time of day variations. The recent advanced methods [17], [18], [19] etc. inspired from SeqSLAM further improve the state-of-the-art for place recognition. In this paper, we use the vanilla approach to show the performance improvement of a place recognition system, under the influence of variations in the surrounding environment, with the help of semantic information associated with those places. The detailed methodology of SeqSLAM can be referred to in [3].

SeqSLAM performs place recognition using Sum of Absolute Difference (SAD) scores represented as D between preprocessed reference and query images. The preprocessing step involves down-sampling of image to size S_x and S_y and patch normalizing it with a fixed square window of side length P.

$$D_i = \frac{1}{S_x S_y} \sum_{x=0}^{S_x} \sum_{y=0}^{S_y} |p^j_{x,y} - p^i_{x,y}| \tag{8}$$

where $p^i_{x,y}$ and $p^j_{x,y}$ are the pixel intensities of patch normalized reference and query images.

The difference vector obtained for each query image undergoes neighborhood normalization within a sliding window of size R, also termed as neighborhood normalization zone width. The neighborhood normalized difference for a given query image, $\hat{D_i}^R$ is calculated using the local mean difference $\bar{D_i}^R$ and local standard deviation σ_i^R.

$$\hat{D_i}^R = \frac{D_i - \bar{D_i}^R}{\sigma_i^R} \tag{9}$$

The neighborhood normalized SAD matrix is then searched for local image sequence trajectories of length d_s, within a limited range of velocities, originating from each of the reference image. The sequence trajectory with the best score is then selected using a trajectory uniqueness threshold μ.

2) Localized and semantically-informed matching: The neighborhood normalization of place matching scores within the window R, as calculated in Eq. 8 and 9, reflects the emphasis on matching a local physical region of the environment, instead of finding a global minima. In general, finding a global match is prone to false noisy matching and doesn't take into consideration the temporal nature of reference image database, which can help in identifying similar patterns of matching scores in any local region of the database. Hence, the parameter R represents the span of environment, where the matching scores can be locally enhanced. This helps in preventing the dissimilar images from unnecessarily deviating the mean and increasing the variance of the matching scores in these regions, which otherwise beats the purpose of finding a local match. Our aim is to pre-define these physical regions of the environment that share similar semantic labels.

The segmentation of the dataset as described in earlier sections using HMM, is a way of separating the physical space into regions with similar environmental conditions. As shown in Fig. 1, in general, a place recognition system can use the semantic information from the place categorization module to enhance its affinity scores for matching places. Instead of arbitrarily choosing the neighborhood for the reference image as in Vanilla SeqSLAM method, we propose to use the neighborhood regions obtained using labels L_t generated using HMM. The segmented regions are denoted as a set of pairs R'_t:

$$\begin{aligned} R'_t = \{(i,j) \mid t \in [i,j) \text{ and } L_k = L_{k+1} \quad \forall k \in [i,j) \\ \forall i,j \in [1,T]\} \end{aligned} \tag{10}$$

where t iterates over all the reference images and a pair in R'_t defines the lower and upper limit of the segmented region within the reference database. The neighborhood normalization equation (9) is therefore updated as below:

$$\hat{D_i}^{R'_i} = \frac{D_i - \bar{D_i}^{R'_i}}{\sigma_i^{R'_i}} \tag{11}$$

Fig. 5 shows the method described in this section for choosing R. The incorporation of segmented regions based neighborhood normalization as shown above, makes sure that different environmental conditions encountered within a traversal are handled separately for finding a local best match.

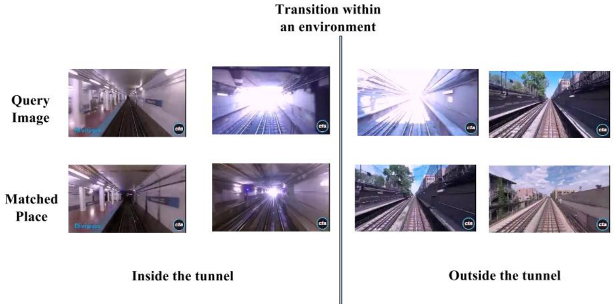


Fig. 4. Matched places at the point of transition within an environment for CTA-Rail dataset where environment changes from being inside the tunnel to outside the tunnel.

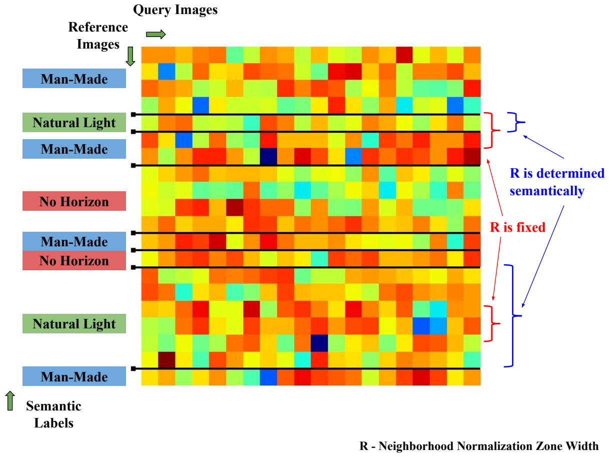


Fig. 5. The semantic segmentation of environment decides the normalization regions for better place recognition. The matrix represents the Sum of Absolute Difference score between reference and query images of CTA-Rail dataset. The black horizontal lines mark the transitions from one type of environment to the other. The red markers on the right show the fixed neighborhood normalization zone width (R) for SeqSLAM and blue markers refer to the proposed method for determining R.

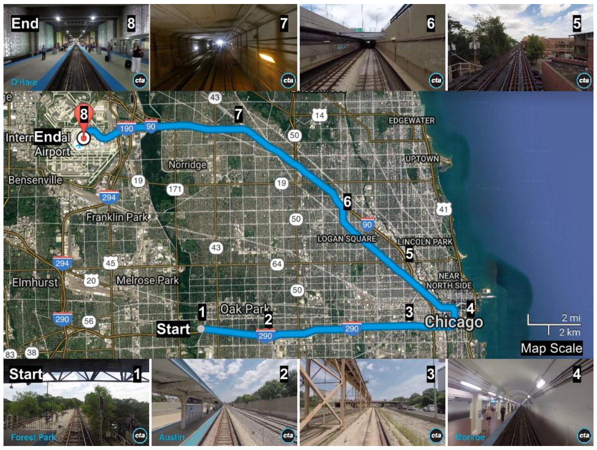


Fig. 6. CTA Dataset Trajectory Aerial View with sample images. (Marked Trajectory Source - [20])

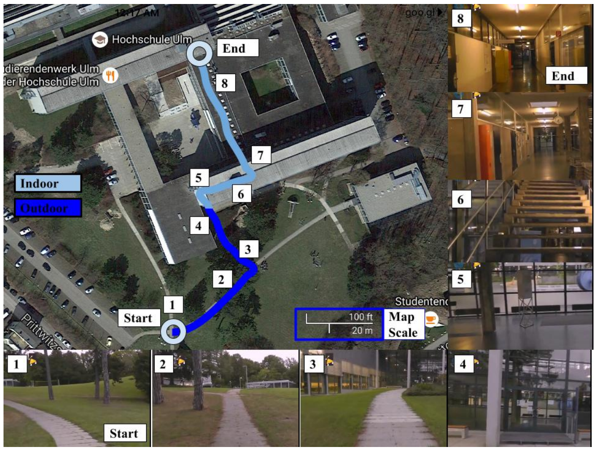


Fig. 7. Campus Indoor-Outdoor Dataset Trajectory Aerial View with sample images. (Marked Trajectory Source - [20])

IV. Experimental Setup

The experiments are performed using four different datasets described in following subsections. The image classification for place categorization is performed off-line as a preprocessing step and all the experiments are conducted using Dell Latitude E7450 Intel Core i7-5600 CPU @ 2.6 GHz x 4 processor having 16 GB RAM and running Ubuntu 14.04.

A. Datasets

The two datasets used in the experiments exhibit variations in environmental conditions within the traversal, while the other two exhibit condition variations across as well as within the traversals.

1) CTA-Rail: The CTA-Rail (Chicago Transit Authority) dataset (Fig. 6) comprises of two videos traversing a 23 km railway route (Blue Line, Forest Park to O'Hare), recorded once in 2014 [21] and then in 2015 [22], available online. A single camera is placed at the head of the train facing forward towards the railway track. The videos comprise of scenes from train stations platforms, subway station platforms, subway tunnels, and railroad tracks within highways and urban areas. The raw videos are approximately 73 and 84 minutes in duration with 132670 and 149090 frames respectively. We used the 480p version of the video and processed every 200th frame for all the experiments. The resultant reference and query databases have therefore 656 and 738 image frames respectively.

2) Campus Indoor-Outdoor: The Campus Indoor-Outdoor dataset comprises of two videos with repeated traversal of a part of Ulm University of Applied Sciences' campus from an outside lawn to an inside corridor [23], [24]. The videos have been recorded using a hand-held device with single camera and exhibit jerky motion with huge motion blur. The raw videos are cropped to remove the comments at the bottom and an overlaid navigation display on the right side. The videos are also snipped from beginning so that the starting point is aligned in both the datasets. The datasets comprise of scenes from outside the campus, with trees, grass and pavement, and from inside the campus, traversing through entrance hall, staircase, lobby

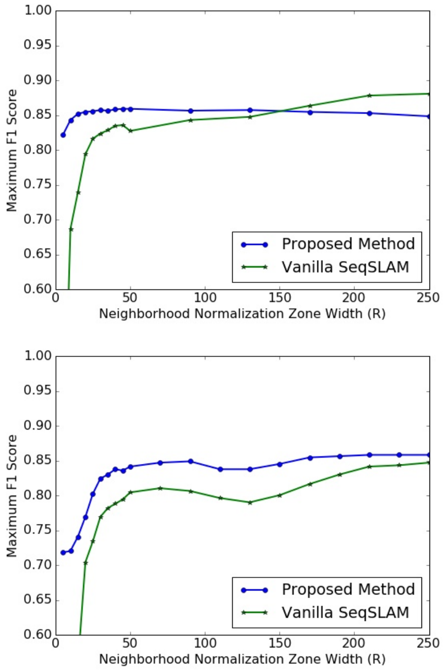


Fig. 8. Performance comparison of proposed method and vanilla SeqSLAM with respect to parameter R for CTA (top) and Campus (bottom) datasets.

and corridor. The reference and query database is processed by using every 10th image and therefore uses 355 and 300 frames respectively.

B. Parking Lot

The Parking Lot dataset is captured inside a society of residential buildings, traversing through the underground as well as open parking area. It comprises of two videos traversing the same path, once during daytime and then at night. The dataset exhibit transition from underground parking area having artificial lighting to open naturally lit space during day time, and to the dark sky during night time with some street lights. This dataset hence possess variations in environmental conditions within and across the route traversals. The videos have been captured using hand-held mobile device while driving on a motor-bike and contain 6407 and 6396 image frames respectively for day and night traversal. We process every 20th frame, therefore processing 320 frames for each of reference and query database.

C. Residence Indoor-Outdoor

The Residence Indoor-Outdoor dataset comprises of two traversals from outside of a house and then entering inside the house via corridors to the common area and then to the bedroom via stairs. The reference database was captured during daytime with good natural lighting outside the house and with minimum lighting inside the house. The query database was captured at night with street lights lighting the way outside of house and adequate lighting inside the house. Therefore, in this dataset as well, there are variations in the environmental conditions within and across the traversals. Moreover, the path traversed outside the house also exhibits a change in viewpoint in the two traversals, due to lateral offset of around 1m while walking down the pavement. The videos are captured using hand-held camera. The reference and query database comprise of 2200 and 2180 image frames respectively and are processed by skipping 10 frames, therefore comparing 220 and 218 image frames.

1) Ground Truth: The place recognition ground truth for all the datasets was generated manually for intermittent frames and then interpolated for the rest of the image sequence. A query image is considered to be a true positive match for the reference image if its index lies within a range of 5 image frames from the ground truth index.

2) SeqSLAM parameters: The parameters for SeqSLAM used for all the experiments are shown in Table I.

TABLE I
SEQSLAM PARAMETERS.

S_xxS_y	Image Down-sampling Size	w=64 and h=32
P	Patch Normalization Window Size	2,4,8,16
O	Image Matching Offset Range	±10
d_s	Sequence Length	15
R	Neighborhood Normalization Zone Width	Varies from 5 to 1280
V	Sequence Search Velocity Range	$(1 \pm 0.2)d_s$
μ	Trajectory Uniqueness Threshold	Varied

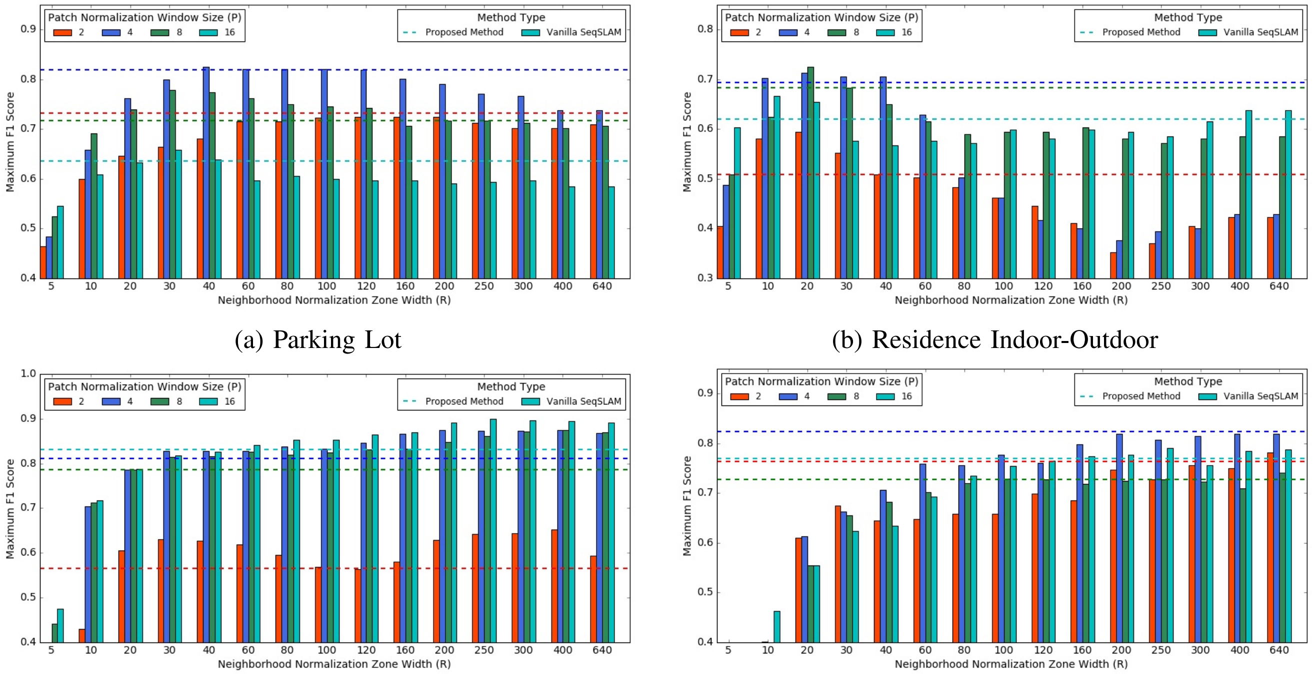
V. Results and Discussion

We used maximum F1 score to measure changes in place recognition performance using the proposed approach. The trajectory uniqueness parameter (described in [3]), that is, the threshold for deciding a correctly matched place was varied to calculate precision-recall curve and maximum F1 score. The comparative results were generated between the proposed method and vanilla SeqSLAM for four real world datasets. In order to gain an in-depth understanding of the place recognition performance changes due to proposed approach, we used two parameters of SeqSLAM method, patch normalization window size (P) and neighborhood normalization zone width (R), to measure the trends in performance change. The results are as shown in Fig. 8 and 9, and the significance and effect of these parameters is discussed in subsequent section.

In this work, we presented a framework which combines place categorization information to inform and improve place recognition results. The system was tested by using four real world datasets, highlighting the proposed system's superiority over a state-of-the-art place recognition system. Here, we discuss the effects of system parameters and the improvements achieved by the proposed approach.

A. Neighborhood Normalization Zone Width (R)

The neighborhood normalization zone width R defines a temporal region around the reference image in order to find a local best match for the query image. As shown in Fig. 9, the proposed approach outperforms the vanilla method by adequately segmenting the reference image database and



(a) Parking Lot

(b) Residence Indoor-Outdoor

(c) CTA-Rail

(d) Campus Indoor-Outdoor

Fig. 9. Performance charts showing maximum F1 Score w.r.t. different R (Neighborhood Normalization Zone Width) values. R is varied to the maximum value, that is, the size of reference database, after which maximum F1 score becomes constant. The patch normalization window size (P) parameter with value 4 happens to perform better as compared to others most of the times.

selecting the right temporal region for enhancing the place matching scores. The regions R' being determined using semantics are independent of the parameter R, hence the performance measure is always constant w.r.t. R.

It can be noted in the Fig. 9, that performance of vanilla SeqSLAM for CTA-Rail and Campus Indoor-Outdoor dataset gets better with increasing the parameter R, but for the Parking Lot and Residence Indoor-Outdoor datasets, it achieves a maxima and then starts to fall before becoming constant. This happens because of the fact that the former datasets do not exhibit variations in conditions across the traversals, whereas the latter do. A large normalization zone essentially means finding a global minima in the entire reference database and variations in environmental conditions across traversals give rise to false matches for such cases. For example, in Residence Indoor-Outdoor dataset, reference database has its outdoor images captured in natural daylight which then transits to indoor environment images captured in darkness of enclosed room and hall. On the other hand, the query database images initially traverse the outdoor environment at night under street light and then transit into indoor areas which are well lit with lamps and bulbs. This is shown in Fig. 10, where 10(a) shows the query images, (b) shows the correct matches from the reference database using the proposed method and (c) shows false matches that occur using vanilla SeqSLAM with large R value ($R = 640$). The false matches show that the vanilla approach finds a global minima that happens to be matching of dark images to other similar dark images and well-lit images to other similarly-lit images. This drawback is easily avoided by using the local best match with R chosen using the proposed approach which works well irrespective of changes in environmental conditions within or across the traversals.

The neighborhood normalization parameter R is used to set the window size for locally enhancing the match scores. As shown in Figure 9, performance of vanilla SeqSLAM gets better with an increase in R. This can be expected because normalizing over a larger image sequence balances the overall variation in scores for varying conditions within an environment, but it leads to suppressing of correct matching pairs corresponding to images having low matching scores, especially in the smaller zones. On the other hand, using segmented regions to set the normalization zone width, effectively highlights the matching scores in appropriate regions and generates more true positives. The performance is, therefore, most of the times, better than the best achieved using vanilla approach with any value of R. It can also be noted that wider neighborhood zones for normalization, are not appropriate for large datasets and long time navigation due to computational burden.

B. Patch Normalization Window Size (P)

The images used for finding SAD score are preprocessed by down-sampling them to the size of 32x32 and then patch normalized in order to counter the changes in appearance of their matching counterparts. Depending on the type of environment and corresponding imagery, the choice of patch normalization window size can lead to changes in performance. In the experiments performed for current work, we

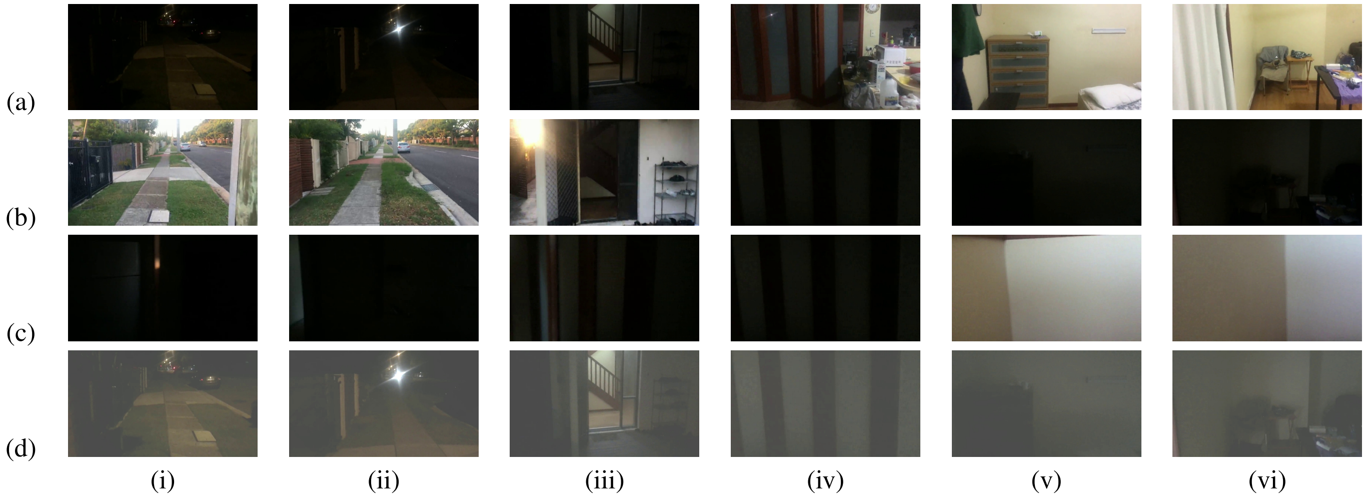


Fig. 10. (a) Query Images from the Residence Indoor-Outdoor dataset intermittently selected in temporal order from beginning till the end. (b) Correct matches obtained using proposed method. (c) False matches that occurred using vanilla SeqSLAM. (d) Manually brightened images representing first three query images (i,ii,iii from (a)) and last three correctly matched reference images (iv,v,vi from (b)) for sake of clarity as the original images are too dark to interpret.

found that patch normalization window size of 4 for the given down-sampling image size performs better.

C. Physical Space Segmentation

Fig. 8 shows a performance comparison for both the datasets with respect to the parameter R alone. The curves here give us an insight to understand how an optimal value for segmenting the physical space can be chosen. For both the datasets, the performance of vanilla SeqSLAM and the proposed approach becomes almost similar at a certain point, beyond which no significant improvement occurs. This happens when R is approximately between 20 and 25, which is almost 1 km of journey in the CTA Rail dataset captured at speed of train and about 50 m for Campus dataset captured at normal human speed. The visual data captured in both the cases is therefore sufficient enough to correctly segment its physical space. If the physical region spanned were to be smaller than this, it would have created an inter-region redundancy of visual data which would mean more confusing matching places. Hence, the optimal value for segmenting the environment would be based on the average rate of persistence of particular environmental conditions. However, it would still fail for the cases where there is a large variance in the span of different conditions existing within the environment, and a proper segmented environment based on semantic information will be the key to perform better.

D. Environmental Transitions

We have demonstrated performance improvement for a place recognition system by appropriately handling different visual conditions within an environment, but one also needs to be careful about the exact point of transition within these different conditional settings. In general, there is a sequence of images, that are encountered, for example, while moving from outside the tunnel to inside the tunnel and vice versa. The current state-of-the-art place categorization module trained on limited number of places or scene attributes cannot always effectively discriminate the exact transition point/region from the environments between which the transition takes place. This leads to false matching of possibly false semantic labels and hence poor performance at those points. Moreover, in our current approach, the transition areas, that span only few images, also get ignored during the label filtering process. Though, it can be taken care of by using smaller filtering window size s (described in earlier sections), but then it would demand correct semantic labels with temporal consistency. This problem makes more sense to be solved from the place categorization side, by training place categories at a further fine level, such that being inside the tunnel or outside of it is also discriminated from starting to seeing the tunnel entry or the exit, which actually marks the transition to a new environment, and thus becomes a part of our future work.

VI. Conclusion and Future Work

The current work can be extended to incorporate labels of place categories or scene attributes defined at finer levels, as also discussed in previous section. Such fine level place categorization will be directed towards the traditional place recognition problem where each place, despite being from same semantic category, is treated as a separate place. It would also be worth exploring ways to dynamically determine the sequence length for matching places while using the semantic place information. We would also like to investigate better ways of generating semantic labels with temporal coherence, given that the research problems of object recognition and place categorization usually focus on single images instead of image sequences. Another interesting direction could be a deep-learning framework, using a combination of LSTM and CNN to effectively exploit the temporal and spatial information respectively and infer relationship between places with similar visual appearances.

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