Change Detection under Global Viewpoint Uncertainty

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Abstract—This paper addresses the problem of change detection from a novel perspective of long-term map learning. We are particularly interested in designing an approach that can scale to large maps and that can function under global uncertainty in the viewpoint (i.e., GPS-denied situations). Our approach, which utilizes a compact bag-of-words (BoW) scene model, makes several contributions to the problem: 1) Two kinds of prior information are extracted from the view sequence map and used for change detection. Further, we propose a novel type of prior, called motion prior, to predict the relative motions of stationary objects and anomaly ego-motion detection. The proposed prior is also useful for distinguishing stationary from non-stationary objects. 2) A small set of good reference images (e.g., 10) are efficiently retrieved from the view sequence map by employing the recently developed Bag-of-Local-Convolutional-Features (BoLCF) scene model. 3) Change detection is reformulated as a scene retrieval over these reference images to find changed objects using a novel spatial Bag-of-Words (SBoW) scene model. Evaluations conducted of individual techniques and also their combinations on a challenging dataset of highly dynamic scenes in the publicly available Malaga dataset verify their efficacy.

I. INTRODUCTION

Change detection is a key component for long-term map learning [1]–[3] and has been attracting extensive research interest in recent years [4]. In this paper, we address the problem of change detection from a novel perspective of long-term map learning. Given a single-view image acquired by a car-like robot, our approach localizes changed objects (e.g., other cars) with respect to a pre-built view sequence map (Fig. 1). Specifically, we are interested in designing an approach that can scale to large maps and that can function under global uncertainty in the viewpoint (i.e., GPS-denied situations). Addressing this problem at large scale is of fundamental importance, particularly in the context of long-term map learning, owing to the requirements of scalable map representation and global viewpoint localization.

Thus far, the problem of change detection has been widely studied in the areas of computer vision and robot vision for various application domains including city model maintenance [5], visual inspection [6], disaster monitoring [7], and patrol robots [8]. The solutions include view registration [9], 3D line features [10], view synthesis [5], occlusion reasoning [11], and deep learning of patch-level similarity [12].

Formulation as a scene comparison task, in which operations are carried out on a given pair of query and reference images, is common to the majority of these applications. To date, most of the state-of-the-art systems simply assume that relevant reference images are given, or rely on the availability of rough GPS information. However, providing relevant reference images is a non-trivial task in the case of long-term map learning. This is the main topic of our study.

This paper reformulates change detection as a scene retrieval task, in which both viewpoint localization and change detection are achieved by a scalable nearest neighbor algorithm with a compact bag-of-words (BoW) [13] scene model.

Our approach is related to previous work on scene retrieval but with key differences: In contrast to visual place recognition or map relative viewpoint localization [14], we focus on retrieving not the whole image but a small object (i.e., the change) in the scene. Unlike particular object retrieval [15], we cannot assume the knowledge on where the target object (i.e., the change) is located in the input scene. Compared with common object discovery (COD) [16], we need to identify not only common part but also changed part between scenes.

More specifically, our approach brings three contributions to the problem:

1) View Sequence Map as Prior: A view sequence map
provides two kinds of prior information: appearance prior and motion prior. The former can be naturally used as training data for vocabulary learning by the BoW model. The latter provides prior for relative motions of stationary objects and anomaly ego-motion detection, which can be useful for distinguishing stationary from non-stationary objects and also for evaluating the reliability of detection results.

2) Bag-of-Local-Convolutional-Features (BoLCF): Our viewpoint localization strategy is motivated by the recent success in the local convolutional features from deep convolutional neural network (DCNN) [17] and their scalable BoW representation [18]. We adopt the BoLCF technique to retrieve a small set of relevant reference images (such as 10) given a query image that is then used for change detection.

3) Spatial-Bag-of-Words (SBoW): Change detection is reformulated as a scene retrieval over these reference images to find changed objects. The results of viewpoint localization, motion prior, and appearance prior, are combined to compute the likelihood of change using a novel spatial Bag-of-Words (SBoW) scene model.

We evaluated the effectiveness of individual techniques and also their combinations using a challenging dataset of highly dynamic scenes in the publicly available Malaga dataset [19]. In addition to the above contributions, our experimental system can also be viewed as a novel solution to the moving object detection (MOD) alternative task, which is complementary to existing MOD approaches based on motion cues (e.g., motion segmentation, moving camera background subtraction) and appearance cues (e.g., particular moving object recognition).

In previous work, we investigated the problem of global localization with change detection [20], cross-domain localization [21], and localization from images with small overlap [22]. Our approach is also inspired by existing techniques for self-localization in dynamic environments [23], change detection [24], motion anomaly detection [25], and tracking learning detection [26]. However, the problem of change detection under global viewpoint uncertainty has not yet been addressed in existing work.

II. PROBLEM

A. Dataset

In contrast to previous change detection approaches, we focus on single-view recognition under highly dynamic scenes. This is more challenging than a typical scenario in which a complete 3D city model [5] or a full 3D structure reconstruction from multi-view images is used [27]. In our experiments, we utilized the publicly available Malaga dataset [19], which contains a set of view sequences for different robot trajectories. Although ground-truth GPS data and stereo images are also available in this dataset, only a single-view image (left-eye view of the onboard stereo camera) is used by our change detection algorithm. In the datasets, occlusion is severe in the scenes, and stationary objects can even have relative motions caused by the complex ego-motions of the robot-self, which makes our change recognition task a challenging one.

B. Performance Index

The performance of a change detection algorithm is evaluated over a set of query images. The output of a change detection algorithm is a collection comprising the likelihood value for every local feature in every query image. We merge the outputs over all the query images and sort them in descending order of likelihood value. Then, the rank values of features that belong to the ground-truth changed objects with respect to the sorted feature list is used as a measure for performance evaluation. For the ground-truth changed objects, changed objects are manually annotated in the form of bounding boxes by comparing query and reference images. As the evaluation is based on ranking, a smaller value signifies better performance. If multiple local features belong to the ground-truth bounding box, the rank value of the feature that is assigned the largest likelihood of change is used for the evaluation.

C. Global Viewpoint Uncertainty

In order to conduct change detection experiments under the challenging scenario of global viewpoint uncertainty, the a-priori view sequence map is customized for individual query input images. Instead of using the full image dataset, a subset of the images in the dataset whose time stamps are too close (closer than 400 frames) to the input image are considered nonmembers of the view sequence. The customized view sequence map consists of a union of the image collections #5, #6, #7, #8 and #10, minus the above mentioned subset of images. Note that this is a challenging setting, known as loop closure in the field of robotic mapping and localization, in which the viewpoint localization requires loop-closure detection [14].

III. APPROACH

A. Overview

Our change detection task formulation follows a classical formulation, formulation as a regression problem, in which the goal is to evaluate the likelihood of change for every local image feature in every query image. The standard solution for this task is scene comparison between input and reference (i.e., mapped) scenes. As stated by many researchers, pre-registration between the input and reference scenes is a necessary pre-processing step for reliable change detection [28]. There are primarily two solutions for the pre-registration. In one solution, availability of a complete 3D reference scene model or full 3D reconstruction from a sequence of images (i.e., SLAM) or a collection of multi-view images (i.e., SIM) is assumed, and the 3D model for the query is compared to those of the reference scenes [27]. The other solution is to directly compare the 2D input and reference images without assuming the availability of a 3D model. In this study, we employed the latter setting with global viewpoint uncertainty. This is a very challenging setting because the viewpoint uncertainty influences the pre-registration performance in a more direct manner than in the former case, in which the 3D model is available.
Fig. 2. Anomaly motion detection using motion prior. Top: Samples from the motion vocabulary learned from Malaga sequence #9. Each line segment corresponds to a motion word or a motion exemplar that is a 4D vector consisting of a pairing of 2D vectors, a vector at the start position and a vector at the end position, of a feature track on the image plane. Middle: Each line segment indicates the motion between each keypoint in the query image (2D) and its nearest neighbor keypoint in the reference image. Bottom: Nearest neighbor motion exemplars (4D vectors) explaining the current viewpoint in the observed feature.

More formally, we formulate the problem as follows. The basic idea is to predict the appearance \( a \) and pose \( p \) of an input local image feature, and then evaluate the difference in the observed feature \( v = (a, p) \) from the prediction. The amount of difference can be viewed as anomalyness [29], or the likelihood of change [28]. The prediction can be defined as the posterior distribution \( P(a, p|I) \) of feature \( v \) conditioned on the given input image \( I \). The key observation is that the posterior distribution can be approximated by a set of features \( V = \{v\} \) sampled from a subset of view images \( I_1, \cdots, I_R \) in the prior view sequence map. It is natural to sample such a subset from the posterior distribution \( P(v|I) \) of the current viewpoint \( v \) given the input image \( I \). A possible approach to compute this probability distribution is to utilize probabilistic localization algorithms such as Monte Carlo localization [23]. In this study, we simply approximated the sample set with a set of images in the view sequence map that are top-ranked by map relative localization, image retrieval, or place recognition subsystem. Let \( I_i (i \in [1,R]) \) denote the set of top-ranked \( R \) reference images in the retrieval result. Let \( W = \{w_{ij}\}_{j=1}^{K_i} \) denote a feature set that consists of the feature \( w_{ij} = (a_i, p_j) \) of each \( i \)-th top-ranked image. We approximate the likelihood of change as:

\[
L(w) = \min_{i \in [1, R]} \min_{j \in [1, K_i]} D(w, w_{ij}).
\]

Note that we use min operation instead of the average operation. This is because we discovered that the average operation yields poor performance due to the fact that the majority of local features are contaminated by noise. In contrast, the min operation enables the filtering of such random noise because the chance of dissimilarity between input and random features being the min value is very low.

In the remainder of this section, we focus on the view sequence map of the target route and discuss the algorithm proposed for feature comparison (i.e., the \( D \) function) and effective representation of features (i.e., \( p, a \)). More specifically, we consider 1) how to obtain the prior model for relative motions of stationary objects caused by ego-motion of the robot (III-B), 2) how to obtain the prior model for BoW appearance representation of objects used by both the viewpoint localization and change detection tasks (III-C), and 3) how to utilize these prior models for change detection tasks.

B. Motion Prior

Understanding the relative motions of stationary objects from visual experience along the target route is key to discriminating stationary and changed (dynamic/non-stationary) objects. In general, the relative motion of a static object between query and reference images can be explained by several factors, such as the robot’s ego-motion, relative distance to the object, and the object’s size and shape. In other words, if the relative motion of an object cannot be explained by these factors, the object can be changed (i.e., non-stationary or dynamic) object with high probability. We employ this idea to detect changed objects.

In the training phase, the view sequence map is the sole information source for learning. We learn the characteristics of the relative motions of static objects from the available view sequence map (Fig. 2). Conceptually, our approach is analogous to tracking learning detection (TLD) in the visual tracking community [26]. The algorithm consists of two steps. 1) In the first step, we extract KLT features from each frame in the view sequence map and track them between adjacent frames. The trajectories of the KLT features during a unit length ego-motion can be viewed as motion features. For the ego-motion estimation, we use a monocular visual odometry with the five-point algorithm in [30] in our own implementation. We simply approximate the trajectory as a
not always reliable. Specifically, it tends to be reliable while the robot is in non-anomaly ego-motion such as straight-line motion, but becomes unstable when the robot is in anomaly ego-motion such as curved motion or slip motion.

For each frame, we monitor the ego-motion measurement and if the curvature of the ego-motion trajectory exceeds a predefined threshold $T_c = 5$ deg, we simply do not use the relative motion measurement for that frame. For a given trajectory length $L$, the curvature is defined as the deviation of exemplar directions [rad], computed from a pairing of the start and end points. For these start and end points, we use the $i$-th viewpoint and $i + L/2$-th viewpoint, respectively, for each different $i$ in $[0, L/2 − 1]$. Fig. 3 visualizes samples of tracking data for non-anomaly and anomaly ego-motion classes, as discussed in [11–13].

In order to reduce the storage cost for the view sequence map, we also consider the keyframe selection task. Keyframe selection involves finding representative frames in the view sequence map. Once the keyframe set is determined, the change detection task approximates each input image by its nearest neighbor keyframe in terms of the view ID. In our baseline strategy, we sample a keyframe every 10 frames in the view sequence map.

C. Appearance Prior

We employ the BoW representation for appearance features that are used for change detection. Two types of BoW representations with different levels of trade-offs between compactness and discriminativity and between accuracy and robustness are used for the two different tasks: map relative localization and change detection.

1) Bag of Local Convolutional Features: BoW representation compactness and discriminativity are basic requirements for viewpoint localization [14]. In general, compactness is realized by limiting the number of visual words per mapped image. Conversely, discriminativity depends strongly on the choice of the local feature descriptor. Considering these requirements, we employ local convolutional features with BoW representation—a technique developed in the image retrieval community [18]. The basic idea of this technique is to pre-train a deep convolutional neural network on big data (e.g., imagenet), and then view responses from its convolutional layer as a grid of high-dimensional (e.g., 256-dim) local feature descriptors. The technique has been found to be computationally efficient and competitive with other state-of-the-art scene matching and retrieval algorithms [18].

In our approach, we adopt Caffenet and use its last convolutional layer as a size 169 set of 256-dim local feature descriptors. A fine vocabulary with size 1M is learned from an independent dataset and used to convert every local convolutional feature to a 20-bit code. As several researchers have stated, and as also discovered by us in our preliminary experiments, a key limitation of such a fine vocabulary is that sensitivity increases in the vector quantization. To address this issue, we employ asymmetric feature comparison using the NBNN distance metric, as detailed in our previous study [21]. In this method, the distance between a query image’s feature set.

Fig. 3. Training data for motion prior. Bird’s eye views of several samples of the trajectories are shown in the graphs. The top panel shows non-anomaly ego-motion samples in [m], while the bottom panel shows anomaly ego-motion samples.
I panel. the local feature keypoint of interest is located at the center of the last column shows the 1st, 2nd, ... nearest neighbor features. For each random instance of local feature in the query image, while the second to the last column shows the 1st, 2nd, ... nearest neighbor features. For each random instance of local feature in the query image, while the second to

Fig. 4. Feature-level nearest neighbor search. Each row corresponds to different features in different query images. The left-most column shows a random instance of local feature in the query image, while the second to the last column shows the 1st, 2nd, ... nearest neighbor features. For each panel, the local feature keypoint of interest is located at the center of the panel.

\[ I_{\text{query}} = \{ f \} \text{ and a reference image’s word set } I_{\text{reference}} = \{ w \} \]

is computed as follows:

\[
D_{\text{NBNN}}(f_{\text{query}}, f_{\text{reference}}) = \sum f \min_w |f - \hat{f}(w)|, \tag{2}
\]

where \( \hat{f} \) is a function that returns the exemplar feature corresponding to an input visual word \( w \). As also shown in our previous work [22], viewpoint localization using the NBNN distance metric is stable and works even when there is no common visual words between query and reference images.

2) Bag of Binarized SIFT Words: Feature representation accuracy and robustness are basic requirements for change detection [28]. In general, accuracy is realized by employing a fine vocabulary. On the other hand, robustness depends on the choice of local feature descriptor. We employ the combination of harrislaplace detector and SIFT feature descriptor, which has proven to be robust in various change detection tasks [27]. A random projection technique as in [22] is employed as a dictionary to translate each SIFT vector to a more compact \( B = 128 \)-bit binary code, to obtain a BoW representation in the split of bag-of-binary-words [2]. Our fine vocabulary requires a number of bits per local feature descriptor and the database of BoW representations cannot operate in main memory. Fortunately, we can expect that the map relative localization provides a sufficiently small set of \( K = 10 \) reference image candidates, which requires a reasonably small space per query image. Fig. 4 shows random examples of nearest neighbor search. The examples include dynamic objects such as cars, and static objects such as road, wall, shop, and sky. It can be seen that similar objects are successfully found in the examples shown.

3) Nearest Neighbor Anomaly Detection: The results of above tasks—map relative localization, motion prior, and appearance prior—are combined to compute the likelihood of change. Incorporating motion prior to evaluate the likelihood of change is a non-trivial task. In our SBoW approach, we represent a hypothesized motion of a query local feature of interest by a 4D vector \((x^q, y^q, x', y')\), where \(x^q, y^q\) represents the 2D pixel location of a query local feature, and \(x', y'\) represents the 2D pixel location of its nearest neighbor reference local feature. Then, we test if the distance between the query and its nearest neighbor motion feature in the 4D motion feature space is greater than a pre-defined threshold \( T_m = 10 \). If it is greater, the query motion feature is considered as belonging to the anomaly motion class. Our criterion for evaluating the likelihood of change of a given query local feature \( f \) is in the form:

\[
L(f) = \min_{\hat{f} \in A(f)} \left( |f - \hat{f}| + M(f)|f - \hat{f}| \right), \tag{3}
\]

where \( A(f) \) is a function that returns nearest neighbor \( K = 10 \) features in the reference image, and \( M(f) \) is a function that takes one if the motion feature of \( f \) belongs to the anomaly motion class, and zero otherwise.

IV. Experiments

Experiments were conducted to validate our approach on several change detection tasks. Their results indicate that the proposed algorithm is memory efficient, performs well, and scales to large maps. We also compared our approach with a baseline method that does not use the motion prior, and also analyzed the sensitivity of the approach to viewpoint uncertainty.

Fig. 5 gives a bird’s eye view of the viewpoint trajectory of the mapper robot of the view sequence maps used in the experiments. We used sequences #5, #6, #7, #8, and #10 in the Malaga dataset. This is because they are reasonably long sequences and, more importantly, they contain the loop-closure situations, which correspond to the map relative localization under global viewpoint uncertainty. We also used sequence #9 (length 1,018) as the training data for learning motion prior and appearance prior, in the procedure described in subsections [ILL-B] and [ILL-C]. Each image in the dataset is sized 1,024 × 768. Sequences #5, #6, #7, #8, and #10 contain 4,816, 4,618, 2,122, 10,026, and 17,310 images, respectively.

We created the test set considering two requirements. 1) The timestamps of all the images in the view sequence map should not be close (closer than 400 frames) to that of the query image. This setting, comparison between new and old images, is common to many change detection applications. This requirement is met by the procedure described in [ILL-C]. 2) The query image’s view should partially overlap at least one reference image in the view sequence map. Otherwise, change detection algorithms can fail badly as pre-registration usually requires partial view overlap between query and reference images. To meet this requirement, we select query
Fig. 5. Bird’s eye view of the experimental environments. Colored lines and points, respectively, indicate the robot’s trajectories in [m] and the viewpoints where the robot’s ego-motions are recognized as non-anomaly ego-motions.

Fig. 6. Change detection performance. (a) IAIR (inverse average inverse rank) versus $R$. (b) IAIR versus #bits. (c) Effect of motion prior versus keyframe sampling ratio. The vertical axis shows ratio of tasks in which performance is better when motion prior is used than when not used. (d) Influence of the ground-truth localization error. (e) Influence of the dissimilarity estimated by the localization algorithm.

Fig. 7. Individual localization results. (a) Top-10, top-5, top-2, and top-1 recognition rates are shown in different colors. For the purpose of visualization, localization errors greater than 1,000 m are treated as 1,000 m in the graph. (b) Localization result for an example query image. Left: Dissimilarity of the BoLCF histogram between the query image and each $i$-th top-ranked reference image. Right: Localization error in [m] for each $i$-th top-ranked reference image.

Fig. 8 shows change detection results for individual query images. It can be seen that the method that combines the appearance and motion priors more frequently assigns a distance between the ground-truth viewpoint of the query image and that of the reference image that is top-ranked by the map relative localization. Our change detection algorithm is frequently successful even when the localization error is large (e.g., 100 m). In fact, success in global viewpoint localization is not a necessary condition for change detection. The map relative localization often found reference images with a similar landscape to that in the query image, and then our change detection algorithm was able to identify change using the difference in the appearance and location of the changed object as a cue. In summary, we obtained the following results.

1) $B = 128$ binary code was necessary for reliable change detection.
2) Top $R = 10$ -ranked reference image set was already sufficient for viewpoint localization.
3) In 94% of the tasks, motion prior was effective to improve change detection performance.

Fig. 7 shows map relative localization results for individual query images. It can be seen that the top-$R$ ranked reference image set is reliable when $R$ is equal or larger than 5 in these cases considered here.

Fig. 8 shows change detection results for individual query images. It can be seen that the method that combines the appearance and motion priors more frequently assigns a
small rank value to the ground-truth changed features. Fig. 8 shows examples of change detection. It can be seen that change detection was frequently successful even when the query image was not well registered against the reference image, which corresponds to the conditions of local or global viewpoint uncertainty. It can be also seen that due to the dynamic nature of the traffic environments, the algorithm was often confused by visually similar but different dynamic objects the robot encountered. It is natural that change detection becomes a difficult task when the scene contains confusing changed objects. Note that such changed objects can be detected and removed from the view sequence map to some extent in the TLD framework. Despite the difficulty, our approach was more frequently successful by making use of the appearance and motion prior as a cue.

V. CONCLUSIONS

In this paper, we addressed a novel problem of change detection under global viewpoint uncertainty. For compactness and efficiency, the proposed method employs two types of BoW scene models—BoLCF and SBoW—using the view sequence map as a prior. In addition, we proposed a novel prioritization scheme, called motion prior, to represent the difference in the local or global viewpoint uncertainty. It can be also seen that change detection was frequently successful even with a small rank value to the ground-truth changed features.

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Fig. 9. Visualization of change detection. Each panel shows for each query image, the nearest neighbor feature pair that is used to compute the likelihood of change. The blue circles and red colored bars show locations of the features and the likelihood of change. Each nearest neighbor feature pair is selected among every possible feature pair, one from the query image and the other from the top-$R$ ranked reference images.

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