Domain Invariant Siamese Attention Mask for Small Object Change Detection via Everyday Indoor Robot Navigation

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Abstract—The problem of image change detection via everyday indoor robot navigation is explored from a novel perspective of the self-attention technique. Detecting semantically non-distinctive and visually small changes remains a key challenge in the robotics community. Intuitively, these small non-distinctive changes may be better handled by the recent paradigm of the attention mechanism, which is the basic idea of this work. However, existing self-attention models require significant retraining cost per domain, so it is not directly applicable to robotics applications. We propose a new self-attention technique with an ability of unsupervised on-the-fly domain adaptation, which introduces an attention mask into the intermediate layer of an image change detection model, without modifying the input and output layers of the model. Experiments, in which an indoor robot aims to detect visually small changes in everyday navigation, demonstrate that our attention technique significantly boosts the state-of-the-art image change detection model. Our dataset is available at https://github.com/KojiTakeda00/Small_object_change_detection

I. INTRODUCTION

Attention is a technique for selecting a focused location and enhancing different representations of objects at that location. Inspired by the major success of transformer architectures in the field of natural language processing, researchers have recently applied attention techniques to computer vision tasks, such as image classification [1], [2], object detection [3], semantic segmentation [4], video understanding [5], image generation [6], and pose estimation [7]. Currently, attention technique is showing it is a potential alternative to CNNs [8].

This study explores the attention technique in the context of image change detection for robotics applications. Image change detection in 2D perspective views from an on-board front-facing camera is a fundamental task in robotics and has important applications such as novelty detection [9] and map maintenance [10].

The problem of image change detection becomes challenging when changes are semantically non-distinctive and visually small. In these cases, an image change detection model (e.g., semantic segmentation [11], object detection [12], anomaly detection [13], and differencing [14]), which is trained in a past domain to discriminate between the foreground and the background, may fail to classify an unseen object into the correct foreground or background class. Intuitively, such a small non-distinctive change may be better handled by the recent paradigm of self-attention mechanism, which is the goal of our study.

Incorporating a self-attention mechanism into an image change detection model is not straightforward owing to the unavailability of labeled training data. Existing attention models have primarily been studied in such application domains where rich training data are available [1]. They are typically pre-trained on big data and further fine-tuned in the target domain. This training process is very expensive for robotics applications, where robots need to adapt on-the-fly to a new test domain and detect change objects. Therefore, a new unsupervised domain-adaptive attention model is required.

We propose a new technique called domain-invariant attention mask that can adapt an image change detection model on-the-fly to a new target domain, without modifying the input or output layers, but by introducing an attention mechanism to the intermediate layer (Fig. 1). A major advantage of our proposed approach, owing to its reliance on high-level contextual attention information rather than low-level visual features, is its potential to operate effectively in test domains with unseen complex backgrounds. In this sense, our approach combines the advantages of two major research directions in the change detection community: pixel-wise differencing [11], [15] and context-based novelty detection [9], [16], by incorporating all available information into the attention mechanism.

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Our contributions can be summarized as follows: (1) We explore a new approach, called domain-adaptive attention model, to image change detection for robotics applications, with an ability of unsupervised on-the-fly domain adaptation. (2) Instead of considering pixel-wise differencing [11], [15] and context-based novelty detection [9], [16], as two independent approaches, our framework combines the advantages of both approaches by incorporating all available information into the attention mechanism. (3) We present a practical system for image change detection using state-of-the-art techniques such as image registration [17], pixel warping [18], and Siamese ConvNet [11]. Experiments, in which an indoor robot aims to detect visually small changes in everyday navigation, demonstrate that our attention technique significantly boosts the state-of-the-art image change detection model. (4) We will make this new dataset publicly available for future research in this area.

II. RELATED WORK

A. Image Change Detection

Image change detection is a long standing issue of computer vision and it has various applications such as satellite image [19], [20], and autonomous driving [14], [21]. Existing studies are divided into 2D or 3D, according to the sensor modality, and we focus on image change detection in 2D perspective views from an on-board front-facing camera in this study. Since the camera is a simple and inexpensive sensor, our 2D approach can be expected to have an extremely wide range of applications.

Pixel-wise differencing techniques for image change detection rely on the assumption of precise image registration between live and reference images [22]. This method is effective for classical applications such as satellite imagery [22], in which precise registration is available in the form of 2D rotation-translation. However, this is not the case for our perspective view applications [23], in which precise pixel-wise registration itself is a challenging ill-posed problem. This problem may be alleviated to some extent by introducing an image warping technique, as we will discuss in Section III-B. However, such pixel warping is far from perfect, and may yield false positive in image change detection.

Novelty detection is a major alternative approach to image change detection [24]. In that, novelties are detected as deviations from a nominal image model that is pre-trained from unlabeled images in a past training domain. Unlike pixel-wise differencing, this technique can naturally capture the contextual information of the entire image to determine whether there are any changes in the image. However, on the downside, the change regions cannot be localized within the image even if the existence of the change is correctly predicted. Therefore, existing researches of novelty detection in the literature have focused on applications such as intruder detection [25], in which the presence or absence of change, not the position of the changing object, is the most important outcome information.

Several new architectures targeting small object change detection have recently been presented. For example, Klomp et al. proposed to use Siamese CNN to detect markers for improvised explosive devices (IEDs) [26], where they tackled the resolution problem by removing the output-side layer of ResNet-18 [27] to improve the detection performance of small objects. Our approach differs from these existing approaches in that (1) it does not require to modify the input and output layers of the architecture, and (2) it is able to utilize contextual information.

B. Attention

Inspired by the major success of transformer architectures in the field of natural language processing, researchers have recently applied attention techniques to computer vision tasks, such as image classification [1], [2], object detection [3], semantic segmentation [4], video understanding [5], image generation [6], and pose estimation [7]. Because self-attention captures long-range relationships with low computational complexity, it is considered a potential alternative to convolutional neural networks (CNNs) [8].

Recently, several studies have reported the effectiveness of attention in change detection tasks. HPCFNet [28] represents attention as a correlation between feature maps, DR-TA Net [15] evaluates temporal attention by computing the similarity and dependency between a feature map pair, to realize attention-based change detection. CSCDNet [11] employs a correlation filter to compensate for the uncertainty in the non-linear transformation between live and reference images.

From the perspective of robotic applications, one of major limitations of the current self-attention techniques is that they require a large training set to reduce domain dependency. In our contribution, we introduce a novel domain-adaptive attention technique that is specifically tailored for unsupervised on-the-fly domain adaptation.

III. APPROACH

Our goal is to incorporate an unsupervised attention model into the image change detection model without modifying the input and output layers of the model (Fig. 2). In this section, we implement this idea on a prototype robotic SLAM system. First, we perform a preprocessing to compensate for the viewpoint error and the resulting uncertainty in non-linear mapping from the 3D real environment to a 2D image plane of the on-board camera. This preprocessing consists of LRF-SLAM based viewpoint estimation (Section III-A) followed by pixel-wise warping ¹ (Section III-B). However, even with such a preprocessing, the images are often affected by unpredictable nonlinear mapping errors. To address this, we introduce a novel attention mask to direct the robot’s attention to differentiate the foreground from the background (Section III-C). As an advantage, our approach can insert this attention mask into the intermediate layer, without modifying the input or output layers (Section III-D). Furthermore, we

¹Raw and pre-processed images with ground-truth mask annotations will be available in the public dataset.
make use of the pixel-wise confidence to further improve the image change detection performance (Section III-E). The individual modules are detailed as followings.

**A. Dataset Collection**

Figure 3 shows the indoor robot experimental platform. We employ LRF-SLAM in [29] as a method for aligning live images with the reference images. An input live image is paired with a reference image if its angle deviation from the live image is less than the threshold of 1 degree. If no such reference image exists, it is paired with the nearest neighbor viewpoint to the live image’s viewpoint, without considering the angle information.

**B. Pixel Warping**

We further compensate for the viewpoint misalignment in LRF-SLAM by introducing an image warping technique. A warp is a 2D function, $u(x, y)$, which maps a position $(x, y)$ in the reference image to a position $u = (x', y')$ in the live image. Dense image alignment, which is recently proposed in [18], is employed to find an appropriate warp, by minimizing an energy function in the form:

$$-\log p(Y | \Phi(X; \theta)) = \sum_{ij} \log p(y_{ij} | \phi_{ij}(X; \theta))$$  \hspace{1cm} (1)

where $X$ is input image pair $X = (I^q, I^r)$, $Y$ is ground-truth flow, $\Phi$ and $\phi$ are predicted parameters. An example of pixel warping is shown in Fig. 4.

**C. Attention Mask Generation**

We here introduce a novel domain-invariant attention mask (Fig. 5), inspired by self-attention mechanism [2]. Recall that in standard self-attention [30], the interrelationships of the elements in the sequence are obtained by computing a weighted sum over all values $v$ in the sequence for each element in an input sequence $z \in \mathbb{R}^{N \times D}$. The attention weights are based on the pairwise similarity between two elements of the sequence and their respective query $q$ and key $k$ representations:

$$[q, k, v] = zU_{qkv} \quad U_{qkv} \in \mathbb{R}^{D \times 3D_h}$$  \hspace{1cm} (2)
Algorithm 1 Attention Mask Generation

Require: Live image $l_t$ acquired at time $t$, reference image sequence $R_t = \{r_i\}_{i=t-T}^{t+T}$ acquired within the time-interval $[t-T,t+T]$. 

Ensure: Binary matrix variable $Mask$ with size $W_p \times H_p$

1: Set 1 to each element of $Mask$
2: $LPF \leftarrow ExtractPF(l_t)$
3: for all $r_i \leftarrow R_t$ do
4: $RPF \leftarrow ExtractPF(r_i)$
5: $MatchMat \leftarrow MNN(LPF, RPF)$
6: $Inliers \leftarrow RANSAC(MatchMat)$
7: $Mask \leftarrow Binarize(Inliers, Mask)$
8: end for
9: $Mask \leftarrow Inverse(Mask)$
10: return $Mask$

$$SA(z) = \text{softmax}(q_k^T / \sqrt{D_h}) v$$ \hspace{1cm} (3)

In the proposed method, this SA term is replaced with:

$$Proposed(q_p, k_p, m_{cnn}) = \text{PatchMatch}(q_p, k_p) \odot m_{cnn}. \hspace{1cm} (4)$$

Here, $q_p \in \mathbb{R}^{h_q \times w_q \times D_p}$ and $k_p \in \mathbb{R}^{h_p \times w_p \times D_p}$ are patches extracted from live and reference images, respectively. $m_{cnn} \in \mathbb{R}^{h_{cnn} \times w_{cnn} \times D_{cnn}}$ is an intermediate feature of the Siamese CNN. The $PatchMatch$ is the function that predicts whether or not a pair of $D_p$-dim vectors of $q_p$ and $k_p$ match.

We generate a binary attention mask by incorporating the attention mechanism. First, the image is reshaped into a sequence of 2D patches, each of which is described by a local feature vector. We employ the 128-dim deep PatchNetVLAD [17] descriptor as the local feature vector. The attention score is then computed for each region of interest. We then evaluate the attention score as the patch-wise dissimilarity (i.e., L2 distance) between live and reference image pairs. Then, RANSAC geometric verification is performed to filter out false positive that are originated from change patches. Finally, we obtain the attention regions as scattered discrete regions of live patches with positive attention score, which makes a binary attention mask.

Algorithm 1 presents the algorithm for creating the attention mask. It aims to compute a binary attention mask $Mask$ for an array of $W_p \times H_p$ patches at time instance $t$ from a sequence of reference images within the time interval $[t-T, t+T]$. The algorithm begins with the initialization of the mask variable $Mask$, and iterates for each live/reference image, the following steps: First, it extracts from an input image a set of PatchNetVLAD feature vectors (“ExtractPF”), each of which belongs to one of reference patches. Then, for each live feature, it searches for its mutual nearest neighbor (“MNN”) reference patch in terms of the L2 norm of their PatchNetVLAD features. Here, the mutual nearest neighbor search is defined as the process of searching for pairs of matching live and reference elements that are closest to each other. Only feature pairs that have passed the mutual nearest neighbor search are sent to the next RANSAC process. Then, it performs geometric verification by RANSAC [31] (“RANSAC”). Then, the function (“Binarize”) is used to acquire the binary mask. The function (5) shows output of the function (“Binarize”) at coordinate $[i,j]$:

$$b[i,j] = \begin{cases} 
1 & \text{If Inliers}[i,j] \text{ passed RANSAC} \\
0 & \text{Otherwise} 
\end{cases} \hspace{1cm} (5)$$

Finally, the function (“Inverse”) invert 0 and 1.

D. Attention Mask Layer

We now insert the attention mask into the standard image change detection model of the Siamese CNN (Section III-C). For the Siamese CNN, we use the state-of-the-art architecture of CSCDNet [11]. The attention mask layer takes the CNN feature map and attention mask as inputs and outputs the CNN features masked in the channel direction. We inserted the attention mask before correlation operation (i.e., before concatenating decoded feature).

We perform the process of masking the CNN Siamese feature map in the channel direction. Let $f_{\text{map}}_{\text{new}} \in \mathbb{R}^{W \times H}$ denote the feature map after attention is applied. Let $f_{\text{map}}_{\text{old}} \in \mathbb{R}^{W \times H \times C}$ denote the feature map obtained from Siamese CNN. Here, $W$ denote the tensor width, $H$ denote the tensor height, and $C$ denote the tensor channel. Let $\text{mask} \in \mathbb{R}^{W \times H}$ denote the attention mask. Then, the attention mask element at the $i$-th row, $j$-th column and $k$-th channel is:

$$f_{\text{map}}_{\text{new}}[i, j, k] = f_{\text{map}}_{\text{old}}[i, j, k] \cdot \text{mask}[i, j]. \hspace{1cm} (6)$$

This operation is applied to the both branches of the Siamese CNN.

E. Post Processing

Post-processing is introduced to eliminate false positive in the detection results. We evaluate the uncertainty in the output layer of the dense image alignment model and use it to evaluate the confidence of prediction at each pixel. Intuitively, a high probability of pixel warping uncertainty indicates that no corresponding pixel exists; therefore is a high possibility of change. Conversely, low probability indicates that the corresponding pixel exists; therefore is a low possibility of change. This masking process can be simply expressed as an Hadamard product operation, in the following form:

$$\text{output}_{\text{new}}[i, j] = \text{output}_{\text{old}}[i, j] \cdot \text{uncertainty}[i, j]. \hspace{1cm} (7)$$

Here, $\text{output}_{\text{old}} \in \mathbb{R}^{W \times H}$ represents the change probability value map of the output of the Siamese CNN. $\text{uncertainty} \in \mathbb{R}^{W \times H}$ represents the uncertainty of each pixel warp of a live image. $\text{output}_{\text{new}} \in \mathbb{R}^{W \times H}$ represents the probability of change for each pixel after the merging process.
IV. Evaluation Experiments

A. Dataset

We collected four datasets, “convenience store,” “flooring,” “office room,” and “hallway,” in four distinctive environments. Eight independent image sequences are collected from the four different environments. The number of images are 534, 491, 378, and 395, respectively for “flooring,” “convenience store,” “office,” and “hallway”. Examples of these images are shown in Fig. 6. The image size was 640 × 480. The ground-truth change object regions in each live image are manually annotated using PaddleSeg [32], [33] as the annotation tool.

B. Settings

The state-of-the-art model, CSCDNet [11], is used as our base architecture, which we aim to boost in this study. It is also used as a comparing method to verify whether the proposed method can actually boost the CSCDNet. The network is initialized with the weight pre-trained on ImageNet [34]. The pixel-wise binary cross-entropy loss is used as loss function as in the original work of CSCDNet [11]. PDCNet [18] is used to align reference images. Adam optimizer [35] is used for the network training. Learning rate is 0.0001. The number of iterations is 20,000. The batch size is 32. A nearest neighbor interpolation is used to resize the attention mask to fit into the attention mask layer. The length of reference image sequence is set to $T = 10$ in default. A single Nvidia GeForce RTX 3090 GPU with PyTorch framework is used. Pixel-wise precision, recall, and F1 score are used as performance index.

C. Quantitative Results

Figure 7 shows performance results. As can be seen, the proposed method outperformed the comparing method for almost all combinations of training and test sets considered here. Notably, the proposed method extremely outperformed the comparing method when it was trained on the “flooring” dataset. The “flooring” is the simplest background scene. Therefore, the image change detection model trained on that could be generalized to other complex domains as well. However, the proposed method performed almost the same as the comparing method when it was trained on the other complex background scenes. As an example, for the convenience store dataset, the robot navigates through a narrow and messy passage that makes its visual appearance very different from that of the other two datasets. This makes the proposed training algorithm less effective for the training set. It is noteworthy that such an effect of visual appearance might be mitigated by introducing view synthesis technique such as [36], which is a direction of future research.

D. Qualitative Results

Figure 8 shows example results in which the proposed attention mechanism was often successful in improving the performance of the CSCDNet. Especially, the proposed method was effective for complex background scenes, owing to the ability of the proposed attention mechanism to make use of contextual information.

E. Ablation Study

Table I presents the results of a series of ablation studies by turning off some of the modules in the proposed framework. For all ablations, the flooring dataset is used
as the training data. For the “convenience store” dataset, the performance is significantly higher with than without the post-processing technique in Section III-E. Because of the complex background of this dataset, pixel warping often fails, and the proposed method was effective in suppressing such effects that are originated from complex backgrounds. For the “office” and “hallway” datasets, the performance is almost the same between with and without the technique. Since the background was less complex in these datasets, pixel warp failures were less common, therefore the effect of estimating uncertainty was small. Next, another ablation with different settings of the length of reference image sequences are conducted. As can be seen, the performance is best at T=10. As expected, higher performance was obtained with longer reference sequences. From the above results, it could be concluded that both of PDCNet and pixel warping play important roles and can actually improve the performance of image change detection.

F. Future Work

In the current experiment, we considered a simple typical scenario in which the number of objects per image is 1-2. Image processing on complex scene scenarios containing many objects are an important direction for future research. We also plan to evaluate the performance of the current framework in such complex scenarios.

V. Conclusions

In this research, we tackled the challenging problem of small object change detection via everyday indoor robot navigation. We proposed a new self-attention technique with unsupervised on-the-fly domain adaptation, by introducing an attention mask into the intermediate layer of an image change detection model, without modifying the input and output layers of the model. Experiments using a novel dataset on small object change detection verified that the proposed method significantly boosted the state-of-the-art model for image change detection.

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