BASD-SLAM: A Deep-Learning Visual SLAM System Based On Binary Adaptive-Scale descriptor

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Abstract— **The feature quality plays an important role in visual SLAM (Visual Simultaneous Localization and Mapping) based on feature descriptor matching, and becomes the bottleneck of positioning accuracy improvement. Now lots of handcrafted descriptors like BRIEF and ORB don't work very well in complex scenarios. The Convolutional Neural Network is proved to have tremendous advantages on image feature extraction. In this paper, we design a CNN model to extract binary visual feature descriptor from image patches. Based on this deep feature descriptor, we design a monocular SLAM system, named BASD-SLAM, by replacing ORB descriptor in ORB-SLAM2. We also train visual Bag of Words to detect loop closure. Experiments show that our BASD achieves better results on the HPatches dataset and UBC benchmark. In the meantime, the BASD-SLAM system outperforms other current popular SLAM system on KITTI odometry dataset and Tartanair dataset.**

I. INTRODUCTION

Visual SLAM has got prosperous development in recent years. The result of feature matching in the keypoint-based vSLAM system depends on the local descriptor quality. The traditional descriptors rely on the pixel-level match,and the match error will accumulate slowly, finally impact the pose estimation result. So improving the descriptor quality is of high significance.

With the fast development of deep learning in recent years, image proccessing based on DL has become more and more popular. And vast researches have proved the unparalleled advantages on image feature extraction and data association, which are the bottleneck of traditonal visual SLAM pipeline. As a result, lots of researchers are committed to apply deep learining to SLAM,and solve the bottleneck problems,like feature extraction and data association.

There have tremendous researches indicate the application of deep learining in SLAM improving the accuracy of vSLAM. Many researchers take advantage of deep learing ,and substitute some modules in the traditional SLAM pipeline, such as feature matching, relocalization, and so on. Some also use high-level semantic information, which can help the SLAM relocalization, bundle adjustment, etc. And some end-to-end SLAM system ,which generates pose estimation directly from pictures ,also achieve better results in specific scenarios.

However, there are many problems on the application of deep learning in SLAM system. For example, end-to-end SLAM systems are dependent on specific scenarios, and generalization ability are not strong.Semantic SLAM cannot guarantee the appearance of specific semantic information,like the chairs in SLAM++; While the extraction of low-level features does not take into account the scale problem[ASD-SLAM],which makes the descriptors such as hardnet not suitable for SLAM.

To address the limitation of above researches, we propose our local feature descriptor extraction neural network, whcih address the scale problem causing deep descriptor aren't suitable for SLAM. the propoesed descriptor shares same structure with ORB, so it can be easyily implemented on popular SLAM framework.To achieve better efficiency, we binarize our descriptor,which can vastly speed up the descriptor matching process.We also train Bag-of-Words for our deep descriptor to realize loop closure.

In addition, our descriptor can also be extended to other similar fields like SFM. In summary, our main contributions are the following:

- We propose a binary descriptor with CNN model using four loss function, and outperforms other traditional descriptor on accuracy and effectiveness.
- We design a monocular system with our learned descriptor, and achieve better results than other traditional visual SLAM system on several benchmark datasets.

II. RELATED WORK

Since this paper is aimming at learning suitable local descriptor which can enhance visual SLAM system, in this section we review related works with respect to the two fields that we integrate within our research, local feature descriptor learning and deep learning enhanced SLAM.

A. *Local Feature Descriptor*

Parallel with the long history of local feature, numerous researchers have made considerable attempts.

First,

Second,

B. *Deep learning enhanced SLAM*

Deep learning is a powerful method to solve feature extraction and data association problems encountered in the traditional SLAM framework. DeepVO abandoned traditional SLAM pipeline, and proposed a novel compact end-to-end SLAM system using recurrent convolutional neural networks,which could directly infer camera poses from raw RGB images(videos) .They firstly adopted RNNs to model sequential learning,and achieved better results on KITTI datasets. [Unsupervised Learning of Depth and Ego-Motion

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from Video] explored an unsupervised learning framework,which consisted of two CNNs to infer depth and pose respectively, to estimate monocular depth and camera motion simultaneously. They just used video data to train their network,which can be heful to network training.[DeMoN] proposed multiple encoder-decoder convolutional neural networks to estimate depth and ego-motion from two successive images.It learned matching concept from training.Althought end-to-end SLAM makes SLAM system more compact, it lacks of model generalization ability.

As can be seen from the above, triplet losses play an important role on feature descriptor learning and SLAM.

III. System Overview

In our BASD-SLAM system, we still adopt traditional visual SLAM pipeline. ORB-SLAM2 is a classical visual SLAM system. Unlike other end-to-end SLAM system, we just replace the traditional hand-crafted descriptor ORB with our learned descriptor and evaluate the efficiency and effectiveness of our descriptor. This also enables our descriptor suitable to other SLAM system like SFM.

A. Local feature design

Compared with hand-crafted methods, learned descriptors has tremendous advantages, such as compact structure, evenly distribution, robust to noise and so on. Moreover, learning-based descriptors are data-adaptive. In order to make our descriptor more effective, we just adopt shallow convolutional neural network to generate our descriptor, and the shallow network has also been proved to be suitable to extract low-level image information [14]. float descriptors sacrifice the effectiveness of feature matching and loop closure. Instead, our shallow network will obtain binary local feature descriptor, and also maintain the high precision. [15] reveals that triplet network has greater advantages in metric learning than Siamese network, so we also adopt the former to train our descriptor. There are eight convolutional layers, each of which is followed by a Tanh non-linearity and Batch Norm operations. And the output of network is normalized to unit-length. In order to reduce the possibility of overfitting, we add a dropout layer in the last of our network. After lots of tuning step and training process, we set the dropout rate to 0.3. Loss function plays an important role in descriptor generation. We adopt four loss type to train our descriptor. We will describe in detail below.

1) Adaptive-Scale Triplet Loss: Triplet loss has been proved to have great advantages in descriptor generation. So we also adopt this loss function. [ASD-SLAM] proposed the scale uncertainty influence in triplet loss, and modified the prime triplet loss function to reflect the changes of scale by adding a scale reminder factor. Given three image patches, Pa, Pb and Pc, which represent the anchor, positive and negative image patches. After the reasoning of network, we get descriptors xa, xb and xc respectively. And the adaptive-scale triplet loss function is defined as:

$$d_+ = \|x_a - x_p\| \tag{1}$$

$$d_- = \|x_a - x_n\| \tag{2}$$

$$\xi = \frac{d_-}{d_+} \tag{3}$$

$$L_{trip} = -\frac{1}{\xi}\log(smax(\xi(d_- - d_+), 0)) \tag{4}$$

Where d- and d+ is the L2 distance of anchor descriptor with negative descriptor, anchor descriptor with positive descriptor, respectively.

Because we set batch size to 1024, so the choice of d- and d+ matters. We also adopt the adaptive-scale sampling strategy to obtain suitable d- and d+.

The native training strategy is too complex and performs not well, so we turn to the hard negative mining strategy proposed in [hardnet], which is proved to be effective and easy to converge in training.

2) Even-Distribution Loss: The distribution of binary bits reflects the encoding quality of neural network. In large dataset, same bit of every descriptor generated by all image patches should have same numbers of -1 and +1 roughly. However, the sign function is not differentiable, so we cannot reduce even-distribution loss by optimizing the numbers of -1 and +1. We just constraint the means of every float descriptor dimension in one batch size descriptors to 0. Even-distribution loss is defined as :

$$L_{even_dis} = \frac{1}{2k}\sum_{j=1}^{k}\left(\frac{\sum_{i=1}^{N} f_i(j)}{N}\right)^2 \tag{5}$$

3) Quantization Loss: In quantization step, we use sign function to obtain binarization result of float descriptor. However, the difference between real-value and ±1 can bring a great drop in accuracy. So we minimize the quantization loss to get a better binary descriptor. Quantization loss is defined as:

$$L_{quan} = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{k}(f_i(j) - B_i(j))^2 \tag{6}$$

4) Correlation Loss: In order to make the descriptor contain more information, the bits of every descriptor should have less correlation[L2-net]. So we introduce the correlation loss penalty to get more differentiable descriptors. We use the descriptor $Y_{anchor} = [y_{a_1}, y_{a_2}, \cdots y_{a_k}]^T$ generated from anchor image patch, where y_{a_i} is row vector of one image descriptor.

The correlation matrix $R = [r_{ij}]_{k\times k}$is defined as:

$$r_{ij} = \frac{(y_{ai} - \bar{y_{ai}})^T(y_{aj} - \bar{y_{aj}})}{\sqrt{(y_{ai} - \bar{y_{ai}})^T(y_{ai} - \bar{y_{ai}})}\sqrt{(y_{aj} - \bar{y_{aj}})^T(y_{aj} - \bar{y_{aj}})}} \tag{7}$$

Where $\bar{y_{ai}}$ is mean of i_{th} row of Y_{anchor} . Obviously, the off-diagonal elements of R should be 0. So the correlation loss is:

$$L_{corr} = \frac{1}{2}\left(\sum_{i \neq j} r_{ij}^2\right) \tag{8}$$

B. SLAM System

ORB-SLAM2 is a fantastic visual SLAM work in recent year, which is suitable for monocular camera based on PTAM structure. So we choose ORB-SLAM2 as our SLAM system. we can substitute our learned descriptor for ORB easily, because our learned descriptor has same structure with ORB. The CNN model is embedded in descriptor extractor after FAST keypoint detection using the implementation of pytorch c++ API. We organize the image patches as a single tensor, and transfer to CNN model, so the model can reason all the image patches with one step, which can accelerate the reasoning time.ORB-SLAM2 implement the Bag of Words to detect loop closure, so we also train Bag of Words with the descriptor reasoned by our CNN model. Because the difference of descriptor, we adjust the matching threshold in SLAM system.

IV. EXPERIMENTAL RESULTS

desplay some results.

A. descriptor evaluation

1) UBC benchmark dataset: UBC benchmark dataset, consisting of three datasets, Yosemite, Notredame and Liberty, is suitable for training descriptors, whose patches are centered on real interest point detection. So we use it to evaluate our model. We just use one dataset to train our model, and the other two to evaluate the model output. We compare it with other hand-crafted and learned local descriptors with FPR95 standard. The result is listed in TABLE I. We can conclude that our descriptor outperforms others

TABLE I: Patch Verification Performance On UBC Benchmark Dataset. The BOLD Implies The Best Performace.

Suquences	Train	YOS	YOS	ND	ND	LIB	LIB
	Test	ND	LIB	YOS	LIB	NOD	YOS
BRIEF [1]		0		0		0	
ORB		54.57	59.15	54.96	59.15	54.57	54.96
Deepbit		29.6	34.41	63.68	32.06	26.66	57.61
DBD-MQ		27.2	33.11	57.24	31.1	25.78	57.15
CDbin		2.05	5.55	4.31	4.08	1.48	4.53
BASD		**1.3**	**4.4**	**2.7**	**2.76**	**1.0**	**3.5**

2) HPatches dataset: The HPatches dataset results is

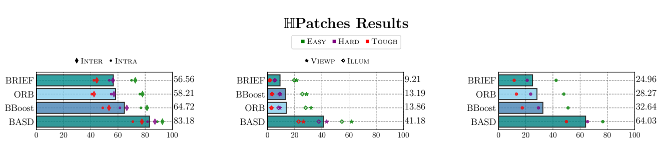
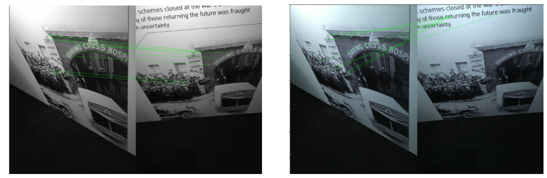


Fig. 1: The HPatches Results.



(a) BASD (b) ORB

Fig. 2: general title.

3) Matching result in hard scenarios: The performance in dealing with hard scenarios like illumination change and view change is very important to SLAM. So we choose the hand-crafted descriptor, ORB, to make a comparison with our learned descriptor. Although we do RANSAC in SLAM system, the performance will be bad if the mismatch number exceeds the match number. We choose large illumination change and large view change pictures to evaluate descriptors. From the match results, our descriptor outperforms the ORB descriptor, which show the robustness of our descriptor.

B. SLAM system evaluation

1) Evaluation of KITTI Odometry dataset: Our descriptors can initialize faster than orb on Kitti, which shows that our descriptors are more robust when the perspective switches quickly.

2) Evaluation of Tartanair dataset: To evaluate the accuracy and robustness of our learned descriptor in BASD-SLAM, we introduce the Tartanair dataset for localization and mapping evaluation. We compared our system with ORB-SLAM2, including the evaluation standard, ATE(absolute trajectory error) and SR(success rate). In order to present the robustness of our descriptor, we respectively choose three contexts in Tartanair, Soul-City, Japanese-Alley, Ocean. The evaluation results are shown in TABLE I. The bold represents the better result. We also choose the evo evaluation tool to estimate and visualize some context trajectory. And the results are shown in TABLE II. From the evaluation results above, we can easily draw the conclusion that our learned descriptor SLAM system outperforms the traditional descriptor SLAM system ORB-SLAM2.

V. CONCLUSIONS

In this paper, we have presented a novel

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