Data-Efficient and Hardware-Efficient Decentralized Monocular Visual SLAM

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Abstract— With the gradual improvement of the single-agent capabilities, it is possible to build up the multi-agent collaborative intelligence system. Distributed simultaneous localization and mapping (DSLAM) can share location and environmental information between robots and is the basis for many multi-agent applications. With the development of algorithms and computing platforms in recent years, convolutional neural network (CNN) has been widely used in SLAM systems, especially in visual-based SLAM systems. CNN can directly predict the pose with the absolute scale from two successive monocular frames, which can be easy to deploy on real robots and can make SLAM more robust in scenarios with pure rotations. Further, with CNN's versatility, it is easy to use the same network structure for many other tasks rather than depth or pose estimation, such as object detection and semantic segmentation. Finally, CNN's computational structure is uniform and can be individually optimized when resources are limited on embedded systems.

In this work, we aim to build a fully CNN-based hardware-software co-design monocular DSLAM system. There are two keys components in DSLAM system: 1) Visual Odometry (VO) and 2) Place Recognition. We use fixed-point fine tune method to enhance the accuracy of CNN-based monocular VO and make it possible for acceleration on the Xilinx DPU accelerator. The same DPU also supports the place recognition component. We also propose a pipeline scheduling method to make full use of the DPU. To the best of our knowledge, this work is the first to implement all components of monocular DSLAM with CNN. We use the Xilinx ZU9 embedded MPSoC and the DPU IP core to validate the proposed DSLAM framework on the public dataset.

I. Introduction

In recent years, with the development of the hardware and algorithms, the capabilities of a single agent have been significantly improved. To further expand the capabilities of intelligent robots, using several robots can accelerate many tasks, such as localization, exploration, and mapping. As simultaneous localization and mapping(SLAM) is an essential component in many tasks, it is important to do SLAM across different robots in many multi-agent applications. The camera is a widely used sensor in SLAM for its rich information and low cost. The previous work [?] proposes a data-efficient decentralized SLAM(DSLAM) system based on the stereo camera. Especially, because it is simpler to deploy and does not require calibration, the monocular camera has become a hot topic in academic research. We aim to build up a monocular visual-based DSLAM in this work.

The goal of DSLAM is to share the maps and trajectories among the robots in a communication-constrained scenario. Also, because the communication is limited, there is not a central node that obtains all the sensor information from each agent, so that we need to design a specially optimized communication mechanism. There are three kinds of data need to be shared among agents: 1) the trajectory of each robot for merging, 2) the encoded information of place recognition for the coarse matching of inter-robot tracks, and 3) the details of the matched frame for inter-robot pose calculation and trajectory merging. The previous work [?] uses ORB feature-point based method to estimate the trajectory from the sequence of the stereo camera, and use NetVLAD [?] to do place recognition. Once the coarse matching of inter-robot tracks based on the NetVLAD succeeds, the ORB feature points of the corresponding frames are communicated for fine-grained inter-robot trajectory merging. However, [?] needs to calculate the ORB feataure extraction and matching algorithm as well as the CNN-based NetVLAD algorithm simultaneously on the embedded system. These two algorithms both consume a large amount of computation and storage, and pose a great challenge to DSLAM on the embedded system. The DSLAM frame in [?] is illustrated in fig 1(a).

With the development of neural networks in recent years, many CNN-based algorithms can also be applied to DSLAM systems. With the help of CNN, we can reconstruct the depth and pose with the absolute scale from the monocular camera. Monocular systems are much easier to deploy than binocular systems. The tracking based on CNN can be made more robust, as the CNN-predicted depth and pose does not suffer from the accumulated errors from previous frames, as CNN processes on each pair of two frames individually [?]. As CNN is a versatile and widely researched method for image processing, it is easy to use the same network structure for many other tasks rather than depth or pose estimation, such as object detection [?] and semantic segmentation[?]. Last but not least, CNN's computational structure is uniform and can be individually optimized when resources are limited on embedded systems such as embedded GPU[?] and embedded FPGA[?], [?]. Xilinx DPU[?] is one of state-of-the-art FPGA-based CNN accelerators, and is used in this work.

Though DSLAM system can benefit from the development of CNN, the fully CNN-based DSLAM system faces several key issues: 1) The DSLAM system needs to run multiple CNNs simultaneously for multitasking. The requirement of huge computing resources brings a challenge to real-time implementation. 2) Due to the lack of feature point extraction, we need to explore new

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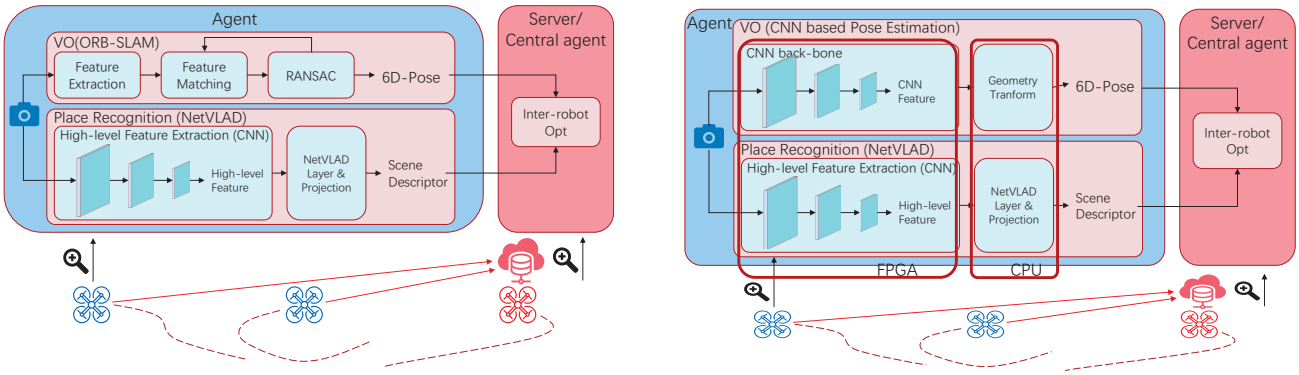


(a) DSLAM in [?]

(b) Our hardware-software co-design DSLAM.

Fig. 1. Overview of the DSLAM in [?] and our hardware-software co-design DSLAM. Each agent (blue drones) will send the result of 6-D pose estimation and scene descriptor to a server or a central agent (red server or drone in figure) to do inter-robot place recognition and optimization. We use CNN instead of feature points to do pose estimation so that we can use CNN accelerator to speed up the whole process.

data-efficient communication mechanism for inter-robot trajectory merging.

To solve the problems mentioned above, we propose a hardware-software co-design DSLAM framework with the following contributions. The proposed DSLAM framework is illustrated in fig 1(b):

- To the best of our knowledge, this work is the first to implement all components of monocular DSLAM with CNN. We adopt Depth-VO-Feat [?] in DSLAM system to estimate the pose from the input monocular camera. We use the same method of NetVLAD in [?] to do place recognition.
- We use Xilinx DPU to accelerate the DSLAM system on embedded systems. We use fixed-point fine tune method to transformed the original floating-point Depth-VO-Feat model to fixed-point for deploying on Xilinx DPU. The accuracy of the fixed-point model is even better with the floating-point model.
- We communicate the down sampled images of corresponding matched frames for inter-robot trajectory merging, so that we can also use Depth-VO-Feat and the accelerator.

The rest part of this article is orgnized as follows. Section II will give the basic idea of CNN based methods and the hardware architecture of embedded FPGA. Section III will detail the implementation of our hardware-software co-design DSLAM system. The experiment result will be given in Section IV. Section V will conclude this paper.

II. Background

A. CNN based methods in DSLAM

As described before, there are two essential components on each agent: 1) Visual Odometry (VO) and 2) Place Recognition.

1) Visual Odometry (VO): Visual odometry estimation is the task to infer ego-motion from a sequence of images and is an essential component in the SLAM system. Some feature-based SLAM systems have enjoyed great success, like ORB-SLAM[?] and ORB-SLAM2[?]. Recently, several studies have shown that these feature-based SLAM systems require high computing resources. [?] shows that the feature extraction stage is the most computation-intensive, consuming over 50% of the CPU resources.

As FPGA is one of the most promising platforms as the accelerator for VO, the SLAM system on FPGA has become a hot research topic. However, FPGA-accelerated feature extraction still consumes a lot of time and computing resources, which cannot be deployed simultaneously with an FPGA-accelerated neural network.

2) Place Recognition: The goal of place recognition is to calculate a given frame into a limited set of places. Each place can be encoded as a concise code which can be easy transferred with low communication cost. Traditional place recognition method usually translate the input frame as the aggregation of handcrafted feature point and local descriptors, like SIFT [?] or ORB [?], using vectorization techniques like bag-of-words (BoW) [?] or vector of locally aggregated descriptors(VLAD) [?].

Recent advances in the deep learning and the convolution neural network (CNN) enable powerful end-to-end mode for place recognition [?], [?], and the NetVLAD method is one of the most accurate methods based on CNN. The NetVLAD algorithm based on VGG-16 model [?] consumes more than $80G$ operations for a single 300×300 input image (each operation means addition or multiplication). It is very challenging to deploy the NetVLAD on a traditional embedded hardware platform.

B. Hardware architecture of Zync MPSoC

The Xilinx Zync MPSoC is a chip with ARM cores and FPGA fabric. The system is illustrated in fig 2. The

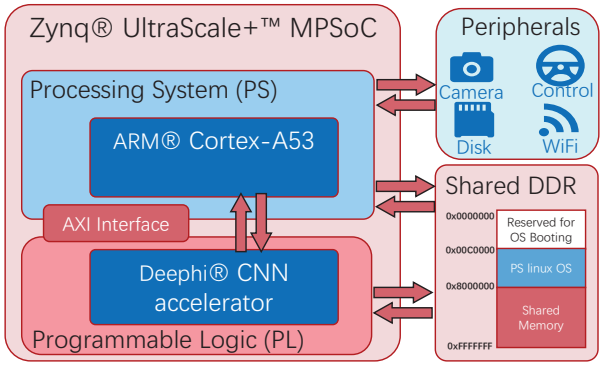


Fig. 2. Hardware architecture of Zynq SoC

ARM cores with an embedded Linux operation system are called Processing System (PS). The FPGA fabric is called Programmable Logic (PL). The peripherals like camera and communication unit (WiFi or others) are accessible with PS. The high-bandwidth on-chip AXI interface is used to communicate between PS and PL. PS and PL can also share the DDR to transfer a large volume of data such as each frame of the camera. Deephi CNN accelerator, which is called DPU [?], is one of the state-of-the-art accelerators and is famous for high energy efficiency on various CNN structure. We deploy the accelerator on the PL side of Zynq SoC with the help of DPU.

Though FPGA can significantly improve the performance and energy efficiency of CNN inference, FPGA cannot efficiently calculate the floating-point number and requires fixed-point parameters and intermediate data in CNN.

III. Hardware-Software Co-design DSLAM

Our hardware-software co-design DSLAM system contains two essential improvements in the pose estimation and place recognition tasks. As illustrate in fig 1(b), both of these two components are divided into two stages: 1) CNN front end to extract features which is deployed to the DPU on PL and 2) geometric operations to present final results which are deployed on the PS ARM cores. To make full use of the Zynq MPSoC (illustrated in fig 2), we optimize the data follow for both of these components.

A. Pose Estimation

We adopt Depth-VO-Feat [?] in DSLAM system to estimate the pose from the input monocular camera. Monocular visual SLAM is a key issue in the field of robotics, while there are two challenging problems: 1) it is difficult and expensive to obtain accurate labeled data, 2) the methods that use monocular sequences in training always suffer from the scale-ambiguity problem, i.e., the actual scale of translations is missing, and only the direction is learned. In Depth-VO-Feat [?], we use image reconstruction loss as a self-supervised signal to train the convolutional neural networks and jointly train

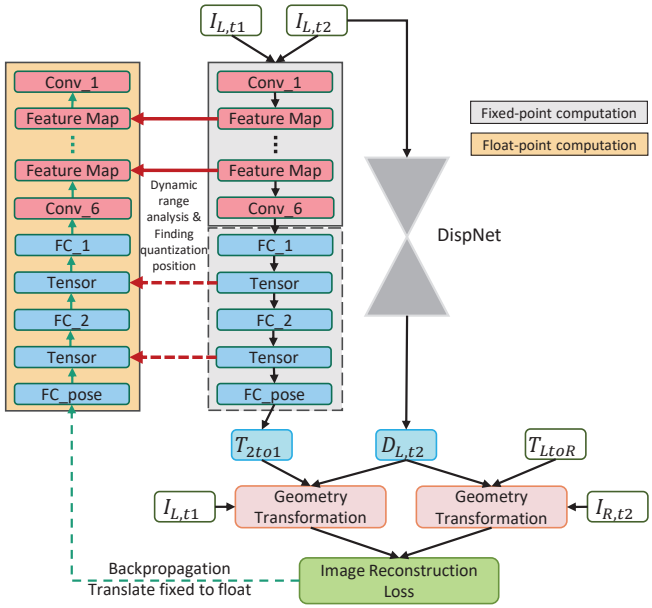


Fig. 3. Illustration of training framework for visual odometry, where T_{LtoR} is the relative camera pose transformations between left and right views. To speed up the inference, we attepmt different quantization strategies to fixed-finetune the network for VO with fixed-point feed forwarding and floating-point backpropagation.

two networks for depth and odometry estimation without external supervision, which can be used independently in the testing phase. Besides, to fix this scale-ambiguity issue, we use stereo sequences in the training phase and monocular sequences in the testing phase. With the known spatial relationship between the left and right cameras, our neural networks can learn the real world scale. Moreover, we use depth smoothness loss to encourage the predicted depth to be smooth, which demonstrated success in prior works. Then the final loss becomes:

$$L = \lambda_{ir} L_{ir} + \lambda_{ds} L_{ds} \tag{1}$$

where L_{ir} and L_{ds} are image reconstruction loss and depth smoothness loss respectively, λ_{ir} and λ_{ds} are the loss weightings for each loss term. The training framework is illustrated in section III.

In order to run our networks efficiently on the FPGA platform, we use fixed-point arithmetic units in the hardware to replace the floating-point number format in GPU and CPU. Many previous works have shown that 8-bit quantization for weights and featuremaps can make the networks run faster on FGPA. Here we adopt the fixed-point finetune method in [?], in that we use the fixed-point number representation in the feed forward phase and keep floating-point number representation for backpropagation, and both weights and data will be re-quantized after each backpropagation. The fixed-point method will lead to a slight accuracy loss of the model, and the performance of the fixed-finetuned Depth-VO-Feat will be shown in detail in section IV.

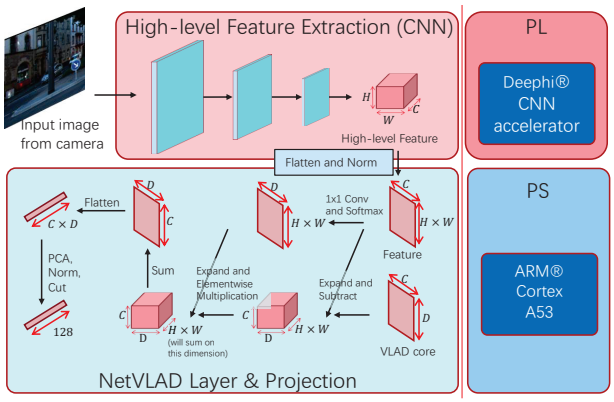


Fig. 4. Process of NetVLAD. The CNN encoder is running at the CNN acclerator on PL side, and the VLAD layer as well as the PCA is running at the ARM core at PS side.

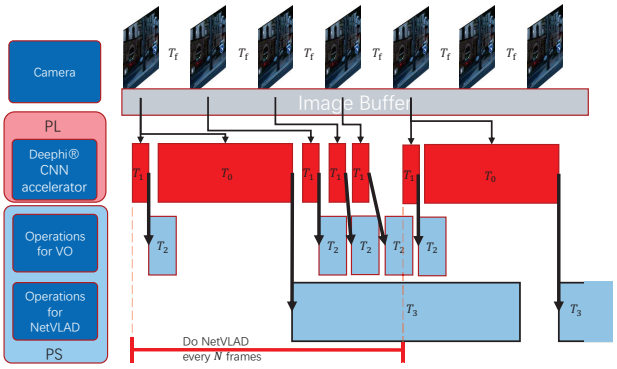


Fig. 5. Scheduling pipeline. There are four threads: Camera read, Deephi core at PL, PS Operations for VO, and PS Operations for NetVLAD.

B. Place Recognition

The place recognition method provide the encoded vector transferred to the central agent for inter-robot place matching. As described in section II, CNN has achieved significant improvements in place recognition tasks, and NetVLAD [?] is one of the most impressive methods. The computation flow of NetVLAD is illustrated in fig 4. The CNN-based place recognition methods give the global descriptor of a camera frame in a two-step manner: 1) Firstly, a CNN encoder fetches the high-level feature map. 2) A vectorization component that aggregates the feature map into a shot global descriptor. The VLAD layer [?] is a recently proposed plug-and-play operation that greatly improves the performance of place recognition. In the original work with the VLAD layer [?], the feature extraction encoder is a typical CNN named VGG-16 [?]. The output dimension of original NetVLAD is usually tens of thousands, which is very difficult to be stored on the embedded system, not to mention in the communication-constrained environment. The PCA and the projection method can drastically reduce the output dimension. The previous works[?] show that 128 dimension is plenty for DSLAM. The data flow and operations of the NetVLAD layer and the projection are complex and require the floating-point number, which cannot be supported with Deephi DPU. We implement the NetVLAD layer and the projection on the PS side of Zynq MPSoC.

Unlike the fixed-point finetune method used for pose estimation. The training procedure with huge non-public datasets is very complicated, and also we cannot finetune the NetVLAD model because of the lack of training data. We simply analyze the dynamic range of the weight and intermediate feature map of each CNN layer and figure out the optimal decimal point position for each layer respectively to minimize the truncation error of each layer. This method is proposed in [?] and is used in many tasks such as image classification and image detection.

C. Parallel Scheduling for VO and NetVLAD

The time consumption of NetVLAD and VO is imbalanced. We do pipeline optimization to schedule the two components on Zynq MPSoC efficiently. The pipeline is illustrated in fig 5. The interval time for reading camera is T_f. The CNN time for NetVLAD and VO is T_0 and T_1. The computation time cost on PS for VO and NetVLAD is T_2 and T_3. We do VO every input frame and do NetVLAD every N frames.

Considering the thread on PL, the time constraint is given as eq. (2).

$$N \times T_f > T_0 + N \times T_1 \tag{2}$$

The thread for VO on PS constrains the NetVLAD frequency as eq. (3).

$$N \times T_f > T_0 + T_1 + (N-1) \times T_2 \tag{3}$$

The PS part of NetVLAD should finish before computing the PS part of next NetVLAD frame. This constraint can be written as eq. (4).

$$N \times T_f > T_3 \tag{4}$$

The execution time of our design will be given in section IV.

IV. Experiments

The speed and the accuracy of our proposed hardware-software co-design DSLAM will be evaluated in this section.

A. Run-Time

We evaluate our DSLAM on two intelligent cars which are controlled by the Deephi Aristotle board with a ZU9 MPSOC. The intelligent car and the board is illustrated in fig 6. Table I shows the run time of each part of our DSLAM system. The pipeline of scheduling of these parts is shown in section II.

Substituting the run-time of each part into eqs. (2) to (4). We find out that the run-time of NetVLAD on

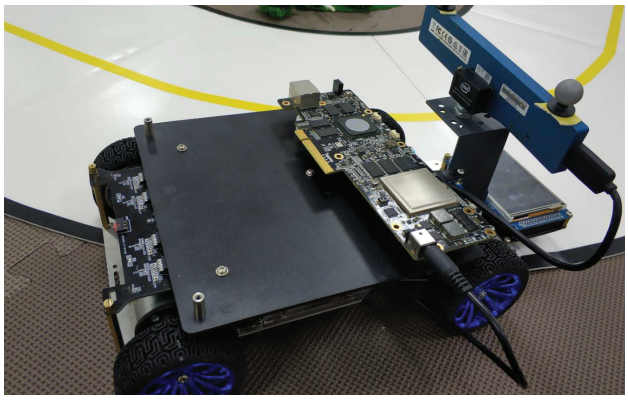
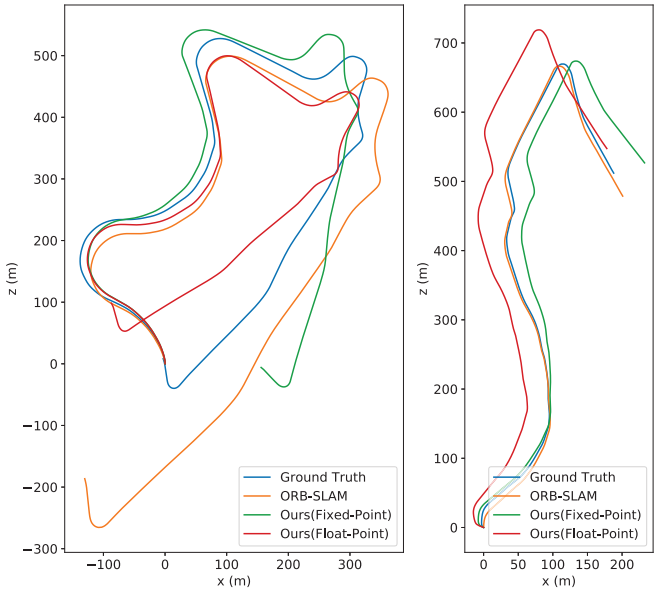


Fig. 6. The intelligent car with the Zynq MPSoC board.

TABLE I
Run-Time of each part in our DSLAM

	NetVLAD, PL (T_0)	VO, PL (T_1)	VO, PS (T_2)	NetVLAD, PS (T_3)
Execute time (ms)	66	3	10	354

* We read the camera at 20fps, so the T_f in fig 5 is 50ms.



(a) Traj. on Seq. 09 (b) Traj. on Seq. 10

Fig. 7. Qualitative evaluation of odometry on the KITTI Odometry test sequences (09, 10).

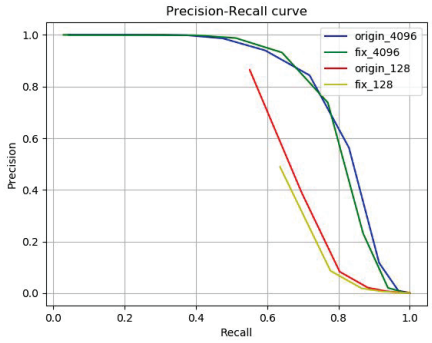


Fig. 8. ROC curves on sequence 00.

PS (T_3) becomes the bottleneck of the system and eq. (4) constrains the NetVLAD frequency (N) to 8.

We calculate the relative 6-D pose between every two successive frames and the NetVLAD code every 8 frames in the following experiments.

B. Visual Odometry with DPU

We evaluate our VO approach with DPU on KITTI dataset [?]. The dataset contains 11 labeled video sequences with stereo pairs, with original image size at 1242×375 pixels. In our design, we resize the image to 608×160 as the original Deepth-VO-Feate does [?].

At the fixed-finetune procedure, we use the stereo pairs in sequences 01 to 10 as the training set. The training super parameters in eq. (1) are $[\lambda_{ir}, \lambda_{fr}, \lambda_{ds}] = [1, 0.1, 10]$. At the evaluation procedure, we use the left-eye input images of the stereo pairs of the 00 sequence of KITTI as the test set.

We evaluate the VO on the sub-sequences at length of [100,200,...,800] and report the average translational and rotational errors for the testing sequence 09 and 10 in table II. The comparison of the estimated trajectory for the methods is illustrated in fig 7.

Because of the fixed-point number used in our design, which sacrifices the precision of the CNN, the VO accuracy is not as good as the previous works [?], [?]. On the other hand, our VO can calculate the 6-D pose within $20ms$ on a resource-constrained embedded platform.

C. NetVLAD with DPU

We evaluate the NetVLAD performance on the loop close dataset for KITTI[?]. The dataset labels the ground truth of loop closure for these sequences based on the metric positions of each image. Specifically, it compares the position of each image to the others in the sequence and regards the one as a loop if it lies within a radius of $6m$.

The precision-recall curves of the original NetVLAD with an output of 4096 dimensions (Blue), fixed-point NetVLAD 4096-D output (Green), original NetVLAD with 128-D output (Red), and fixed-point NetVLAD 128-D output (Yellow) are shown in fig 8. We use sequence 00 as the test sequence.

Our NetVLAD with DPU performs similarly to the original NetVLAD with the same output dimension but runs much faster with the help of the acceleration techniques on FPGA and architecture design. Even if there are sightly accuracy reduction on the ROC curves, the following experiment shows that the slight drawback would not make the overall DSLAM performance decline.

TABLE II
Visual odometry (VO) results on test sequences (09, 10)

Method	Quant. Strategy Fixed Part	Float Part	Seq. 09 t_{err}	Seq. 09 r_{err}	Seq. 10 t_{err}	Seq. 10 r_{err}	run time $(ms/frame)$
ORB-SLAM	-		15.30	0.26	3.68	0.48	
Depth-VO-Feat[?]	-		11.92	3.60	12.62	3.43	
Ours	Conv+FC1,2	FC_pose					
	Conv+FC1	FC2+FC_pose					
	Conv	FC1,2+FC_pose	10.27	4.08	8.84	4.01	12

* $t_{err}(\%)$ is the average translational drift error. $r_{err}(°/100m)$ is average rotational drift error.

D. DSLAM Evaluation

With the help of our hardware-software co-design VO and place recognition components on the embedded system, we can build up the DSLAM system like the previous work [?]. However, unlike the feature point based method in previous [?], our approach does not necessarily compute the feature point for each frame. The previous work [?] transfers the ORB feature points among agents to do inter-robot pose estimation and trajectory merging.

A possible way to solve the inter-robot pose estimation is to calculate the feature points and descriptors of the corresponding robot and frames when the inter-robot loop closure occurs. However, on the one hand, the traditional feature point detection and description method cannot get the absolute scale from a single image. On the other hand, it is resource consuming to do feature point algorithms like SIFT[?] and ORB[?]. The agents may stop and solve the feature points. We directly transfer the down-sampled 608×160 image among the agents and use the same method as the proposed VO with DPU to do the inter-robot pose estimation. The result of the merged trajectory is illustrated in fig 9.

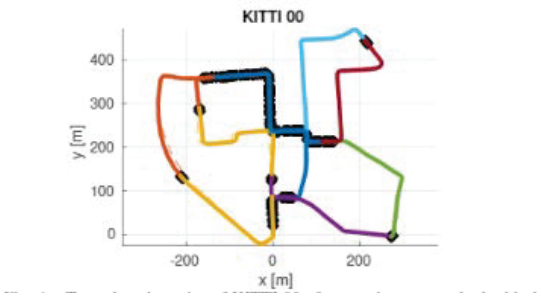


Fig. 9. ??? The sub-trajectory of each agent and the merged trajectory.

There are three kinds of data need to be transferred among the agents and the server: 1) the VO results of each frame (VO), 2) the NetVLAD results of every 8 frames (NetVLAD), 3) the image need for inter-robot relative pose estimation (RelPose).

At the beginning of the task, there is no inter-robot loop closure detected, so there is no data traffic for RelPose. When inter-robot loop closure occurs, the data traffic for RelPose increases rapidly. The previous work[?] also faces this problem though it uses feature point for inter-robot relative pose estimation.

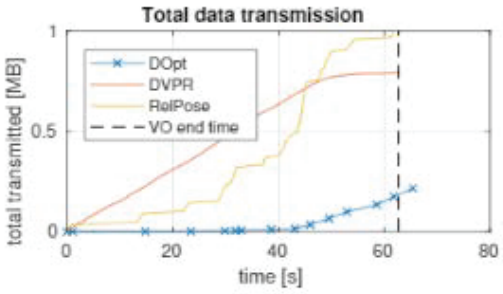


Fig. 10. ??? The total communication traffic of the propsoed DSLAM

The total communication traffic of the proposed DSLAM system on KITTI 00 is increasing with time and is shown in fig 10.

V. Conclusion

We propose a hardware-software co-design DSLAM system with the help of Xilinx Zynq MPSoC and Deephi DPU. We optimize two essential components of the DSLAM system, 1)Visual Odometry(VO) and 2) Place Recognition on the embedded system. From the aspect of calculation, the vectorization and projection operations on the PS side of Zynq MPSoC needed by NetVLAD is the bottleneck in doing more frequent place recognition. From the aspect of communication, the data traffic for inter-robot relative pose estimation consumes the most communication resources. The accelerator for vectorization based on FPGA and more data-efficient inter-robot pose estimation method could be researched in future work.

Acknowledgment

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