Depth estimation on embedded computers for robot swarms in forest

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Abstract—Robot swarms to date are not prepared for autonomous navigation such as path planning and obstacle detection in forest floor, unable to achieve low-cost. The development of depth sensing and embedded computing hardware paves the way for swarm of terrestrial robots. The goal of this research is to improve this situation by developing low cost vision system for small ground robots to rapidly perceive terrain. We develop two depth estimation models and evaluate their performance on Raspberry Pi 4 and Jetson Nano in terms of accuracy, runtime and model size of depth estimation models, as well as memory consumption, power draw, temperature, and cost of above two embedded on-board computers. Our research demonstrated that auto-encoder network deployed on Raspberry Pi 4 runs at a power consumption of 3.4 W, memory consumption of about 200 MB, and mean runtime of 13 ms. This can be to meet our requirement for low-cost swarm of robots. Moreover, our analysis also indicated multi-scale deep network performs better for predicting depth map from blurred RGB images caused by camera motion. This paper mainly describes depth estimation models trained on our own dataset recorded in forest, and their performance on embedded on-board computers.

I. INTRODUCTION

Forests are complex and changeable, including not only relatively flat terrain but also terrain with steep slopes, bare rocks, fallen tree branches and shrubs. In such an environment, swarm of robots [1] are used as effective tool to explore and monitor forests. This requires robots to be capable of operating in the forest so as to explore the forest details. Navigating uneven outdoor terrains in the forest floor is an arduous task and an unresolved problem for field robotics [2]. As it may not be possible to receive GPS signal, relying on on-board sensors the robots are required to percept an unknown terrain and estimate its traversability under varying lighting (different times of day) and weather conditions. The varying nature of terrain traversability reflected by different types of forest terrain makes the problem more difficult.

In order to accurately explore terrain details, we are interested in deploying robots in forest to percept terrain from low perspective. There are many types of terrain that can be swarmed, such as ground robots and drones. However, exploring forest terrain details from low-perspective makes drones more likely to crash when they encounter a close-range obstruction. Besides, due to limitation of non-windproof and non-waterproof, drones are more susceptible to weather conditions, especially it is difficult to safely fly outdoors in windy or rainy days. Thus, we take an interest in ground robots, which are small enough to be transported with a backpack. In addition, the total cost of each robot should be low enough to be feasible for large swarms. As the object researched is forest, the scale of swarm should be sparse, we consider a sparse swarm of a dozen terrestrial robots being responsible for monitoring a large area of woodland in kilometers.

Our robots that are navigated in off-road in the forest face even greater challenges. Almost everything appeared in the forest can be seen as an obstruction because of robot small-size characteristics, in such a case these robots are more likely to tip over. Off-trail environment that the robot may have to encounter includes wet leaves on the woodland, ditches with varying slopes, muddy tracks, shrubs, and fallen tree branches and trunks.

Depth estimation plays important role in path planning and obstacle avoidance in mobile robot navigation. Traditional methods for depth estimation mainly focus on multi-view geometry [3], [4]. However, it is constrained with computational complexity and high energy demands [5]. Current depth estimation via deep learning can be to achieve relatively accurate results with low computational and low energy, especially deep neural network architecture has been applied to achieve depth estimation ([6], [7], [8], [9], [10]).

Developing computationally inexpensive computer vision and deep learning algorithms that contribute to enabling small-robots to sense the forest environment and effectively navigate on a priori unknown terrain is our goal to achieve sparse swarms, so we propose a novel and elegant solution that developing a low-cost vision system deployed on embedded on-board computers to predict depth map from single RGB image captured from monocular camera, aiming to replace costly depth sensors, such as LIDAR and stereo camera. The above depth sensors are not only large in size, high in power consumption, but also expensive. These limitations make such sensors not suitable for low-cost small robots, especially swarm of robots used to explore forest floor. Due to the low-cost, low mechanical-complexity, medium robustness and small size of the monocular camera [11], it has received a lot of research attention stimulating the motivation to be used for depth estimation.

Depth estimation model, i.e. low-cost vision system, will be deployed on embedded computing hardware, which has increasingly enabled small robots to perform on-board image processing. Embedded on-board computer, such as NVIDIA Jetson products, has attracted research attention in robotics cases due to its low-power consumption and high-performance. Such embedded platforms are capable of large processing power and allow parallel execution of functions, because of that they are with Graphics Processing...
In our paper, we are evaluating two different deep neural networks for depth estimation. The first network is multi-scale deep network (MSDN) [8] designed for addressing monocular depth prediction and obstacle avoidance with a lightweight probabilistic CNN (pCNN) runs images (KITTI) at 76 ms on NVIDIA TX2 in applications of small drones for package delivery, and surveillance in cramped and cluttered environments. FastDepth [25] deploying encoder with MobileNet [26] and decoder with NNConv5 is capable to predict depth map (NYU Depth v2) on NVIDIA Jetson TX2 with GPU (5.6 ms) and CPU (37 ms). An encoder-decoder architecture (EDA) [27] is comprised of encoder MobileNetV2 [28], and learnable decoder, which deployed, compiled, optimized by TVM [29] on NVIDIA Jetson TX2 runs at power consumption of 4.0 W, and runtime by TVM of 30 ms (NYU Depth v2).

With constrain of robot size and its locomotion and mobility, we consider robot is prone to tip over and may fall into a pit if it runs too fast to sense the terrain, so our robots do not have to perceive the terrain quickly. Taking into account this safety factors of the robot navigating in the forest, we expect that the maximum speed of the single robot is not exceed 0.7 m/s, and the average speed is maintained at 0.4 m/s. Since the robot moves slowly, response time for terrain perception does not need to be very fast. Considering above, we expect that depth estimation model deployed on embedded computers predicts depth map at runtime of 1s that can be enough to meet real-time performance.

As we aim to develop swarm of robots platform, our depth dataset performance preference should not only consider runtime cost and accuracy, but also more importantly the embedded on-board computer budget for each of robots, memory consumption, power draw, and stable runtime. Each of robots is equipped with an independent embedded onboard computer, so it has to meet the minimum cost requirements. In our research, considering cost and performance we assess these devices (see Table I) as embeddable on-board computers for swarm of small portable robots in forest floor.

We introduced three contributions: (i) develop vision system via auto-encoder network and multi-scale deep network for predicting depth map from single RGB image under the training of our own low-viewpoint forest depth dataset for sparse rover swarms, (ii) evaluate depth estimation accuracy from the image with Gaussian blur and horizontal motion blur, and eventually determine multi-scale deep network (MSDN) is robust to predict depth map from blurred images, this characteristic is suitable for a rover in the forest, and (iii) deploy above two networks on the embedded onboard computers Raspberry Pi 4 and Jetson Nano to evaluate performance including accuracy, runtime, temperature, memory consumption, and power draw for different image resolutions.

II. DEPTH ESTIMATION ON DEEP NEURAL NETWORKS

In our paper, we are evaluating two different deep neural networks for depth estimation. The first network is multi-scale deep network (MSDN) [8] designed for addressing monocular depth estimation problem by employing two deep
TABLE I: Specification for Jetson Nano and Raspberry Pi 4

| Processor | Raspberry Pi 4 | NVIDIA Jetson Nano |
|-----------|----------------|--------------------|
| RMSv7 rev 3 | ARMv8 rev 1 | ARMv8 rev 1 @ 1.43GHz |
| Core Count | 4 | 4 |
| Graphics | V3D 4.2 4GB | NVIDIA Tegra |
| Display Drive | modesseting 1.20.4 | NVIDIA 1.0.0 |
| Motherboard | BCM2835 Raspberry Pi 4 | NVIDIA Jetson Nano Developer Kit |
| Memory | 4096MB | 4096MB |
| OS | Raspbian 10 | Ubuntu 18.04 |
| Kernel | 4.19.118-vc7+ (armv7l) | 4.19.140-tegra (aarch64) |
| Compiler | GCC 8.3.0 | GCC 7.5.0 + CUDA 10.0 |
| Price | 55 USD | 99 USD |

Fig. 1: Auto-encoder network architecture. Left part and right part represent contracting path and expansive path respectively. The contracting path consists of $3 \times 3$ convolutions, each followed by a ReLU and a $2 \times 2$ max pooling operation with stride of 2 for downsampling. At each downsampling step, we double the number of feature channels. Every step in the expansive path consists of an upsampling of the feature map followed by a $3 \times 3$ convolution (“up convolution”) which halves the number of feature channels, a concatenation with the correspondingly feature map from the contracting path, and $3 \times 3$ convolutions, each followed by a ReLU. These numbers represent height $\times$ width $\times$ channels.

network stacks: one that makes a coarse global prediction based on the entire image, and the other that locally refines the prediction. Most of methods [18] choose it as a baseline, so we also choose it as baseline for depth map estimation. Auto-encoder (encoder-decoder) is the most popular architecture for depth estimation in deep learning, so the second network is auto-encoder network (AEN) based on U-net [30]. We have designed an auto-encoder network deploying encoder part with convolutional layers and decoder part with transposed convolutional layers shown in Fig. 1 and Table II. MSDN reconstructs depth map of 256 $\times$ 256 from feature map of 1 $\times$ 1 (height $\times$ width) taking only one step. However, AEN deconvolutes feature map from $8 \times 8$ to 256 $\times$ 256 to reconstruct depth map by 5 steps (through $16^3$, $32^2$, $64^2$, $128^2$). This is the main difference between their network architectures.

A. Depth estimation accuracy evaluation metric

We evaluate the depth estimation result by threshold accuracy ($\delta_3$) from [10]. This metric is defined as follows:

$$\delta_3 = \frac{\min\{\hat{y}_p, y_p\}}{\max\{\hat{y}_p, y_p\}} = 1 - \frac{\|\hat{y}_p - y_p\|_2}{\|\hat{y}_p + y_p\|_2}$$

threshold accuracy ($\delta_3$): % of $y_p$ s.t. $\max\{\hat{y}_p, y_p\} = \delta < \text{thr}$ for $\text{thr} = 1.25^3$ (Higher is better); where $y_p$: ground truth, $\hat{y}_p$: a pixel in $\hat{y}$; $\hat{y}_p$: depth estimation image, $\hat{y}_p$: a pixel in the $\hat{y}$; $n$: the total number of pixels for each image.

The finding drawn by the above models trained using depth ground truth (GT) with different fill rates [17] is that this method to calculate the depth estimation accuracy is affected by the GT fill rate. The lower the GT fill rate, the lower the accuracy estimated; the lower the GT fill rate, this method to calculate the depth estimation accuracy is.

B. Implementation

We trained above networks by our own low view-point forest depth dataset [17]. As mentioned before, we are going to choose depth ground truth with high fill rate for training and testing.

Training set: We select 1449 RGB-D data through filtering depth map fill rate that is larger than 0.95 from our forest dataset comprising of 9696 RGB-D data as training set, and extract 177 images based on a time interval of 0.6s and depth map fill rate between 0.9 and 1 from that image.

Test set: We randomly select one from 22 videos recorded in forest and extract 177 images based on a time interval of 0.6s and depth map fill rate between 0.9 and 1 from that video as test set that includes both sharp images and blur images.

Auto-Encoder Network (AEN): This is implemented in TensorFlow [32] using NVIDIA RTX 2060 (6GB) GPU. The training duration for AEN is 11h. The input RGB images and their corresponding depth ground truth maps are used to train the depth estimation network. Each RGB image comes with a corresponding ground truth depth map. Adam optimizer [33] is applied to loss minimization with by default parameters of $B_1 = 0.9, B_2 = 0.999, \epsilon = 10^{-8}$, learning rate $\lambda = 0.001$.

TABLE II: Auto-decoder network architecture. c: kernel filter channels, s: stride, k: kernel size

| Input | Operator | c | s | k |
|-------|----------|---|---|---|
| 256 $\times$ 3 | conv2d | 32 | 2 | 3 $\times$ 3 |
| 128 $\times$ 32 | conv2d | 64 | 2 | 3 $\times$ 3 |
| 64 $\times$ 64 | conv2d | 128 | 2 | 3 $\times$ 3 |
| 32 $\times$ 128 | conv2d | 256 | 2 | 3 $\times$ 3 |
| 16 $\times$ 256 | conv2d | 512 | 2 | 3 $\times$ 3 |
| 8 $\times$ 512 | conv2d(transpose) | 512 | 2 | 3 $\times$ 3 |
| 16 $\times$ 512 | concatenation | - | - | - |
| 16 $\times$ 768 | conv2d(transpose) | 256 | 2 | 3 $\times$ 3 |
| 32 $\times$ 256 | concatenation | - | - | - |
| 32 $\times$ 384 | conv2d(transpose) | 128 | 2 | 3 $\times$ 3 |
| 64 $\times$ 128 | concatenation | - | - | - |
| 64 $\times$ 192 | conv2d(transpose) | 32 | 2 | 3 $\times$ 3 |
| 128 $\times$ 32 | concatenation | - | - | - |
| 128 $\times$ 64 | conv2d(transpose) | 3 | 2 | 3 $\times$ 3 |
| 256 $\times$ 3 | - | - | - | - |
Fig. 2: Blurred RGB images categories. The figure shows categories of blurred images. S: Sharp image; Gi: Image with Gaussian blur with kernel size of $i \times i$; Hi: Image with motion blur in horizontal with kernel size of $i \times i$; and batch size of 2. The loss function is mean absolute error (MAE).

**Multi-Scale Deep Network (MSDN):** All of training process parameters are consistent with those trained with NYU Depth-v2 dataset [20] shown in [8]. It is trained with TensorFlow library [32] using NVIDIA GTX 1080ti (11G) GPU for 9h.

**C. Results**

The trained model of AEN and MSDN are with size of 74 MB and 1278 MB respectively. Images with high pixel resolution will lead to out of memory error for computer, too low image resolution is not suitable to navigate small robots in forest. We eventually determine depth estimation accuracy from image resolutions of $128 \times 128$ and $256 \times 256$ are evaluated. By applying nearest-neighbour interpolation to images, we can be able to downscale images.

Besides, depth estimation accuracy may be affected by image blur as this would be quite common for a rover in forest. In order to better explore the blur influence on the above two models, we apply Gaussian blur and motion blur in horizontal to RGB images and evaluate the depth estimation accuracy from blur RGB images. Specially, Gaussian blur and motion blur in horizontal with kernel size of $3 \times 3, 5 \times 5, 7 \times 7, 9 \times 9, 11 \times 11, 29 \times 29$ have been applied to sharp RGB images with image resolution of $128 \times 128$ and $256 \times 256$, images processed are shown in Fig. 2.

**Auto-Encoder Network (AEN):** At testing process, resolution of input RGB image is the same as that of the output depth prediction map. The lowest input image resolution the AEN can get is $32 \times 32$.

**Multi-Scale Deep Network (MSDN):** This network estimates depth map for single image of arbitrary pixel resolution and output fixed depth map of $256 \times 256$ pixel resolution. For input image resolution of $128 \times 128$ by MSDN, we downscale output resolution from $256 \times 256$ to $128 \times 128$ to calculate accuracy.

Depth estimation accuracy distribution from images with Gaussian blur and motion blur in horizontal are shown in Fig. 3. Some sample results are shown in Fig. 4. For sharp image with $256 \times 256$ resolution, AEN and MSDN achieve mean accuracy of around 70% and 60% respectively.

Fig. 3: Depth accuracy from image with Gaussian blur and horizontal motion blur. Data for the distribution were aggregated across 177 images with GT fill rate between 0.9 and 1.
D. Discussion

The above experiments demonstrate that compared with MSDN, AEN performing depth estimation task can achieve higher accuracy at resolution of 256 \times 256. However, it is not robust to predict depth map from blurred images, is seriously affected by Gaussian blur and horizontal blur. The blurrier the image, the lower the accuracy. For AEN, low resolution images (128 \times 128) are more robust to image blur. The depth estimation accuracy provided by MSDN is hardly affected by blurred images. Regardless of the image resolution and the degree of blurring, the accuracy of MSDN can be maintained at a stable value. In violin-plots where AEN at low image resolution and MSDN, the accuracy estimated from blurred image is slightly higher than that from sharp image. Accuracy only decreases when the image is particularly blurred, such as G29 and H29. Thus, MSDN seems to be suitable for a rover in forest. In next section, we are going to run depth estimation models on embedded computers.

III. PERFORMANCE ON EMBEDDED COMPUTERS

As MSDN model occupies more resources (1278 MB), it cannot be run on embedded devices. We retrain a new MSDN model (317 MB and training duration of 4h) outputting depth map resolution of 74 \times 55, which is also robust to image blur. The accuracy \((\text{Mean} \pm SD)\) of this new 74 \times 55 MSDN model is similar to that of 256 \times 256 MSDN model. This new model can be deployed on embedded computers.

Predicting the depth map from too many RGB images at a time by using the AEN model on Jetson Nano results in reporting memory exhaustion errors. Through constant trial and error, we determine that the maximum number of RGB images applied to predict depth maps on Jetson Nano at a time is 30. To better evaluate and compare embedded computers performance and visualize their difference, we decide to select the first 30 images from testset as sub-testset, and run them with image resolutions of 128 \times 128, and 256 \times 256. Running above depth estimation models on Jetson Nano and Raspberry Pi 4 reaches the same accuracy as that on laptop. In this section, we mainly discuss runtime performance and embedded computers attributes performance.

A. Runtime and embedded computers attributes performance

Runtime is defined to execution time consumed by the application during the depth estimation task for processing one image. The AEN and MSDN runtime performance operated on Jetson Nano and Raspberry Pi 4 are shown (see details in Fig. 5). Based on the above experimental results, our analysis demonstrates that runtime performance on Jetson Nano is better than that on Raspberry Pi 4 at resolution of 128 \times 128 and 256 \times 256. Especially the runtime (8.72 ms) on Jetson Nano at 256 \times 256 image resolution is almost 50% faster than that (13.53 ms) on Raspberry Pi 4. For depth estimation by MSDN model, regardless of the size of the image resolutions, the overall runtime of Jetson Nano is faster than that of Raspberry Pi 4, which is almost less than half of the Raspberry Pi 4. Jetson Nano and Raspberry Pi 4 temperature, used memory, cache and runtime during performing AEN and MSDN for different image resolutions are recorded in Table III. In next subsection, we are going to test benchmark for Raspberry Pi 4 and Jetson Nano to quantitatively evaluate which one has superior performance.

B. Benchmark of embedded computers

We test benchmark of Jetson Nano and Raspberry Pi 4 through Phoronix Test Suite (PTS) [34]. The result composite for both of them and other NVIDIA Jetson and
Fig. 5: AEN and MSDN runtime performance. The figure shows runtime for depth estimation from AEN and MSDN performed on Jetson Nano and Raspberry Pi 4. Data for the distribution were aggregated across 30 images. The above models running 30 images are replicated five times.

Raspberry Pi products is evaluated by geometric mean of all test results shown in Table IV. Other devices scores are from OpenBenchmarking platform (https://openbenchmarking.org/). Installed with the same libraries to meet depth estimation requirements, Raspberry Pi 4 gets the higher score than Jetson Nano.

C. Discussion

The above experiments demonstrate that long-term use does not cause performance degradation, such as temperature and used memory, are also maintained at stable values. The temperature at running depth estimation model on Jetson Nano is about 10°C lower than that on Raspberry Pi 4 equipped with a heat sink. Power consumption of Jetson Nano (10 W) is about three times that of the Raspberry Pi 4 (3.4 W), so Raspberry Pi 4 is suited to the requirements of low power consumption. Although AEN predicts depth maps much faster than MSDN, both of runtime from above two models can be able to meet real-time requirement for terrain perception. In the case of installing the same deep learning libraries required for depth estimation, Raspberry Pi 4 consumes much less memory than Jetson Nano, and it does not cause out of memory errors. Based on the above analysis, Raspberry Pi 4 is better than Jetson Nano in power and memory consumption performance. Although it is not as good as Jetson Nano in runtime, it can also meet the requirements of real-time prediction. Besides, considering minimum cost requirements, we intend to deploy models on Raspberry Pi 4 for swarm of small robots navigated in the forest to perform depth estimation, then determine which depth estimation model to be used according to the image blur degree depending on robot speed.

IV. CONCLUSIONS

In this paper, we have developed two depth estimation models on low-viewpoint forest depth dataset targeted at low capability embedded on-board computers (Raspberry Pi 4 and Jetson Nano), which will push robot swarms currently operating in carefully controlled laboratory environments out into the real world. This paves the way for the development of computer vision modules for portable small robots that would be navigated in the forest floor. In this case, it is of interest to replace costly depth cameras with the sufficiently low-cost estimated depth information from RGB images. In future work, we plan to deploy depth estimation models on embedded on-board computers and navigate robot in forest to evaluate its generalization capability.
