Development and application of substation intelligent inspection robot supporting deep learning accelerating

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Abstract. Substation inspection robots usually have low computation capability to run deep learning models. In this paper, a substation intelligent inspection robot that can support real time deep learning models is developed. The Nvidia Jetson TX2 module is the accelerating hardware module of the robot, and TensorRT is the software framework for deep learning model inference accelerating. The robot can satisfy the computational requirement of deep learning based applications, and operate in very low energy consumption. Test results on a fault diagnostic task based on object detection and instance segmentation show that with deep learning accelerating, not only high detection accuracy is achieved, but also inference time is short enough for real time fault diagnostic application.

1. Introduction
Substation intelligent inspection robots equipped with infrared imaging sensors, visible light sensors, Lidar sensors, inertial measurement units (IMU), and many other types of sensors, are widely deployed in large substations to reduce cost and improve efficiency[1-5]. Deep learning advanced fast in recent years and surpassed traditional methods and even human level in some domains like object recognition, object detection, etc[6-8]. Hence, deep learning techniques are used in substation intelligent inspection robots to enhance performance for fault diagnosis, gauge recognition, navigation and so on[9-11]. However, deep learning techniques require vast amount of computation. For instance, the AlexNet model needs 700 million floating-point operations per second (FLOPS), while the ResNet-152 model needs 11 billion FLOPS. The main processing units installed in substation intelligent inspection robots, which are CPU, ARM or DSP, cannot meet the computation demand and thus limit the usage of deep learning.

In this paper, a novel substation intelligent inspection robot supporting deep learning accelerating is developed with the Nvidia Jetson TX2 as the hardware accelerating module for deep learning models, and the TensorRT framework as the software accelerating module to increase inference performance. The robot not only can satisfy computational demands of deep learning models, but also operates in real time and low power consumption.

2. System architecture
The system architecture of the substation intelligent inspection robot supporting deep learning accelerating is illustrated in figure 1. It is composed of power module, sensor module, motion module, main controller module, and accelerator module.
2.1. Power module
The power module mainly contains batteries, DC-DC converters and power matching circuits. Ternary lithium batteries accompanied with automatic recharging and power management, can support energy consumption of the robot. The power supply of batteries is transformed by DC-DC convertors to adapt voltage specification of different modules. Power supply and load are connected by matching circuits. The power interface monitors the charging and discharging process of the power module and provide protections.

2.2. Motion module
The motion module includes driving wheels and a Pan-Tilt-Zoom device to install cameras. A wheel includes a wheel motor and its driver. The wheel motors have IP54 enclosure rating, 1024 line encoders, and can operate as electric brakes. The wheel drivers, which are based on FOC and SVPWM, support position, speed or torque control through control input from pulse, analog, and host communication. They have low-voltage, over-voltage, over-load, and over-current protections, and warning outputs. The PTZ has two degrees of freedom-yaw and pitch. In yaw dimension, it can rotate continuously ranging from 0 to 360 degrees, and in pitch dimension from -60 to degrees. It has IP66 enclosure rating and 200 pre-set positions with ±0.1° repeatability.

2.3. Sensor module
Sensor module is composed of infrared image sensor, high resolution visible light sensor, Lidar, IMU, sound sensors, and ultra sound sensors. The infrared image sensor outputs thermal images and videos with 640×480 resolution. High resolution visible light sensor also outputs images and videos, but with 1920×1080 resolution. The infrared image and visible image are co-registered in pixel level by transformation obtained at different distance configuration in laboratory. The Lidar has 16 channels and is mainly used for map creation and navigation with IMU.
2.4. **Main controller module**

Main controller module is an embedded computer with CPU, RAM, SSD, and IO. The type of CPU is an Intel i7 series chip for mobile usage which will reduce power consumption. The amount of RAM is 8GB and can be upgraded to 16GB. A 500GB SSD is able to meet the local storage demand. The IO interface includes Ethernet, Universal Asynchronous Receiver-Transmitter (UART), general-purpose input/output (GPIO), etc. Besides, wireless network card and 4G communication module could be supported with extension IO.

2.5. **Accelerator module**

The accelerator module is a Nvidia Jetson TX2 module. It mainly includes CPU, GPU, RAM, SSD, IO and extension IO. The Jetson TX2 module uses Tegra X2 SOC, which integrates a 256-core NVIDIA Pascal GPU and an ARMv8 (64-bit) Multi-Processor CPU Complex composed of a Denver 2 CPU cluster and an ARM cortex-57 MPCore CPU cluster. The maximal RAM capacity of TX2 is 8GB and its maximal FLASH storage can be up to 32GB. It also includes WLAN, Ethernet, UART, CAN, I2C and other interfaces. TX2 has low power consumption down to 7.5W, and the maximal power required at full performance is under 15W.

3. **Software architecture**

The software architecture of the robot is shown in figure 2. It is divided into two parts: the main controller and the accelerator. The main controller is based on the Robot Operating System (ROS)[12]. Seven application modules running on it are as follows:

- navigation module controls differential drive of the robot, models the robot, computes forward and inverse kinematics, and acquires sensor data for navigation.
- planning module is in charge of speed planning, obstacle avoidance, local and global path planning.
- simultaneous localization and mapping (SLAM) acquires Lidar point cloud data, performs sensor fusion, map building from sensor data, and robot localization.
- image retrieval module acquires infrared and visible images, stores images locally and remotely, preprocesses images, and implements pixel level fusion of infrared and visible images.
- PTZ control involves coarse and fine localization of targets, kinematics computation, and movement control.
- accelerator interface communicates with accelerator module, issues commands of image capture and fault detection, and processes results from accelerator module.
- user interface (UI) provides video preview of image sensors, interactive result display, and enables robot operators to start manual or auto pilot.

The accelerator is based on Ubuntu Linux system, and TensorRT framework accelerates detection and segmentation application and fault diagnosis application. Detection and segmentation application receives images from the main controller, detects objects from images and outputs object segment and classification results. Based on detection and segmentation results, fault diagnosis application extracts target electrical devices from visible and thermal images, and diagnoses if the devices are normal or at fault. If any fault is discovered, its category is determined.
In addition to hardware acceleration, TensorRT framework is used software acceleration of deep learning algorithms. TensorRT includes inference optimizer and runtime that delivers low latency and high-throughput for deep learning inference applications[13]. Typically, models running in TensorRT can be obtained in two methods. The first is to build deep learning models by calling TensorRT layer API, which is suitable for small models. The second is to convert models from other deep learning frameworks to TensorRT models, which is more suitable for large models. Herein the latter method is used to build models. The flow chart for converting models is in figure 3. First, the deep learning model is built in TensorFlow framework, and then it is converted to Universal Framework Format (UFF). Then TensorRT parses from UFF model and generates inference engine which can be serialized to PLAN file. During parse of UFF models, layers that TensorRT does not support need to be coded and compiled as custom plugins.
4. Object detection and fault diagnosis based on deep learning

4.1. Object detection and fault diagnosis method

In this paper, the robot is tested on the application of detecting substation electrical devices and diagnosing fault. Figure 4 depicts the process of the testing application. The robot moves to desired inspecting place according to pilot configuration. And then visible image and infrared image are captured and preprocessed. More than 10k images in substations are collected, with human labeled class and mask, and then split into training and testing dataset. A deep learning model is trained on the visible image dataset to output bounding box, device class, and device mask for every electrical device detected. And then device mask is used to extract thermal distribution from the infrared image. Fault diagnosis is based on the extracted device thermal image.

The deep learning model is Mask R-CNN, and its architecture is as shown in figure 5[14]. The feature map of input image is extracted from the backbone network. And then Region Proposal Network (RPN) proposes the coordinates and scores of the feature map. RoIAlign layer extracts small feature map from the regions of interest (RoI) proposed by RPN. Finally, a full connected network outputs bounding boxes and classes, and a full convolutional network outputs masks.

The diagnostic criterion is based on the DL/T664-2016 standard, which follows the flow chart in figure 6[15].
Ambient temperature as $T_0$, let $r = (T_1 - T_2)/(T_1 - T_0)$

- $T_1 - T_2 \leq 15$ or $r < 0.35$: no defect;
- $T_1 - T_2 > 15$ or $0.8 > r \geq 0.35$: ordinary defect;
- $T_1 > 80$ or $0.95 > r \geq 0.8$: serious defect;
- $T_1 > 110$ or $r \geq 0.95$: urgent defect.

- $T_1 - T_2 < 10$: no defect;
- $T_1 - T_2 \geq 10$ or $0.8 > r \geq 0.35$: ordinary defect;
- $T_1 > 55$ or $0.95 > r \geq 0.8$: serious defect;
- $T_1 > 80$ or $r \geq 0.95$: urgent defect.

Transformer
Radiator

The highest temperature in device area as $T_1$, mean temperature as $T_2$

- $T_1 - T_2 < 2$: no defect;
- $T_1 - T_2 \geq 2$: urgent defect.

- $T_1 - T_2 < 0.5$: no defect;
- $T_1 - T_2 \geq 0.5$: urgent defect.

*Figure 6. Flowchart of infrared fault diagnosis.*

### 4.2. Test Results

Inference test performed in accelerator module indicates that the average detection time per image is 1.4s under 32-bit floating point (FP32) and can be reduced to 0.7s under 16-bit floating point (FP16) with precision and recall drop less than 1%. As shown in table 1, precision and recall for different device types are stable and the difference between FP32 and FP16 is small.

| Device type          | Recall(FP32/FP16) | Precision(FP32/FP16) |
|----------------------|-------------------|----------------------|
| Current transformer  | 96.55%/96.28%     | 98.20%/98.20%        |
| Radiator             | 98.15%/97.30%     | 92.94%/92.84%        |
| Inductor             | 92.35%/91.65%     | 93.45%/92.86%        |
| Surge arrester       | 97.90%/98.14%     | 97.77%/97.69%        |
| Bushing              | 97.60%/97.50%     | 95.31%/94.96%        |
| Voltage transformer  | 96.15%/96.61%     | 97.25%/97.71%        |
| Circuit breaker      | 94.38%/95.06%     | 94.40%/95.22%        |
| Capacitor            | 98.96%/97.92%     | 98.61%/98.26%        |
| Transformer          | 92.46%/92.47%     | 85.50%/85.96%        |
| Insulator            | 96.21%/96.25%     | 88.47%/88.56%        |
| Disconnector          | 95.04%/95.42%     | 92.96%/92.56%        |
An example of object detection result is illustrated in figure 7, which shows that devices are accurately segmented. To the left is segmentation results of the visible image and to the right is extracted thermal image for the target device.

Figure 7. Illustration of detection result and extracted thermal image for target device.

5. Conclusion
Herein a novel substation inspection robot that supports deep learning accelerating is developed. The robot utilizes a low power consumption and high performance Jetson TX2 module specially for deep learning hardware accelerating and TensorRT for software accelerating compared with traditional ones. Test and demonstration on object detection and fault diagnosis task show that the detection accuracy is high, with fast computation, to satisfy real-time application. The performance of the robot can also support speed recognition, deep learning based SLAM, autonomous navigation based on reinforcement learning, and many other applications. In the future, the new substation inspection robot presented in this paper has very broad prospect of application, and provides hardware and software foundation for improvement of inspection robot intelligence level.

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