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The need for speed: How 5G communication can support AI in the field

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***Abstract*—Using AI for agriculture requires the fast transmission and processing of large volumes of data. Cost-effective high speed processing may not be possible on-board agricultural vehicles, and suitably fast transmission may not be possible with older generation wireless communications. In response, the work presented here investigates the use of 5G wireless technology to support the deployment of AI in this context.**

***Index Terms*—robotics, 5G, computer vision, agriculture**

I. Introduction

The agricultural workforce in the UK is both ageing and shrinking in numbers threatening food security of the UK. One response is increased automation, employing robotics and AI to lighten the load on UK farmers [2]. This has the advantage of increasing sustainability, since it allows for more precise targeting of fertilizers, herbicides and pesticides.

For example, herbicide is used to control weeds in fields with young crops. The herbicides are selective, so do not damage the crop, but kill the weeds. Currently, entire fields are sprayed to ensure all weeds are treated. This is wasteful, spraying areas that do not contain weeds. Advances in computer vision mean sprayers can be equipped to only spray where there are weeds to kill. Such an approach is estimated to save up to 90% [6] of the herbicide currently used.

Applications of AI in agriculture, which include the use of robots for fruit harvesting and yield estimation as well as weed and pest control, use cameras as their primary sensors. State-of-the-art methods for processing these images are based on *deep learning*. They therefore have heavy computational demands which may not be met by the relevant vehicles, either because of the power required, or because it is not cost-effective to equip every vehicle with a suitable computer. As a result, the computation may be delivered better through edge or cloud computing. However, this creates a further demand: that of transmitting the data from farm vehicles to the processing. For a field sprayer with a standard 24 meter boom, a spray nozzle per meter and HD cameras associated to each nozzle to scan the ground below it, this can involve transfer rates approaching 1 GBit/s which are beyond WiFi and 4G wireless links.

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In the remainder of this paper we present pilot results from work to demonstrate how 5G wireless can handle such a load.

II. Networking experiments and results

As an experimental platform, we are using a Leo Rover robot (illustrated in figure 1) equipped with a Raspberry Pi 4 and two 5G-SA (stand-alone) enabled mobile phones. The experiments were split into two parts, to evaluate WiFi and 5G network performance. The WiFi network used the 2.4GHz band and the 5G network used the N78 band, which was provided by the 5G mobile phones located on top of the robot platform. In the experiment setup, the Rover (under human control) followed a fixed path while streaming a video of a sequence of images (at a resolution of 1920x1080 and running at 30 frames-per-second) using a wireless connection. The video stream was compressed over the network (H.264) and the throughput was on average 7.64Mbps for WiFi and 6.86Mbps for 5G. The throughput for 5G is 10% better than for WiFi. Due to the H.264 traits, the more unstable the connection the worse the compression algorithm performs [5].

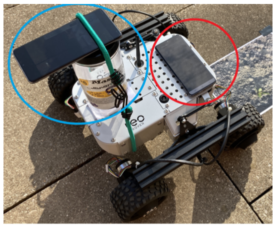

Fig. 1: The Leo Rover setup for 5G. The item in the orange circle is a 5G mobile phone enabled with 5G-SA connectivity.

During the trials, the WiFi station was at a distance of ≈10 meters from the robot, and the 5G antenna was on the roof of a building at a distance of ≈130 meters. For both connections, we evaluated the latency; latency is the time taken for data to travel to the destination and get back to the sender device. To do so, we measured, in milliseconds (ms), the difference between the time when a data packet was sent and the time when the sender got the packet acknowledgement. Figure 2 shows the latency results of the WiFi and 5G networks. The average latency for 5G is ≈18ms and WiFi is ≈227ms, which is over 12 times greater. The lower latency average and the

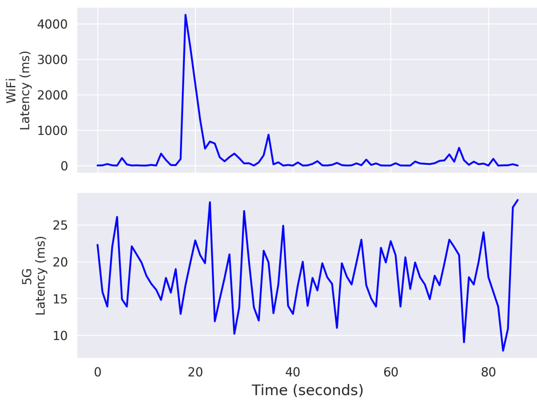

Fig. 2: Latency plot. Note the different y-axis scales between the top (WiFi) and bottom (5G) plots. The maximum latency for 5G is two orders of magnitude lower (better) than for WiFi.

smaller standard deviation for 5G over WiFi indicates that 5G communications are more stable and consistent.

III. Vision Results

As an example task, we are considering spraying for weeds, as described above. From a machine vision perspective, this means running an object detector on image data from the vehicle. However, fast and accurate detectors require GPUs with high specifications, which, in most of the times, cannot be mounted on autonomous systems because high-end GPUs require a lot of energy and need to remain steady. As discussed above, a potential solution is to place the necessary GPU on a remote server at risk of the transmission medium being too slow or unreliable and limiting the vehicle's mobility. However, our experiments suggest that a robot can communicate with a GPU processor without significant issues with latency, and hence reliability, if we are using 5G.

Another potential issue is the speed with which the object detector can operate. We evaluated this using an object detector to identify weeds within a sugar beet crop. The object detector was YOLO5l, which is a one-stage object detector based on a YOLOv4 [1] architecture with a backbone based on CSPNet [7], a PA-NET neck [4], mosaic data augmentation, and auto learning bounding box anchors. The size of the model on the GPU is 3.9GB We trained this detector using the dataset provided in [3], which contains pictures of sugar beets and field bindweed with their corresponding ground truth bounding boxes (fig 3.a). The dataset split was 70% for training, 10% for validation, and 20% for testing. The detector was trained over 300 epochs using a batch size of 16, an SGD optimiser with a learning rate of 0.0001 and a momentum of 0.95, and a image resizing strategy where the shortest image side is converted to 640 pixels and the longest size is resized to keep the original image ratio. The resulting trained model couldn't run on the robot's Raspberry Pi 4, because the Pi's RAM does not meet the memory requirements of the model (3.3GB). However, the model can run suitably quickly on a GPU. Based on the speed with which a single image frame is processed, this model locates sugar beets and weeds at a speed of 104 fps (frames per second) on a GTX1050 Ti and 196 fps on a RTX2080 Ti.

(a) Ground truth data (b) Prediction example

Fig. 3: Sugar beet images with (a) ground truth bounding boxes and (b) predicted bounding boxes. Note that since this work was too early in the season for sugar beet to be growing, our initial experiments involved a simulated field made up of photographs from [3].

We tested the trained model over wireless connections using the setup in section II, where the images contained sugar beets and weeds, and the remote device receiving the video stream had a GeForce GTX1050 Ti to operate the detection model. During the WiFi and 5G trials, the detector identified items on the video frames at a speed of 50 fps. Fig. 3.b shows an example of the bounding boxes inferred by the detector. These results confirm that, with high-end GPUs, vision systems need not be a bottleneck in the detection of items in a video stream as long as the data transmission is fast enough.

IV. Conclusions and Future Work

Robot communication over 5G networks is faster and more reliable than WiFi communications. Using 5G, we provided a successful example of how the vision that is critical for agri-robotics can be carried out on a remote computer.

Future experiments will test whether 5G networks can handle more information (larger images, depth information) from a single camera and information from multiples sources (more cameras and more robots roaming the fields). A particular challenge is scaling up to the number of cameras required on a commerical sprayer.

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