Task Learning for Intention Detection using Deep Neural Networks and Robotic Arm Data in Glovebox

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Task Learning for Intention Detection using Deep Neural Networks and Robotic Arm Data in Glovebox

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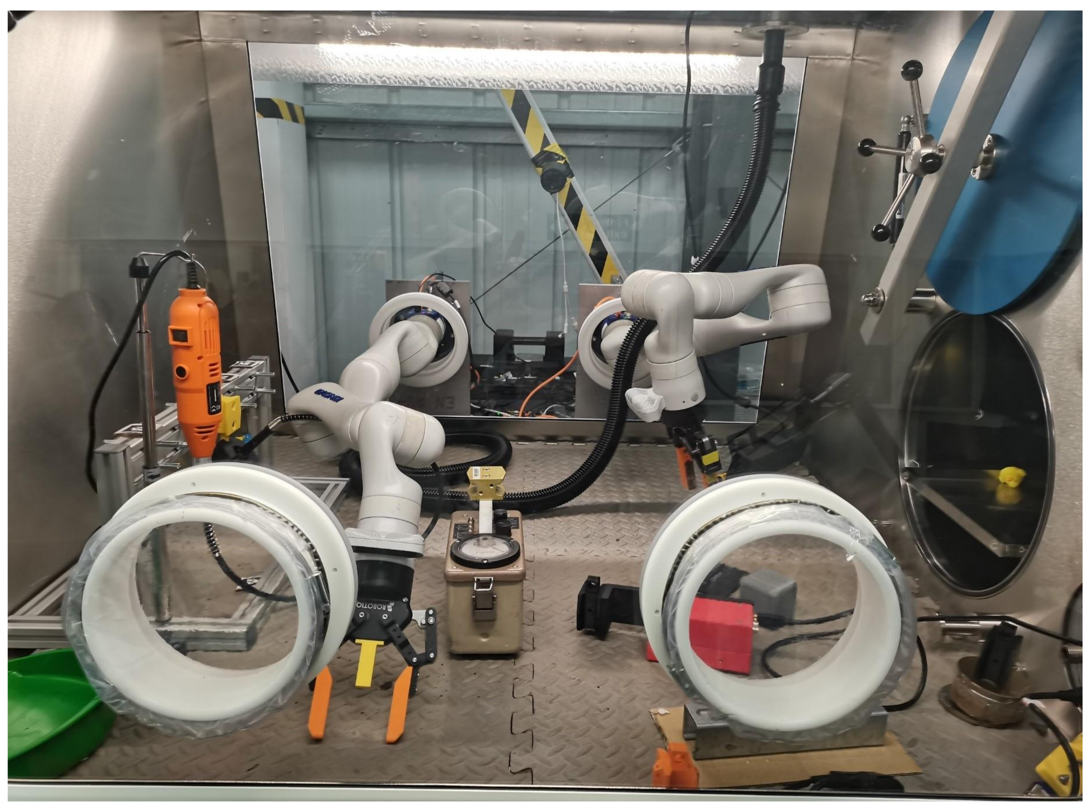
Introduction

Tele-manipulation systems are becoming more reliant on complex local (master) devices with sophisticated control methods; hence, the cognitive load on the operator during labour intensive tasks is increasing. The operator intention detection based on task learning can lead to better robot task performance with less human effort in teleoperation for a glovebox environment (see Fig. 1). Deep Convolutional Neural Networks are proposed to learn and predict the operator intention using robotic arm and its controller spatiotemporal data. Our preliminary experimental study on glovebox tasks for nuclear applications, particularly radiation survey and object grasping, provided promising results and encouraged us for a deeper research.

(a)



(b)

Fig.1. (a): Haption device to control robotic arm. (b): Glovebox environment with two Kinova robotic arms.

Data 1) Autonomous Manipulation of Objects with Robotic Arm

Autonomous manipulation of objects with one robotic Arm open-source benchmark [1] comprise of 210 samples, 20 samples for each task, recorded from kinova mico arm for 10 seconds:

1) Torque & force from a force Robotiq sensor mounted at the wrist joint
2) Finger positions.
3) 6DOF pose and joint torques

Table 1. open-source data classes

Task	Description
1	Kinematic motion of the arm, Simple
2	Kinematic motion of the arm, Complex
3	Plastic & Wooden cube pushing
4	Plastic & Wooden cylinder rolling
5	Plastic & Wooden cone rolling
6	Plastic & Wooden cuboid pushing

Data 2) Object Manipulation and Radiation Survey with Bilateral Teleoperation

Object posting in and out of glovebox and Radiation Survey using one Kinova arm. The data are recorded for 6 tasks (see Fig. 2), 20 samples for each task.

1) Post object in to the glovebox
2) Place object on the glovebox floor
3) Grasp the radiation sensor
4) Radiation survey
5) Return the radiation sensors
6) Grasp the object and post it out of the glovebox

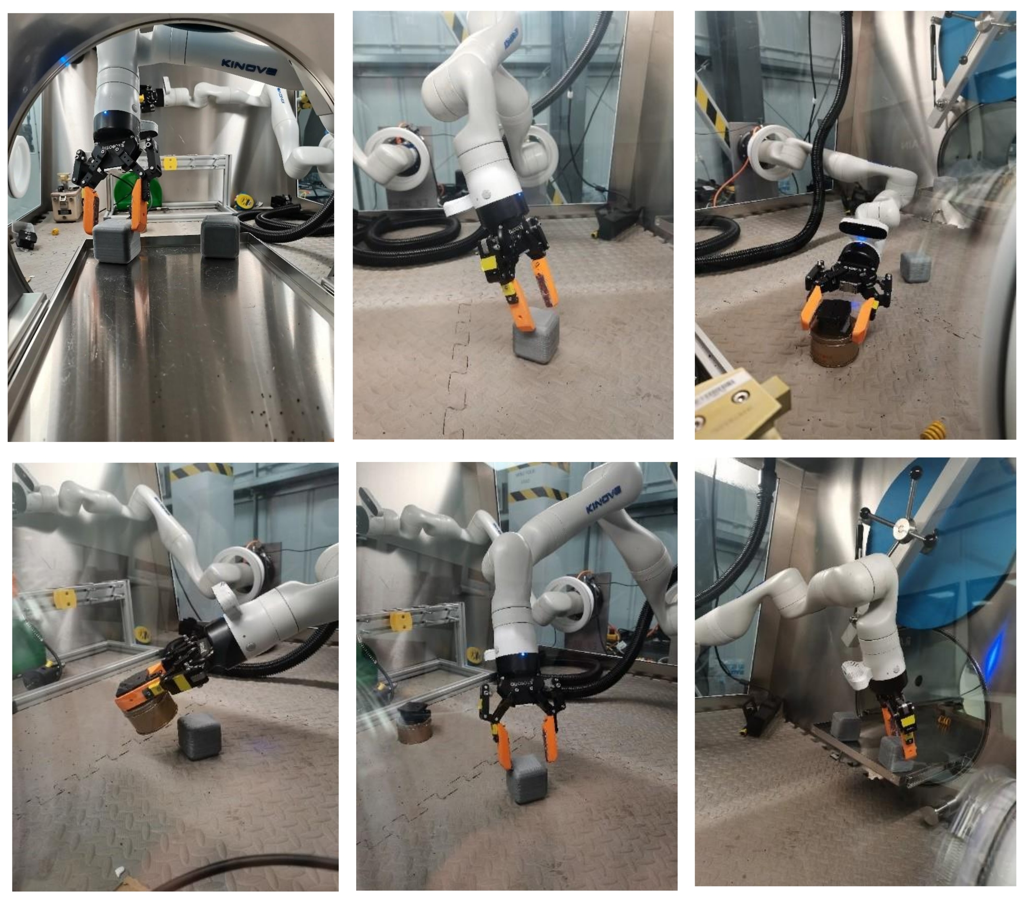


Fig. 2. Object posting in glovebox and radiation surveying for 6 tasks

Data 3) Radiation Survey on a Grid Using a Bilateral Teleoperator

Grid radiation survey in Glovebox environment. The data are recorded for 6 operators from one Kinova Arm and a Haption.

4 samples recorded for each operator while performing radiation survey see Fig. 3, with a data comprise of 32 samples.

Fig. 3. Grid radiation Survey

Deep Convolutional Neural Networks for Task Learning for Intention Detection

Intention detection is handled as a supervised learning process. The data are manually labelled to train a Deep Convolutional Neural Networks (DCNN) to detect the operator intentions from task learning.

The DCNN model (see Fig. 4) is implemented to map the robotic arm's spatiotemporal data $\widehat{x_{n,s}}$ to an output label y by learning an approximation function $y = f(\widehat{x_{n,s}})$, n denotes time and s denotes data point recorded from the robot. The network consists of an input layer, 4 convolution layers, 4 pooling layers, 2 fully connected layers, 1 batch normalization, and an output layer with a softmax classifier. The set of 12 stacked layers in Fig. 4 utilizes Conv1D kernels (filter size × number of feature maps × number of filters), MaxPooling strides of 2 and pool size of 2. The models' classification performance is evaluated using confusion matrices and F1 scores for 20% of the data .

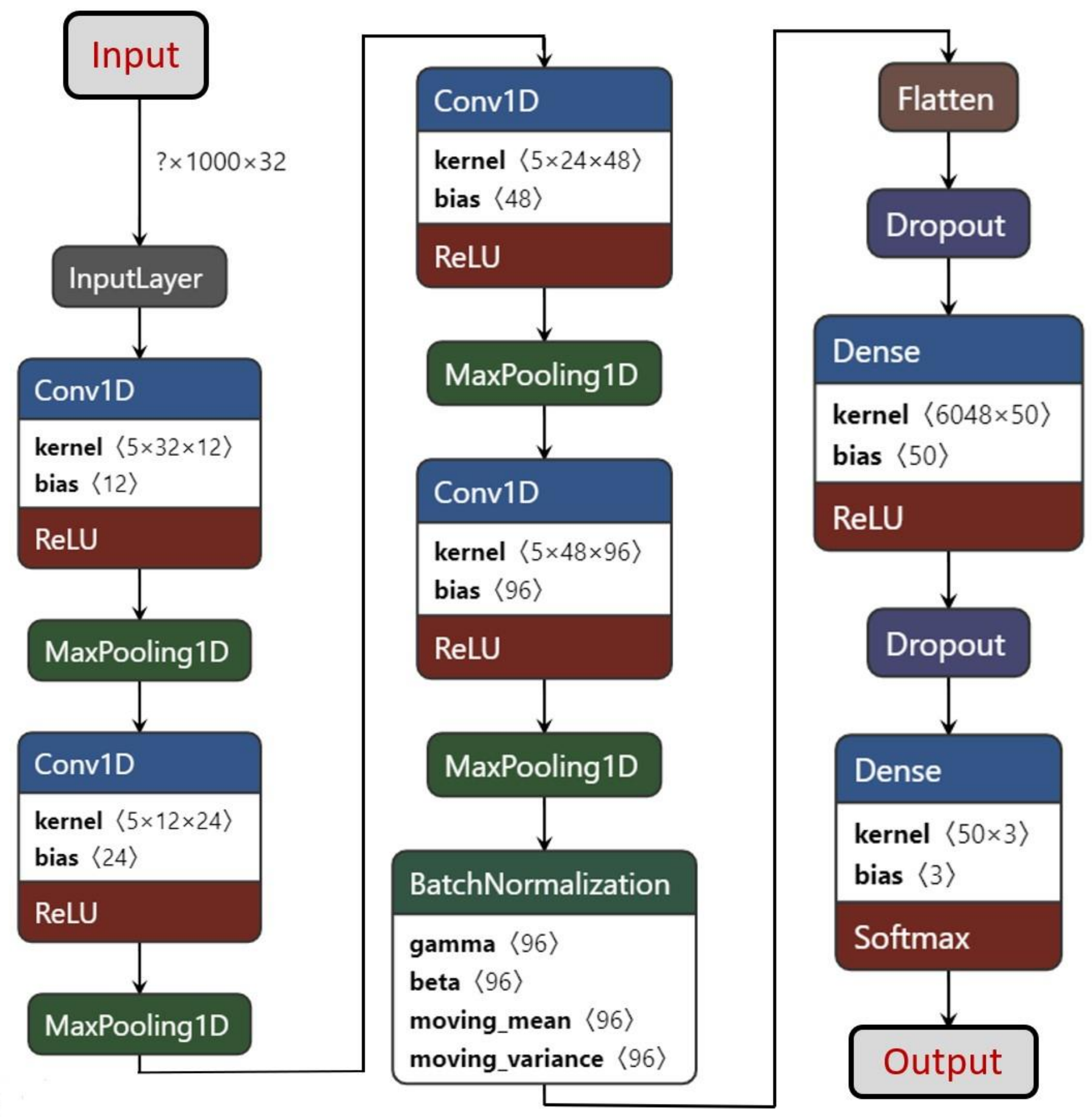


Fig. 4. DCNN network architecture for intention detection.The diagram is generated using Neutron repository based on the models' weights and biases.

Classification Results

Data 1) The DCNN successfully classified the tasks in table 1 by 100% ± 0.2% F1-score, depending on data split for training and testing. The confusion matrix in Fig. 5 shows the true positive predictions of the 6 classes.

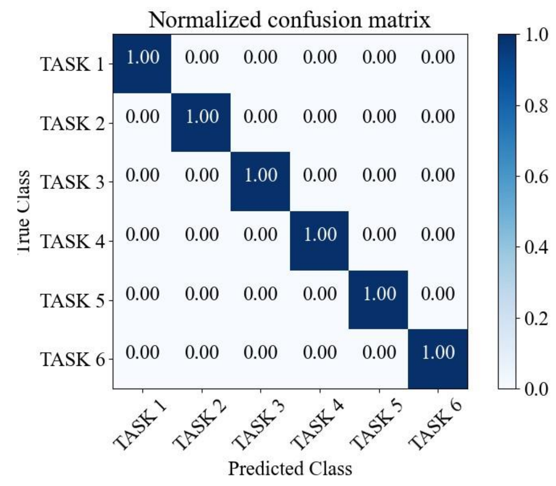


Fig. 5. Data 1 confusion matrix classification

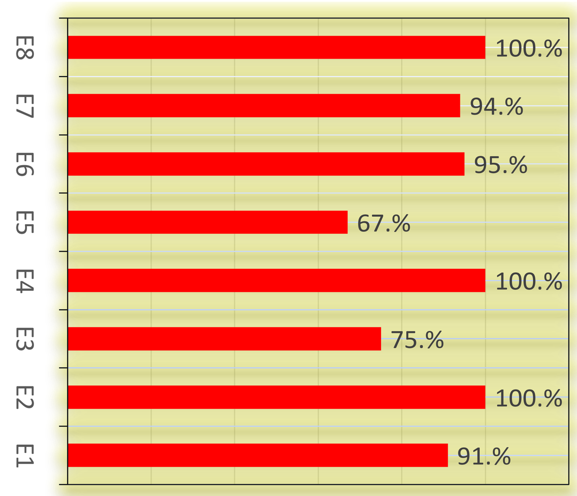


Fig. 6. Classification results in F1 scores for experiments from E1 to E8

Data 2&3) The DCNN is trained and tested to classify object manipulation in the Glovebox environment. Experiments (E) detailed in table 2 are conducted to investigate the ability of the DCNN to identify the operator intention for a number of experiment using F1 scores. In Fig. 6 the model predicted the operator intention by 100% ± 6% F1 when object grasping compared to radiation survey and Grid radiation survey.

Table 2. Experiments in Fig. 6 description

E	Description
E1	Post object in glovebox & Radiation survey (data 2)
E2	Place object in glovebox floor & Radiation survey (data 2)
E3	Grasp radiation sensor & Radiation survey (data 2)
E4	Grasp object and post out the glovebox & Radiation survey (data 2)
E5	6 tasks classes classification (data 2)
E6	Place object in glovebox floor & Radiation survey & Grid radiation survey (data 2&3)
E7	All tasks in data 2 as one class except radiation survey & Grid radiation survey in data 3 as second class
E8	All tasks in data 2 as one class & Grid Radiation survey in data 3 as second class

Conclusion

The findings present valuable insight for operator intention detection for Glovebox environment manipulation. The result presents a promising starting point for understanding, designing, and evaluating robotic systems for use by or with humans. The next step is to detect the operator intentions during online teleoperation manipulation.

[1] https://research.csiro.au/robotics/manipulation-benchmark/dataset/

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