Mobile robot decision-making system based on deep machine learning

Aleksandar Jokić, Milica Petrović and Zoran Miljković

***Abstract*—One of the major aspects of Industry 4.0 is enabling the manufacturing entities to operate in the dynamical systems autonomously. Therefore, to be autonomous, manufacturing entities need to have sensors to perceive their environment and utilize that information to make decisions regarding their actions. Having that in mind, in this paper, the authors propose a mobile robot decision-making system based on the integration of visual data and mobile robot pose. Mobile robot pose (current position and orientation) is integrated with two images gathered by two cameras and utilized to predict the possibility of gripping the part to be manufactured. A decision-making system is created by utilizing the deep learning model Resnet18 with an additional input for the mobile robot pose. The model is trained end-to-end and experimental evaluation is performed by using the mobile robot RACIO (Robot with Artificial Intelligence based COgnition).**

***Index Terms*—Decision-making system, mobile robots, deep learning.**

I. Introduction

Enabling mobile robots to operate in the manufacturing environment autonomously represents one of the fundamental requirements regarding Industry 4.0 concepts [1]. To fulfill this requirement, mobile robots need to localize themselves within the environment and use sensors to perceive the current state of the manufacturing system. In this paper, the authors propose to include both visual information and mobile robot pose in the make-decision process regarding future mobile robot actions. Mobile robot pose (Fig. 1), represented by position (x and y) and orientation (θ), is combined with image data to make a decision regarding the probability of successful gripping of the manufacturing part. The mobile robot's task is to move relatively close to the machine (marked with red color in Fig. 1) and decide if the current pose is adequate for a part (presented with a blue color in Fig. 1) picking process.

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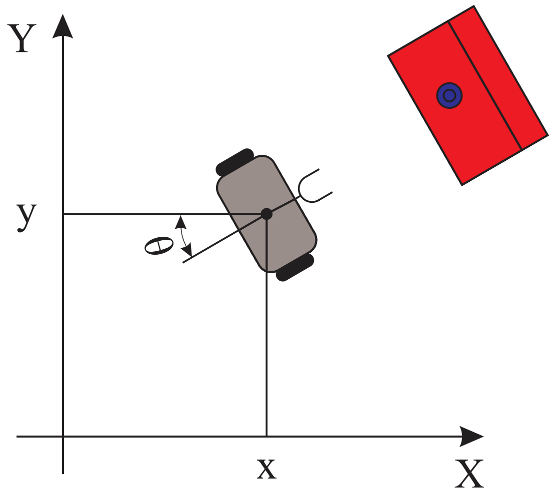

Fig. 1. Mobile robot in the environment with machine tool and part.

The related work regarding the mobile robot decision-making system is as follows. The determination of the next-best-view for environment exploring and mapping algorithm is proposed in [2]. The multi-objective decision criterion for a mobile robot with a 360° laser scanning sensor is proposed and evaluated in simulation. The proposed strategy showed superior performance compared to the other two strategies from the literature. The reinforcement learning approach for developing a mobile robot decision-making system is proposed in [3]. The mobile robot was equipped with an RGBD camera utilized to detect the obstacles. The learning approach was divided into three subtasks (i) reaching the target pose as fast as possible, (ii) obstacle avoidance, and (iii) not losing the target. According to the learned policy, a mobile robot can decide between five actions to reach the desired goal. The proposed system is verified within four simulation studies, and the results show that the proposed system achieves better results compared to the three state-of-the-art strategies.

The learning approach used for mobile robot navigation in both unknown and known environments is proposed in [4]. The model utilized for the mobile robot decision-making system is based on Developmental Networks. An incremental learning paradigm is implemented, allowing mobile robots to learn as they move in the new environment. Experimental results show that the proposed system enables mobile robots to utilize already learned cognitive functions in new environments.

A mobile robot decision-making system for outdoor path planning is proposed in [5]. The mobile robot utilizes the

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information gathered by the lidar sensor to obtain the optimal path in the uneven and obstacle-rich hill environment. In the offline stage, the robot learns in simulation the correlation of a good path with lidar data and utilizes that information in the online stage. The simulation results show the applicability of the proposed methodology for the path selection process.

Different from other approaches, in this paper, the authors propose the end-to-end trainable deep learning model capable of integrating image information and current mobile robot pose to predict the accuracy of the gripping process.

II. The Deep Learning-Based Decision-Making System

The everlasting challenge within the deep learning-based robotic research domain is developing an adequate methodology for adapting heterogeneous data into deep learning models [6]. Examples of such data are different sensor measurements with uncertainty, a priory logical conclusions, or a mobile robot pose.

In this paper, the authors present deep learning-based decision-making system developed by modifying Resnet18 architecture [7]. The first input in the Resnet model is an image created by combining images generated by two mobile robot cameras. Images are stacked on top of each other to produce an image with the same width and height dimensions. Afterward, the additional vector input is added to the network utilized to represent the mobile robot pose (1):

$$\mathbf{x} = \begin{bmatrix} x & y & \theta \end{bmatrix}^{\mathrm{T}}. \tag{1}$$

The change in mobile robot pose is calculated with (2):

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \cos\theta & 0 \\ \sin\theta & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v \\ \omega \end{bmatrix}, \tag{2}$$

where v represents mobile robot translation velocity, and ω is mobile robot angular velocity.

The deep neural network architecture is presented in Fig. 2. Additional input is represented as one pixel in the image. When the feature maps are flattened just before the classification layer, the unchanged value of the mobile robot pose (from the input layer) is concatenated with the rest of the features and utilized in the classification process. The utilized Resnet18 model is created with basic and bottleneck blocks of layers with skip connections after each one; details regarding the implementation of this model can be found in [8].

Dataset for mobile robot training is generated as follows. The mobile robot is positioned to the predefined pose in the laboratory model of the manufacturing environment. Afterward, the mobile robot is set in motion until it reaches the pose close to the machine. The achieved pose is measured according to the data gathered by two wheel encoders. Then, the achieved pose is saved in the text document and two images are generated, combined, and saved. The gripping procedure is initiated, and if the mobile robot manages to grip the part, all the saved data is moved to the "successful grip" category and vice versa.

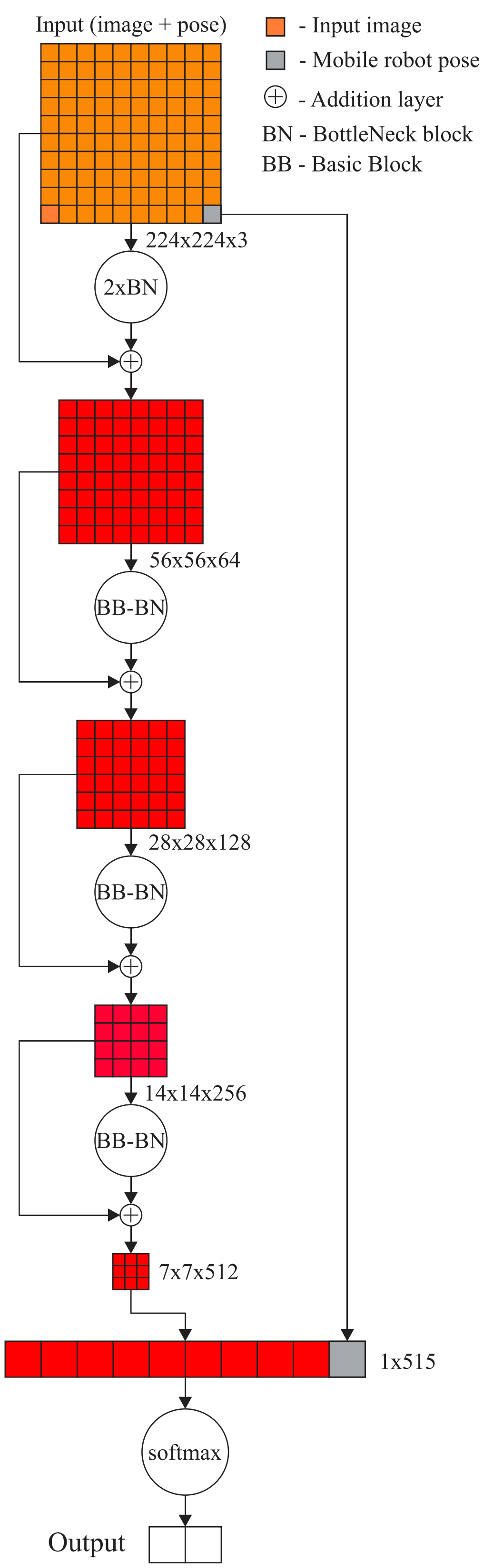

Fig. 2. Graphical representation of the proposed CNN model.

After the dataset is acquired, the training process begins. This problem belongs to the category of the binary classification process, with two outcomes "successful grip" and "unsuccessful grip". The classification is performed with softmax fitness function (3), and the loss function is defined with (4):

$$s_i = \frac{e^{y_i}}{\sum_{i=1}^{N} e^{y_i}} \tag{3}$$

$$\ell(\mathbf{s},\mathbf{c}) = -\sum_{i}^{N} c_i \log(s_i) \tag{4}$$

Where $\mathbf{y}$ represents the output of CNN model, i represents the i-th element of the output vector, N is a number of classes, $\mathbf{c}$ represents one-hot class vector.

The training is performed by stochastic gradient descent with momentum training algorithm with a batch size of one. Initial experiments are performed to determine the best training parameters for Resnet18 model. The learning rate varies from 0.0001 to 0.001, and the momentum is set to range from 0.7 to 0.9. The best performance on the training set is achieved with a learning rate of 0.0005 and momentum of 0.9.

III. Experimental results

The experimental evaluation is done by using the mobile robot RAICO (Robot with Artificial Intelligence based COgnition). RAICO is set to an initial pose in the laboratory model of the manufacturing system, and the movement command is activated. The pose RAICO achieves is relatively close to the machine where the part needs to be picked up; however, the pose is never the same due to slight differences in both the initial pose and movement process. Afterward, the final pose is calculated and integrated into the combined image generated using images from the right and left cameras. Then, the whole input is passed through the CNN network. The output represents the class (i.e., *grip* or no_*grip*) and the confidence in the class prediction. The gripping process is activated, and the outcome (successful or unsuccessful grip) is recorded. The experiment is repeated 10 times, and the results can be found in Table I.

TABLE I
THE EXPERIMENTAL RESULTS OF THE DECISION-MAKING MODEL

Exp. No.	Prediction	Confidence [%]	Successful gripping?
1	Grip	76	No
2	Grip	93	Yes
3	No_grip	83	No
4	No_grip	84	No
5	Grip	95	Yes
6	No_grip	85	No
7	Grip	85	No
8	No_grip	83	No
9	Grip	80	No
10	Grip	97	Yes

As shown in Table I, the mobile robot decision-making system adequately predicts the outcome of the gripping process in 70% of cases. Moreover, in all the cases where the prediction accuracy of the deep learning model for successful gripping is over 93%, the mobile robot actually manages to grip the part. Therefore, the high prediction confidence is highly correlated to the gripping success. Images generated by a mobile robot with prediction accuracy are shown in Fig. 3.

Fig. 3. Two input images for mobile robot decision-making system.

One more important piece of information that can be seen in Fig. 3 is the inference time of the developed deep learning model. Even though the proposed model has more layers and parameters than the original Resnet18, it can be used in real-time (around 60 FPS).

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Moreover, the images of the mobile robot RAICO in the laboratory model of the manufacturing system during the testing of the decision-making system are presented in Fig. 4.

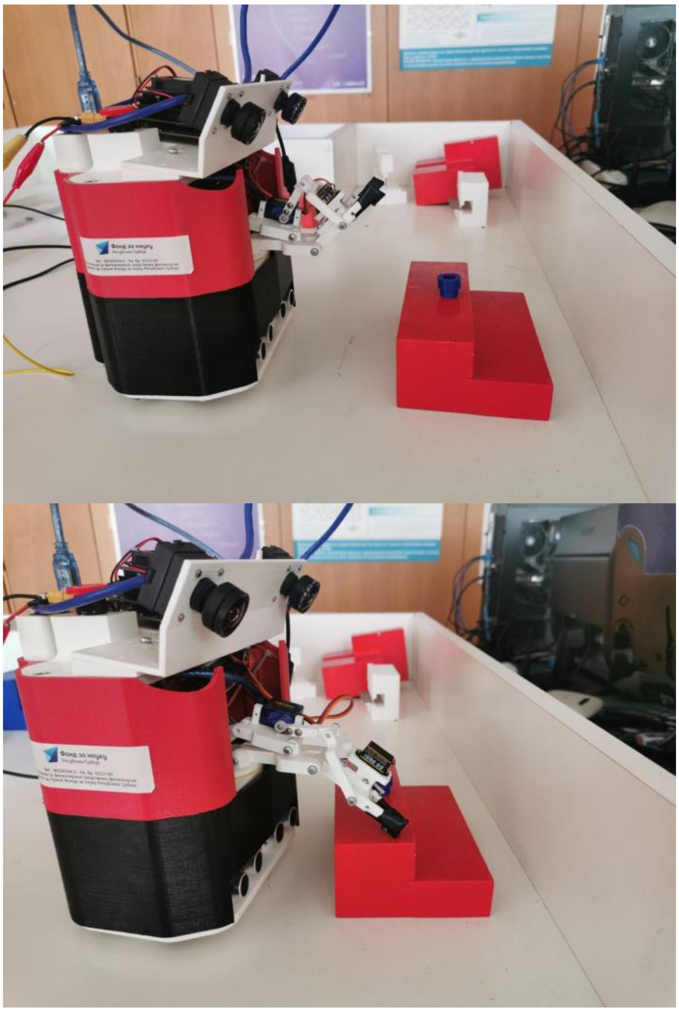

Fig. 4. Mobile robot RAICO in the pose close to the machine tool during the unsuccessful gripping process.

IV. Conclusion

In this paper, the authors propose a decision-making system based on the Resnet18 deep learning model. The input represents the images from the stereo camera pair and the pose of the mobile robot. The Resnet model is trained on the custom dataset to produce the binary classification output regarding the success of the griping process. The experimental results show that the model accurately predicts gripping success in 70% of cases. Moreover, it is experimentally verified that high confidence (93%+) in the prediction of accurate gripping has a strong correlation to the real-world successful griping process. The future research directions will include the extensive testing of the processed system with different state-of-the-art deep learning models that will enable a higher level of accuracy.

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