Improving Decision-Making-Process for Robot Navigation Under Uncertainty

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Abstract: Designing an autonomous system is a challenging task nowadays, and this is mainly due to two challenges such as conceiving a reliable system in terms of decisions accuracy (performance) and guaranteeing the robustness of the system to noisy inputs. A system is called efficient, if it is simultaneously reliable and robust. In this paper, we consider robot navigation under uncertain environments in which robot sensors may generate disturbed measures affecting the robot decisions. We aim to propose an efficient decision-making model, based on Deep Neural Network (DNN), for robot navigation. Hence, we propose an adversarial training step based on data augmentation to improve robot decisions under uncertain environment. Our contribution is based on investigating data augmentation which is based on uncertainty noise to improve the robustness and performance of the decision model. We also focus on two metrics, Efficiency and Pareto Front, combining robustness and performance to select the best data augmentation rate. In the experiment stage, our approach is validated on a public robotic data-set.

1 INTRODUCTION

The autonomy of a system is its ability to analyze the environment, make decisions and perform actions in order to achieve goals assigned beforehand.

Decision-Making Process (DMP) is, then, one of the key elements in the conception of autonomous systems in order to have successful behavior. It requires an accurate and adequate representation of the environment to choose the optimal decision. Often, the environment is uncertain due to external factors that highly impact the system. Generally, these difficulties are related essentially to the fact that: *i*) perception environment is absent or partially observable and *ii*) sensors values are false or disturbed due to a software or hardware anomalies.

In this context, it is important to study the behavior of the DMP in uncertain environment, i.e given noisy inputs. In fact, nowadays, the difficulty is not only to construct a reliable decision-making model in terms of decision accuracy (***Performance***), but also the challenge is to construct a robust decision-making model in terms of stability to noisy inputs (***Robustness***). For a clearer definition of the robustness, it consists in checking the capacity of the neural network to take the same label for all similar inputs even if they are noisy.

In this paper, we focus on the impact of data augmentation on the decision model behavior against noisy inputs. Our intuition leads us to study the capacity of data augmentation to improve the performance and/or the robustness of decision model. Hence, given a decision model based on Deep Neural Networks (DNN), several data augmentation rates are applied. For each rate, the model performance and robustness are evaluated. To measure the robustness, we propose to use the Abstract Interpretation that aims to check systems for resistance to unsatisfied specifications (Cousot, 2008). Its principle consists in checking that DNN still output the same label even if inputs are noisy.

To the best of our knowledge, this is the first paper dealing with the fusion of Performance and Robustness to select the best decision model. We propose to investigate two metrics: Efficiency based on F-score measure (Chinchor, 1992) and Pareto front (Ehrgott, 2005) metric.

Pareto front metric is often used for preferences' comparison when each preference is represented by vectors containing at least two scores. It is based on a set of decision points that are not **dominated** by other points. Further mathematical details and formulations

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on Pareto front points and the notion of Dominance will be provided in next sections. In our case, Pareto front solution will be used to select solutions that meet the multiple objectives or criteria such as robustness and performance trade-offs.

The rest of the paper is organized as follows. In section 2, a state of the art is presented. The structure of our approach is described in section 3. Sections 4 and 5 detail respectively the decision-making model construction and decision-making model evaluation. Section 6 includes the experimental results and section 7 concludes the paper.

2 STATE OF THE ART

In this section, the state of the art is split into two major topics: *i*) the first is about the solutions proposed to construct a DMP model for autonomous systems and *ii*) the second concerns approaches to verify the robustness of a constructed DMP model based on neural networks.

2.1 Decision-making Approaches

Decision-making approaches can be roughly classified into two major approach categories: *i*) Learning-free approaches and *ii*) Learning-based approaches.

Regarding Learning-free approaches, system decisions are taken without any *prior* trained model (Khedher et al., 2012; Khedher and El Yacoubi, 2015). Mostly, it is based on the use of rules, cost functions and graphs. First, Finite State Machines (FSM) and Rule Based manual programming approaches are the simplest. Physically, states correspond to system behaviors and transitions are the rules (or constraints) to transit from one state to another. Second, decision-making can be performed by defining a cost function. It consists in evaluating each action or sequence of actions using optimization algorithms in order to find the one with the lowest cost. Finally, decision-making can be modeled using graphs. Mostly, a tree-like graph is created to model different decisions and their consequences in order to select the optimal action.

In (Kammel et al., 2009; Aleluya et al., 2018), a FSM-based approaches are proposed. The team AnnieWay, authors of (Kammel et al., 2009), uses FSM for autonomous driving decisions where states included driving behavior and transitions are defined according to a manually written conditions. The authors of (Aleluya et al., 2018) use FSM to control a robot in soccer-playing context. It models the process of selecting the optimal robot-action according to its environment.

In (Vitus and Tomlin, 2013), the authors proposed a Chance Controlled Optimization approach to solve lane change overtaking in urban areas. The objective function minimizes, in the one hand, the traditional objectives such as minimization of fuel, and in the other hand, the nominal planned trajectory prediction against potential crashes.

Regarding Learning-based approaches, a *prior* decision-making model is trained (Jmila et al., 2017). Among these models, we quote Support Vector Regression (Zhang et al., 2017), Deep Learning (Shabbir and Anwer, 2018) and reinforcement learning (Hoel et al., 2018).

In (Zhang et al., 2017), a Support Vector Regression is proposed to model the driving decisions. It takes as input the environment parameters (e.g. vehicle states, road conditions, etc.) and retrieves the driving decision (e.g. steering angle, speed, etc.). Using the same technique, authors of (Abdessemed, 2012) propose the use of Support Vector Machine (Vapnik, 1995) to achieve the tracking trajectory task of a robot manipulator.

In the other hand, Deep Learning (DL) approaches have been gaining popularity in recent years across a variety of applications (Khedher et al., 2018; Jmila et al., 2019) such as decision-making. In (Shabbir and Anwer, 2018), a survey of Deep Learning techniques for mobile robot applications including decision-making is proposed. In (Gallardo et al., 2017), authors use Deep Learning techniques to help the navigation of a driverless car through an urban environment.

Besides, the authors of (Hoel et al., 2018) formulate the decision-making task as a reinforcement learning problem. The goal is to learn a policy that aims to automatically generate a decision-making function to handle speed and lane change decisions.

2.2 Neural Networks Verification Approaches

The Neural Network Verification (NNV) is the task studying the evolution of its outputs in uncertain environment. Otherwise, it consists of checking the neural network capacity to take the same output for all similar inputs even if they are noisy. The principle of a NNV system consists in: *i*) first calculating, from the input data, all possible inputs that can be obtained by adding noises and *ii*) second, checking that the properties of the input data is kept for noisy data. The properties are fixed beforehand and, for example, they can be defined as range of values, as an object class,

etc.

To verify a Neural Network (NN), several approaches have been proposed, mainly: *i*) satisfiability approaches and *ii*) reachability approaches.

Regarding satisfiability approaches, it consists in transforming the NN into a feasibility problem to prove the existence of a counter-example. If a counter-example has been found, the NN is not secure, else if no counter-example has been found, the NN is secure.

In (Katz et al., 2017), the authors propose an extension of the simplex algorithm, a standard algorithm for solving linear programming (LP) instances, to support non-linear ReLU activation function (ReLU for " Rectified Linear Unit"). The algorithm is called Reluplex, i.e. ReLU with the simplex method. Reluplex uses the simplex algorithm to search a feasible activation pattern that leads to an in-feasible output. The authors of (Ehlers, 2017) propose PLANET (for "a Piece-wise LineAr feed-forward NEural network verification Tool"). It consists first on replacing the non-linear functions of the NN by a set of linear equations. Then, it tries to find a solution for the resulting system of equations.

Regarding the reachability approaches, it consists in calculating the reachable set (outputs) of all inputs and checking if it is included in the desired set. Given a neural network N and an input set $\vec{X}$, the reachability set $\vec{Y}$ is defined as all the possible outputs: $\vec{Y} = \{\vec{y}, \vec{y} = N(\vec{x}), \forall \vec{x} \in \vec{X}\}$. If the reachable set is included in the desired set, the NN is declared secure, else if the reachable set is not included, totally or partially, in the desired set, the NN is not secure.

The calculation of the reachable set can be exact (Xiang et al., 2017b) or approximate (Xiang et al., 2017a; Gehr et al., 2018).

In (Xiang et al., 2017b), authors compute the exact reachable set for a neural network includes only ReLU activation. In fact, they assume that if the input is a union of polytopes, then the output reachable set is also a union of polytopes. In their paper, the entries of the NN are represented by the union of polyhedra (a polyhedron is an example of the more general polytope in any number of dimensions). Moreover, any over-approximation is applied. Hence, the number of polytopes grows exponentially with each layer.

In (Gehr et al., 2018), authors propose AI2 (for "Abstract Interpretation for Artificial Intelligence") that approximates the reachable set. The main idea is to over-approximate inputs by a set of zonohedron (a special case of the polyhedron geometric form). Then, a set of abstract operators are defined to follow the evolution of the zonohedron through the layers of the network.

The satisfiability approaches does not adopt any assumptions, however their execution time grows exponentially with the augmentation of NN hidden layers (depth). In the other hand, reachability approaches are based on over-approximation but are more scalable to a large NN. Since the importance of the execution time in our study, our approach lies to the reachability approaches.

3 OUR APPROACH

Figure 1 shows the flowchart of our approach. The input is a dataset composed of ultrasound sensor measurements collected from a mobile robot during its movement inside a room. The output is an *efficient* decision model under uncertainly sensor measures. Our approach considers three stages described as follows:

- Data-set augmentation
- Decision model construction
- Decision model evaluation

We start by a data augmentation algorithm which is applied to increase the variety of the training dataset. The original dataset is composed of *i*) ultrasound sensor measurements and *ii*) the corresponding robot decision (label). The data augmentation algorithm consists in injecting a *Gaussian* noise to generate noisy inputs. In this work, several data augmentation rates are used.

Next, a decision model is trained on the augmented training dataset, based on Deep Neural networks. The trained model learns the robot decision depending on sensor measurements.

Hence, for each data augmentation rate, the decision model robustness is evaluated by adapting the Abstract Interpretation algorithm to heterogeneous inputs.

Finally, two metrics are proposed to evaluate the decision model taking into account its performance and robustness. The metric is used to select the best model in terms of performance and robustness tradeoffs.

4 DECISION-MAKING MODEL CONSTRUCTION

Our decision model is based on a Deep Neural Network. In this section, DNN principle and its application in robot decision-making are presented.

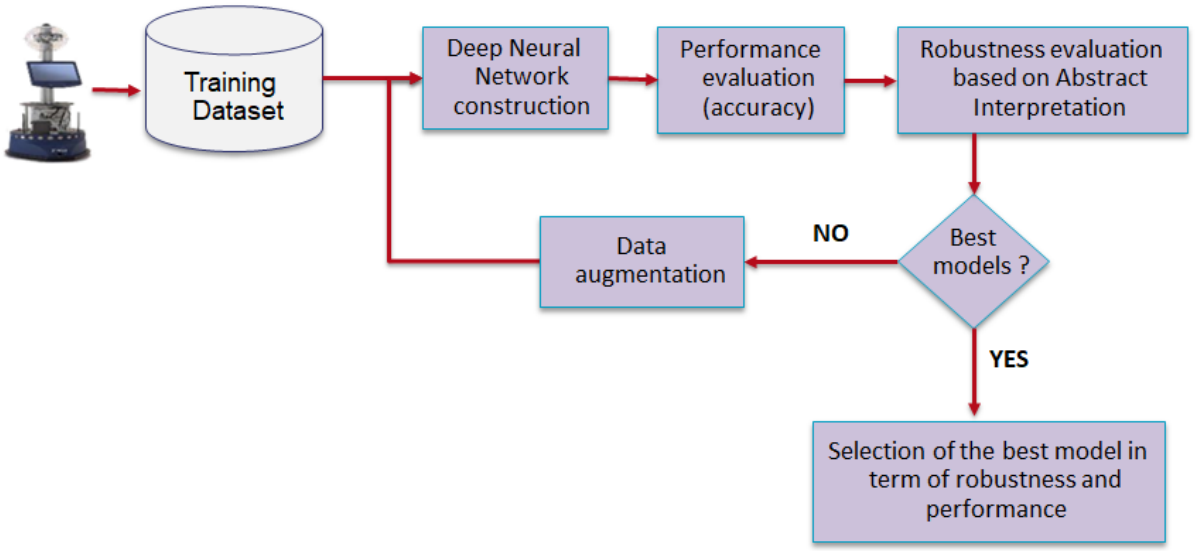


Figure 1: Proposed approach.

4.1 Deep Neural Network Principles

A Deep Neural Network is a extension of neural network with several hidden layers. It consists of three typical types of layers: *i*) an input layer, *ii*) hidden layers of neuron computations and *iii*) an output layer. Each neuron is a simple processing element that responds to the weighted inputs it received from other neurons.

The action of a neuron depends on its activation function, which is described by:

$$y_i = f\left(\sum_{j=1}^{n} w_{ij} \times x_j + \theta_i\right) \quad (1)$$

where x_j is the j^{th} input of the i^{th} neuron, w_{ij} is the weight from the j^{th} input to the i^{th} neuron, θ_i is the bias of the i^{th} neuron, y_i is the output of the i^{th} neuron and $f(.)$ is the activation function. The activation function is, mostly, a nonlinear function describing the reaction of i^{th} neuron according to inputs.

4.2 Model Construction

Our DNN architecture consists of N fully-connected layers, each of them are followed by an activation function and a dropout layer, and a final softmax layer indicating robot decision. As activation function, we used the non-linear function "Rectified Linear Units (ReLU)" defined by:

$$R(x) = \max(0, x) \quad (2)$$

The dropout layer is used to prevent over-fitting (Krizhevsky et al., 2012). Figure 2 shows the detailed architecture of our DNN. It takes, as input, vectors of dimension 24 components and outputs a probability distribution vector of 4 components (the number of decisions in the dataset).

4.3 Data Augmentation

Data augmentation is the process of modifying the available data in a realistic and randomized method. This is used to increase the dataset variety. In this paper, we propose to enhance the training dataset by injecting a *Gaussian* noise. Our intuition that injecting noise during training phase makes the decision model more efficient. This intuition should be confirmed experimentally.

In this paper, we propose to inject a *Gaussian* noise based on the sensor uncertainty. It consists in adding noisy samples x_{noise} to the training set with the following manner: for an input sample x_{init}, we generate: $x_{noise} = x_{init} \pm \varepsilon$, where ε follows a *Gaussian* distribution centred on [-ΔX,ΔX]. ΔX is the sensor uncertainty computed as following: For N multiple sensor measures x_i with average x, ΔX is given by Eq.3.

$$\Delta X = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - x)^2} \quad (3)$$

In our work, the robot is equipped with 24 ultrasound sensors. Hence, the dimension of x_{init} is 24 where each component is associated with a sensor measure. Moreover, each sensor i has its own $(\Delta X)_i$. To form x_{noise}, each component is disrupted independently of the others by adding the term $\varepsilon_i \in [-(\Delta X)_i, (\Delta X)_i]$.

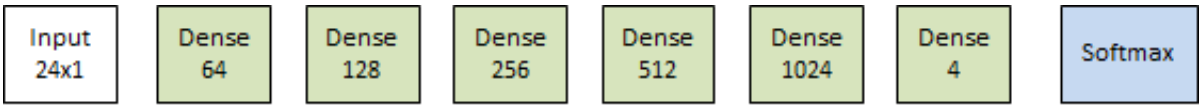


Figure 2: Our DNN architecture.

To prevent overfitting, only a randomly $R\%$ of the training dataset is noisy and injected in the training process. R is a hyper-parameter of our data augmentation algorithm.

5 DECISION MODEL EVALUATION BASED ON ABSTRACT INTERPRETATION

The evaluation of the decision model is based on the abstract interpretation. In this section, abstract interpretation principles and its application in the context of robot navigation are presented.

5.1 Principles of Abstract Interpretation

The abstract interpretation is a technique used for analyzing specifications and checking programs for resistance to specification unsatisfaction (Cousot, 2008). In (Gehr et al., 2018; Singh et al., 2018), authors have reused the abstract interpretation for verifying the robustness of neural networks. This approach lies in the reachability approaches.

The formulation of verifying the robustness of a neural network is detailed as following. Given x_I a sample input and x_N generated from x_I by applying a perturbation A, verifying the robustness $R_{(x_I,A)}$ consists of checking the robustness condition over the whole possible x_N resulting from x_I. The robustness condition is defined as: «the neural network outputs the same label for x_N and x_I i.e. x_N and x_I belongs the same class ».
The condition $R_{(x_I,A)}$ is checked and two cases are possible:

- if all possible x_N verified $R_{(x_I,A)}$, the neural network is called robust to the perturbation A given the input x_I.
- if at least one x_N *not* verified $R_{(x_I,A)}$, the neural network is called *not* robust to the perturbation A given the input x_I.

5.2 Robustness Evaluation based on the Abstract Interpretation

To measure the robustness of the decision model, the abstract interpretation is applied to each sample from the test dataset (Only samples correctly classified by the decision model are used). Hence, each *sample* is represented by a polyhedra. Later should includes all possible samples resulting by adding perturbation related to sensor uncertainty. In other words, the shape should include all possible $sample \in [low, upper]$ (where $low = sample - \Delta X$, $upper = sample + \Delta X$, ΔX is the sensor uncertainty defined in section 4.3). We recall that $(\Delta X)_i$ associated with the i^{th} sensor is different from one sensor to another.

Then, the shape is propagated through the abstract transformer of each layer, obtaining a new shape. Finally, the final shape should be checked if they kept the the same label as the original sample.

Mathematically, the robustness is formulated as follows. Given M the number of correctly classified samples, the robustness is provided by:

$$Robust = \frac{1}{M}\sum_{i=1}^{M} \text{verified}(Net, s_i) \quad (4)$$

where:

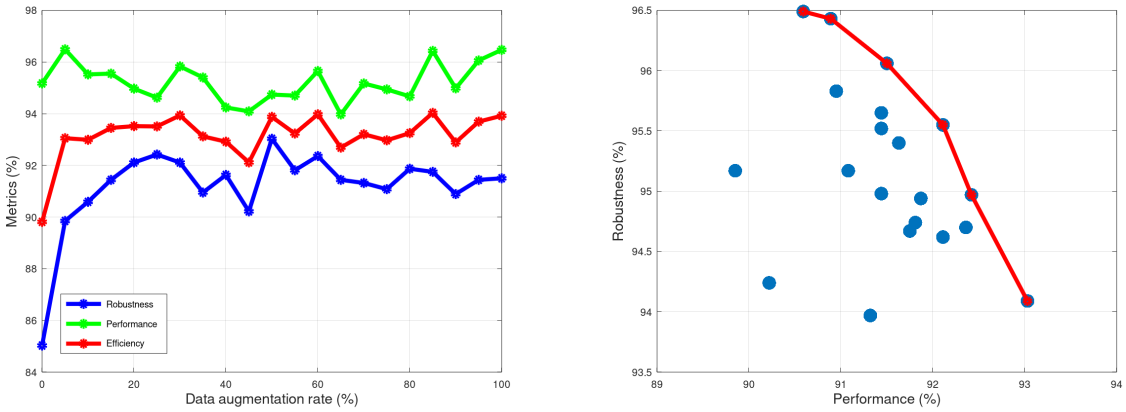
- verified(Net, s_i) = 1, if the neural network Net returns the same label for all points of the shape generated from s_i.
- Otherwise, verified(Net, s_i) = 0.

5.3 Evaluation Metrics

Our goal in this phase is to select the best model in terms of performance ($Perf$) and robustness ($Robust$).

- $Perf$: is defined as the rate of correct decisions predicted by the neural network.
- $Robust$: is defined as the rate of samples keeping their original labels after perturbation (Eq.4).

The proposed metrics are used to combine the two characteristics of the model (performance and robustness) in order to select the best one. The proposed metrics are: the model efficiency and Pareto front.



(a) Performance and robustness

(b) Pareto Front

Figure 3: Decision-making model evaluation.

5.3.1 Efficiency Metric

The efficiency metric is based on the F_1 score (Chinchor, 1992) that is the harmonic mean of the performance and robustness.

Mathematically, the harmonic mean is one of several types of average, and in particular, one of the Pythagorean means. The harmonic mean H of given positive real numbers $x_1, x_2, \ldots, x_n$ is defined by:

$$H = \frac{n}{\frac{1}{x_1}+\frac{1}{x_2}+\cdots+\frac{1}{x_n}} = \frac{n}{\sum_{i=1}^{n}\frac{1}{x_i}} = \left(\frac{\sum_{i=1}^{n} x_i^{-1}}{n}\right)^{-1}$$

In this work, the efficiency metric $Efficiency$ corresponds to the harmonic average of the performance and robustness (Eq.5).

$$Efficiency = 2 * \frac{Perf * Robust}{Perf + Robust} \quad (5)$$

The highest possible value of $Efficiency$ is 1, indicating perfect performance and robustness, and the lowest possible value is 0, if either the performance or the robustness is close to zero.

5.3.2 Pareto Front Metric

Pareto ranking is often used for vectors or tensors comparison with multiple criteria. This metric can be embedded and used easily for evaluation process of a given algorithm.

We first define the concept of dominance that is important to assess the quality of the solutions and to make sure that the best solutions are selected.

Definition 1 (Dominance)**.** For a given problem identified by a vector $\vec{f} = (f_1, \ldots, f_n)$ under a set of defined constraints. Then, vector $\vec{u}$ **dominates** vector $\vec{v}$ if and only if

$$\forall i \in \{1, \ldots, n\}, u_i \leq v_i \wedge \exists j (j \neq i) u_j < v_j$$

This is denoted by $\vec{u} \preceq \vec{v}$.

The above definition reports that a vector is dominated if and only if another vector exists which is better in at least one objective, and at least as good in the remaining objectives. In our work, these objectives are represented by robustness and performance scores. A set of dominant points are representing the Pareto front set.

Pareto front method is based on the dominance strategy considering the bi-dimensional vector of points. This approach is agnostic to the generation of the considered points and will not change for new generated datasets.

6 EXPERIMENTAL RESULTS

6.1 Dataset and Evaluation Protocol

To validate our approach, we use the experimental sensor dataset proposed in (Freire et al., 2009) for wall-following robot navigation. The dataset is a collection of sensor readings obtained by the mobile robot «SCITOS G5» during its navigation inside a room. To navigate, 24 ultrasound (US) sensors were used, and arranged circularly around its waist with an arc distance of 15 degrees. The dataset file contains 5456 rows. Each raw values corresponds to the measurements of all 24 US and the corresponding decision label (i.e. direction where the robot should navigate next). All the 24 US readings are synchronized (i.e collected at the same time step). The possible decisions of the robot are: 1) *Move-Forward*, 2) *Slight-Right-Turn*, 3) *Slight-Left-Turn* and 4) *Sharp-Right-Turn*.

For the evaluation, 70% of the available data is used for training and the resting 30% for evaluation.

6.2 Results

To assess our decision model, several data augmentation rates R are evaluated as described in section 4.3. In our study, R varies from 0% to 1000% by step of 5%. For each rate, performance and robustness are computed to measure the two proposed metrics.

The behavior of our decision model according to the two metrics is presented in Fig.3. Figure 3a shows the evaluation in terms of three indicators: model performance, model robustness and the efficiency metric (Eq.5). Figure 3b shows the evaluation of our model according to the Pareto front metric. It shows the couples ($Performance$,$Robustness$) as well as the pareto front.

Table 1 shows the evolution of model performance, robustness and efficiency according to the data augmentation rate.

6.3 Discussion

The standard experience, where no data augmentation is applied, achieves a performance of 85.03%. Moreover, an improvement of 8% is obtained by augmenting the training dataset by 50%. This improvement is significant given the large size of the test dataset (8% is equivalent to 131 robot decisions) and proves the importance to augment the training dataset by injecting noisy inputs. Afterwards, the decision model performance decreases with the augmentation of training dataset ($R > 50\%$). This is explained by the fact that when the reference dataset is significantly augmented, it becomes slightly different from the test dataset.

Table 1 shows that augmenting the training dataset by 10% led to a stable robustness. Then, by augmenting more the training dataset ($R > 10\%$), the robustness is decreasing. From a data augmentation of 90% ($R >= 90\%$), the robustness attains its initial value (before data augmentation). These results lead us to two remarks: 1) the dataset augmentation is very important to improve the performance of the neural network face to sensor uncertainty perturbation however 2) the data augmentation rate should be controlled to keep a acceptable robustness level.

In the following, we discuss and show the conflicting behavior of robustness and performance according to the data augmentation rate. Taking the experience of a data augmentation of 30%, the performance is improved by 7.08% however, the robustness is decreased by 1.85%. Table 1 illustrates results according to the efficiency metric that combines robustness and performance. Experimentally, data augmentation has a slight impact on the efficiency metric. Table 1 shows that augmenting training dataset by 50% leads to the best model in terms of efficiency. In fact, augmenting the training dataset by 50%, the efficiency is improved by 3.08%.

Figure 3b depicts the results of the Pareto front metric. This metric allowed us to select rapidly few Pareto efficient points (on the Pareto front) dominating the reminder points.

In this Pareto front, the lowest value for the robustness is close to 94.2% while the performance is close to 93%. A major set of points indicated by F-Score metric are dominated by the Pareto Front set. We can conclude that for the considered data set, the Pareto Front set allows to easily eliminating dominated points while considering performance and robustness trade-offs.

7 CONCLUSION AND PERSPECTIVES

In this paper, we examined the efficiency of a robot system navigation against sensors uncertainty. We are interested in the case where the robot decision is based on deep neural network. Our challenge was the impact of noisy inputs on robot decision. To cope with this issue, we proposed to enhance the training dataset by injecting noisy inputs. From one side, An adversarial training based on data augmentation has improved the decision model efficiency by 3.17%, and from the other side the efficiency metric is insufficient to conclude on the best data augmentation rate. The Pareto Front allows us to select a wider value range of data augmentation rates. It allowed us to consider only non dominated points combining the robustness and performance scores at the same time.

In the future work, we plan to study the correlation between sensor measurements. The goal is to select sensors disturbing more the decision-making process. This selection will help experts to replace faulty sensors. Moreover, we plan to validate our proposed approach on several datasets in different contexts.

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Table 1: Decision-making model evaluation.

Data augmentation rate (*R*%)	Performance (%)	Robustness (%)	Efficiency (%)
No augmentation	85.03	96.47	90.39
10	90.59	96.49	93.45
20	92.11	95.55	93.80
30	92.11	94.62	93.35
40	91.63	95.40	93.47
50	93.03	94.09	93.56
60	92.36	94.70	93.52
70	91.32	93.97	92.63
80	91.87	94.94	93.38
90	90.89	96.43	93.58
100	91.50	96.06	93.72

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