Analyzing Adversarial Attacks against Deep Learning for Robot Navigation

Mohamed Ibn Khedher and Mehdi Rezzoug
IRT - SystemX, 8 Avenue de la Vauve, 91120 Palaiseau, France

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Abstract: The autonomous system sector continues to experiment and is still progressing every day. Currently, it affects several applications, namely robots, autonomous vehicles, planes, ships, etc. The design of an autonomous system remains a challenge despite all the associated technological development. One of such challenges is the robustness of autonomous system decision in an uncertain environment and their impact on the security of systems, users and people around. In this work, we deal with the navigation of an autonomous robot in a labyrinth room. The objective of this paper is to study the efficiency of a decision-making model, based on Deep Neural Network, for robot navigation. The problem is that, under uncertain environment, robot sensors may generate disturbed measures affecting the robot decisions. The contribution of this work is the proposal of a system validation pipeline allowing the study of its behavior faced to adversarial attacks i.e. attacks consisting in slightly disturbing the input data. In a second step, we investigate the robustness of robot decision-making by applying a defence technique such as adversarial training. In the experiment stage, our study uses a on a public robotic dataset.

1 INTRODUCTION

Self-driving for autonomous systems is one of the hottest areas of research and business for the last decade. The application of Artificial Intelligence (AI) and, more precisely, Deep Learning (DL) techniques to the development of autonomous driving systems is currently an active area of research.

In fact, recently, some governments, like Japan, has set aside funds to make autonomous driving technology a reality for the 2020 Olympics, because it is considered safe and efficient mode of transportation (Okuyama et al., 2018). Moreover, most major automobile manufacturers worldwide have reached advanced stages of developing self-driving cars.

It is worth mentioning that the advances in the development of autonomous systems are strongly linked to the rapid progression and application of artificial intelligence in several fields. Artificial intelligence and specially Deep Learning has shown great success in diverse areas such as robot navigation (Ruiz-del-Solar et al., 2018), speech recognition (Spille et al., 2018), image recognition (Khedher et al., 2018; Khedher et al., 2012; Khedher and El Yacoubi, 2015) and anomaly detection (Jmila et al., 2017; Jmila et al., 2019). Moreover, DL shows a great success in reinforcement Learning based algorithms widely used for autonomous systems navigation. In fact, contrary to supervised learning where there exists an output (supervisor) for a given input, reinforced learning, is used when an agent has to learn to take the right action to affect a change in the environment in which it is placed. The right action of the agent is reinforced with a reward. Deep Reinforced Learning (DRL) combines reinforced learning with deep learning.

Despite the great success of DL in several critical applications (Jmila et al., 2019), DL faces several challenges such as the lack of transparency of the deep learning model, the explicability of such a decision, the vulnerability of the deep learning models to adversarial attacks. For the scope of this study, we focus on the vulnerability of deep learning models faced adversarial examples. An adversarial example is an instance of the input in which a minimal perturbation is added with the intention of changing the model decision, i.e to produce a wrong decision.

In a real application, the adversarial examples are mostly related to the perturbation of the environment. The perturbation factors are numerous and differ from one context to another (image, audio, video, etc.).

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Taking the example of self-driving system, these factors can be related to: *i*) Environmental factors linked with the external environment such as the weather conditions, the road infrastructure and the traffic behavior. *ii*) Material factors due to system failure related to its service life, configuration and interference with other sensors. and *iii*) Algorithmic/software factors associated, for example, with the error of variable precision.

In this paper, we contribute to the study of the effects of adversarial samples on DL model. In other words, we investigate the ability of DL model to resist adversarial attacks. As use case, we take the example of a Deep Learning model learned to control the navigation of a robot in a smart home. In our second contribution, we demonstrate that applying a defence technique is important to hardness the decision model faced adversarial attacks. Moreover, In this study, we investigate the impact of attack strength on the robustness of the Deep Learning model. The robustness is defined as the ability of the model to maintain its accuracy against adversarial attacks.

The rest of the paper is organized as follows. In the section 2, a state of the art is presented. It concerns the adversarial attacks proposed to fool Deep Neural Network and defence techniques proposed to improve its robustness. The structure of our approach is described in section 3. Section 4 includes the experimental results and section 5 concludes the paper.

2 STATE OF THE ART

In this section, two states of the art are presented: *i*)the first is about Neural Network Attacks (NNA) and *ii*) the second concerns Neural Network Defence (NND) techniques proposed to robustify neural network face to attacks.

2.1 Robustness Terminology

An adversarial example is defined as an instance with a small perturbation to make a false prediction. There are many ways to define adversarial attacks, most of them rely on minimizing the distance between the adverse example and the original one while making sure that the prediction is wrong. Some methods require access to the model gradient while others only need access to the prediction function. According to the degree of access to the classifier, type of attacks can be classified into two categories: white-box attacks and black-box attacks.

- **White-box Attack:** It refers to the scenario in which the attacker has full access to the architecture and parameters of the classifier. To generate attacks, algorithms have access to the model parameters including gradient and loss function.
- **Black-box Attack:** It refers to the scenario in which the attacker does not have complete access to the policy network. In other words, in black-box setting, the model parameters are unknown. For classification models, the attacker has only access to the output for a given input, in one of the following forms: *i*) the classifier decision; *ii*) the loss of the correct label; *iii*) the full response for all classes.

As definitions, we define $\mathcal{X}$ the set of classifier inputs and $\mathcal{Y}$ the set of classifier outputs which corresponds to the possible labels of inputs along K classes: $\mathcal{Y} = \{1, \ldots, K\}$. Finally, we note $C(x)$ the label of x by the neural network $F(\cdot)$.

Regardless of the attack type, it is important to distinct between targeted and non-targeted attack.

- **Untargeted Attack:** an untargeted attack aims to misclassify the input by adding an adversarial perturbation. The predicted class of the input is changed to another class in $\mathcal{Y}$ without a specific target class. Mathematically, an untargeted attack is defined as a function $\rho\colon \mathcal{X} \to \mathcal{X}$ such that the adverse input $x' = x + \rho(x)$ verify: $C(x+\rho(x)) \neq C(x)$
- **Targeted Attack:** a targeted attack aims to misclassify the input to a targeted class $y \in \mathcal{Y}$ by adding an adversarial perturbation. The predicted class of the input x is changed from the original class to a specific target class. Mathematically, a targeted attack is defined as a function $\psi\colon \mathcal{X} \times \mathcal{Y} \longrightarrow \mathcal{X}$ such that the adverse input $x' = x + \psi(x, y)$ verify: $C(x + \psi(x, y)) = y$, while keeping this perturbation as small as possible: $\|\psi(x, y)\|_p \leq \varepsilon$.

2.2 Neural Network Attacks

There are several attacks proposed in the state of the art. In this section, we detail the most popular attacks.

2.2.1 Fast Gradient Sign Method (FGSM)

Goodfellow et al. ((Dong et al., 2018; Goodfellow et al., 2015b)) have developed a method for generating adverse example based on the gradient descent technique. Given an original sample x, each component is modified by adding or subtracting a small perturbation ε.

The method consists in considering the sign of the loss function gradient $\nabla_x \mathcal{L}(x, y)$:

- if $\nabla_x \mathcal{L}(x, y)$ is positive then it means that the increase of x increases the loss function $\mathcal{L}$.
- if $\nabla_x \mathcal{L}(x, y)$ is negative then it means that the decrease of x decreases the loss function $\mathcal{L}$.

FGSM can be targeted or untargeted. For the targeted version, the adverse function ψ is expressed as following:

$$\begin{array}{cccc} \psi & : & \mathcal{X} \times \mathcal{Y} & \longrightarrow & \mathcal{X} \\ & & (x, y) & \longmapsto & -\varepsilon \, . \, \text{sign}(\nabla_x \mathcal{L}(x, y)) \end{array}$$

The adverse sample $x'$is is then generated as following:

$$x' = x - \varepsilon \, . \, \text{sign}(\nabla_x \mathcal{L}(x, y))$$

Regarding the untargeted version, the adverse function ρ is expressed as following:

$$\begin{array}{cccc} \rho & : & \mathcal{X} \times \mathcal{Y} & \longrightarrow & \mathcal{X} \\ & & (x, y) & \longmapsto & \varepsilon \, . \, \text{sign}(\nabla_x \mathcal{L}(x, y)) \end{array}$$

The adverse sample $x'$is is then generated as following:

$$x' = x + \varepsilon \, . \, \text{sign}(\nabla_x \mathcal{L}(x, y))$$

FGSM requires the computation of the loss function gradient, which makes it a simple method. On the other hand, the only hyper parameter of FGSM is ε that affect the class of x'.

2.2.2 Basic Iterative Method (BIM)

Kurabin et al. (Kurabin et al., 2017) proposed an extension of the FGSM attack. It consists on applying FGSM several times iteratively. At each iteration i, the adverse sample is generated by applying FGSM on the generated sample in the iteration $i-1$. The BIM attack is generated as following:

$$\begin{cases} x'_0 = x \\ x'_{i+1} = x'_i + \psi(x'_i, y) \end{cases}$$

where y represents, in the case of a targeted attack, the class of the adverse example and $y = C(x'_i)$ in the case of an untargeted attack. Moreover, ψ is the same function defined in the case of FGSM attack.

2.2.3 Projected Gradient Descent (PGD)

The PGD (Madry et al., 2017) attack is also an extension of the FGSM and similar to BIM. Indeed, it is also an iterative method which consists in applying FGSM several times. The major difference from BIM is that at each iteration, the generated attack is projected on the ball $\mathcal{B}(x, \varepsilon) = \{z \in \mathcal{X} \colon \|x - z\|_p \leq \varepsilon\}$. The adverse example x' is then constructed as following:

$$\begin{cases} x'_0 = x \\ x'_{i+1} = \Pi_\varepsilon \left(x'_i + \psi(x'_i, y)\right) \end{cases}$$

where Π_ε is the projection on the ball $B(x, \varepsilon)$ and ψ is the perturbation function as defined in FGSM.

2.2.4 Jacobian Saliency Map Attack (JSMA)

This attack JSMA differs from the previous ones, since Parpernot et al. (Papernot et al., 2015) did not rely on a gradient descent to generate an adverse example. The idea of authors is to disturb a minimal number of pixels according to a criterion.
JSMA is proposed initially for a targeted version. It consists in controlling the number of pixels of an input image x (or the number of components of an input vector) that should be modified in order to obtain an adverse image associated with a target class y. Iteratively, JSMA consists in modifying pixels until the target class is obtained.

The idea behind is to, on one hand, increase $F_y(x)$ the probability of the target class y and on the other hand, decrease the probabilities of the other classes, until obtaining : $y = \underset{j \in Y}{argmax} F_j(x)$.
To do this, authors introduced the Saliency Map matrix as following:

$$S(x, y)^+[i] = \begin{cases} 0 \;\; \text{si} \;\; \dfrac{\partial F_y(x)}{\partial x_i} < 0 \;\; \text{ou} \;\; \displaystyle\sum_{k \neq y} \dfrac{\partial F_k(x)}{\partial x_i} > 0 \\ \left(\dfrac{\partial F_y(x)}{\partial x_i}\right) \cdot \left| \displaystyle\sum_{k \neq y} \dfrac{\partial F_k(x)}{\partial x_i} \right| \quad \text{sinon} \end{cases}$$

The Saliency Map is used as criterion to select pixels that should be modified. In fact, the way that Saliency Map is computed, allows to reject pixels that will not increase the probability of the target class y or will not decrease the probabilities of the other classes; for these pixels, the criterion is set to 0.

2.2.5 DeepFool

DeepFool is a non-targeted attack proposed by Moosavi-Dezfooli et al. (Moosavi-Dezfooli et al., 2015). The main idea of DeepFool is to find the closest distance from the original input to the decision boundary. Authors assumed the used neural network is completely linear using hyperplanes separating each class from others. To overcome the nonlinearity in high dimension, they performed an iterative attack with a linear approximation. For an affine

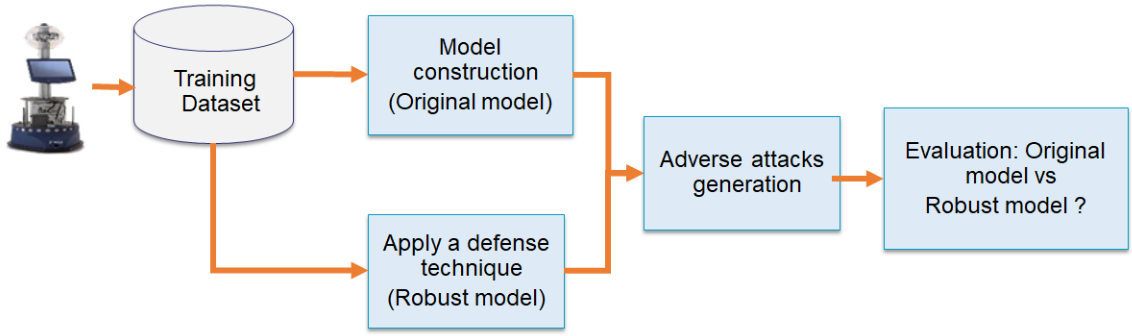


Figure 1: Proposed approach.

classifier $f(x) = wTx + b$, where w is the weight of the affine classifier and b is the bias, the minimal perturbation of an affine classifier is the distance to the separating affine hyperplane $\mathcal{F} = x : wTx + b = 0$,.

Given the example of a linear binary classifier, the robustness of the classifier f for an input x_0 is equal to the distance of x_0 to the hyperplane separating the two classes. In fact, the minimal perturbation to change the classifier's decision corresponds to the orthogonal projection of x_0 onto the hyperplane, given by: $\eta^*(x) = -\frac{f(x)}{\|w\|_2^2} * w$.

For a general differentiable classifier, DeepFool assumes that f is linear around x_i at each iteration. The minimal perturbation is expressed as following:

$$\begin{aligned} &\underset{\eta_i}{arg\,min} \quad \|\eta_i\|_2 \\ &\text{subject to} \quad f(x_i) + \nabla f(x_i)^T \eta_i = 0. \end{aligned}$$

This process runs until $f(x_i) \neq f(x)$, and the minimum perturbation is eventually approximated by the sum of η_i.

This technique can also be extended to the multiclass classifier by finding the closest hyperplanes. It can also be extended to a more general ℓ_p norm, $p \in [0, \infty)$. As mentioned in (Yuan et al., 2019), DeepFool provided less perturbation compared to FGSM and JSMA. Compared to JSMA, DeepFool also reduced the intensity of perturbation instead of the number of selected features (Yuan et al., 2019).

2.3 Neural Network Defences

There are several defence techniques proposed in the state of the art to improve neural network robustness face adversarial attacks. In this section, we detail the most popular defence techniques.

2.3.1 Adversarial Training

The adversarial training (Goodfellow et al., 2015a) consists in improving the robustness of the classifier $C(x)$ by integrating adversarial samples in the training set.

Given an attack ρ, a classifier C and the original training set (x_1, y_1),...,(x_n, y_n), the approach consists in generating the adversarial samples $(\rho(x_i), C(\rho(x_i)))$ for $i = 1, \ldots, n$. After applying the attack to all original training samples, the resulting augmented training set will have a size of $2 \times n$. The augmented data is then used to retrain the classifier $C(x)$. Mostly, adversarial training is used to hardness the classifier faces multiple-attacks (a set of m attacks $\rho_1, \ldots, \rho_m$. After applying the m attacks to all training set, the latter is augmented by $n * m$ samples.

It is worth mentioning that in most cases, adversarial samples are generated only for a subset from the training dataset, and then the training dataset is augmented only by a predefined rate. The data augmentation rate is a hyper parameter of the technique.

2.3.2 Gaussian Data Augmentation

Gaussian data augmentation (Zantedeschi et al., 2017) is a popular technique that has been proposed to improve the robustness of Neural Network faced adversarial attacks. It is a standard technique mostly used in computer visions tasks. Its usage is mostly intended for the augmentation of the training set. It consists in augmenting the original dataset with copies of the original samples to which Gaussian noise has been added. Notice that the labels y are not required, as the method does not apply any preprocessing to them. it is worth mentioning that this technique can be applied only by adding Gaussian noise to an existing sample without augmentation.

3 EXPERIMENTAL APPROACH

Figure 1 shows the flowchart of our approach. The input is a pre-trained model. The output is a robust model face adversarial attacks. Our approach consists basically of four stages:

- Construct an original decision-making model
- Generate adverse attacks allowing disruption of model decisions
- Apply a defence technique to improve model robustness
- Evaluate a decision-making model

3.1 Original Model Construction

The first step of our approach is to construct a decision model based on DNN. As architecture, our DNN composed 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. The decision model takes as input a vectors of 24 components and outputs a probability vector 4 components (the number of decisions in the dataset). Each layer, in the DNN architecture, contains a set of neurons where each one is connected to neurons of the previous layer. Each neuron is a simple processing element that responds to the weighted inputs it received from other neurons (Shrestha and Mahmood, 2019). The action of a neuron depends on its activation function, which is described as:

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

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.

3.2 Attacks Generation

After the construction of the decision model, we test the resilience of the model to adversarial examples. To demonstrate this, we generate our own adversarial samples from the robotic dataset. To generate adversarial samples, we used three techniques proposed in the state of the art. These techniques are: *i*) the Fast Gradient Sign Method (FGSM) , *ii*) the Basic Iteration Method (BIM), and *iii*) the Deep Fool attack. In our study, we assume that attacks are:

- **Evasion-based:** the attacks are injected during the prediction phase of the decision model.
- **White-box:** the attacker has a complete knowledge of the decision model.
- **Untargeted:** we do not target any specific prediction out-come, rather we seek to confuse the decision model to take a bad decision.

3.3 Robustness Model Construction

To improve resilience to adversaries, we test the impact of defence techniques to detect attacks. Whatever the defence strategy, it aims to enforce the security of machine learning based systems against adversarial attacks. In this study, we investigate the adversarial training based technique. Its principle consists in including adversarial examples in the training set, and then retrain the model using the augmented dataset. The adversarial training technique has several advantages:

- It is not data dependant; it can be applicable to any type of data outside images.
- It is easy to implement.
- It is effective when attacks during deployment are similar to ones in training.

3.4 Model Evaluation

To evaluate decision models, whether it was the original model or after adversarial training, performance metric is used. Performance is defined as the rate of correct decisions predicted by the neural network.

4 EXPERIMENTAL RESULTS

Our analyze of Deep Neural Network against adversarial attacks is done on a robot navigation dataset.

4.1 Dataset

To evaluate our experimental approach, a public Robotic dataset is used. It is a sensor dataset proposed in (Freire et al., 2009) for wall-following robot navigation. The dataset is a collection of 24 ultrasound sensors arranged around a mobile robot «SCITOS G5» during its navigation inside a room. The possible decisions of the robot are: 1) *Move-Forward*, 2) *Slight-Right-Turn*, 3) *Slight-Left-Turn* and 4) *Sharp-Right-Turn*. The dataset is composed of 5456 samples: 70% of the available data is used for training and the remaining 30% for evaluation. Notice that the training stage is not considered in this work. Our analysis takes as input a pre-trained model whose vulnerability to adversarial attacks we investigate.

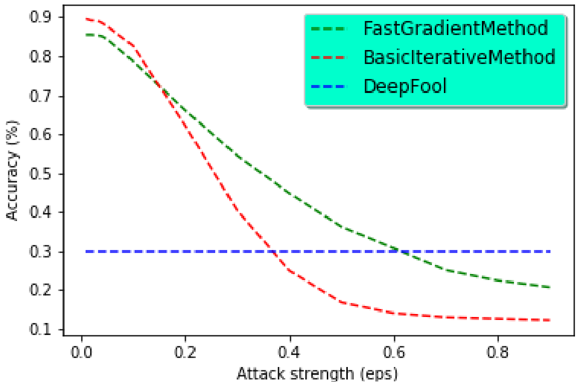


Figure 2: Original model performance according to attack's strength.

4.2 Evaluation Protocol

In the rest of the paper, the Original Model (OM) is defined as the pre-trained decision model without any defence technique; however the Robust Model (RM) is defined as the new model after applying a defence technique (adversarial training for example) and re-training the decision model.

In the evaluation step, to evaluate models against adversarial attacks, three attacks are investigated: Fast Gradient Sign Method, Basic Iterative Method and DeepFool. On the other hand, to improve robustness, two defence techniques are studied: Adversarial training and Gaussian Data Augmentation. As evaluation metrics, the accuracy metric is used. In fact, given a N test samples $\{s_i, \forall i \in [1,N]\}$, each sample is associated with a ground truth label GT_i and a predicted label $Pred_i$. The accuracy is defined as the fraction of samples that verify $(GT_i = Pred_i)$.

4.3 Attacks Evaluation

The evaluation of the original model is performed by varying the attack strength from 0 to 1. Figure 2 presents the comparison of the model's accuracy against three attacks: FGSM, BIM and DeepFool. In Fig.2, the Y-axis represents the accuracy, and the X-axis portrays the strength of the attack.

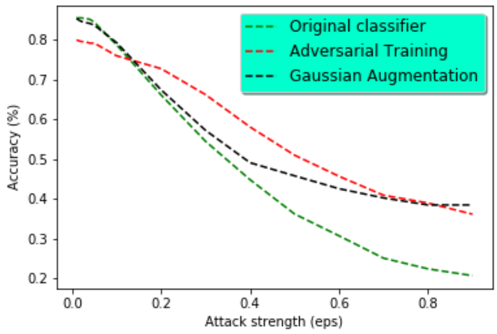
4.4 Defence Evaluation

After the evaluation of the original model against adversarial attacks, two defence techniques are investigated to improve its accuracy: 1) Gaussian Augmentation and 2) Adversarial Training. For both techniques, an augmentation rate of 100% is used. Moreover, for the Gaussian Augmentation technique, a Gaussian distribution with variance equal to 1 is used. Figure 3 depicts the performance of the original model and the robust model. Each sub-figure shows the impact of defence techniques against one from the three investigated attacks. For each sub-figure, the Y-axis shows the accuracy, and the X-axis represents the strength of the attack.

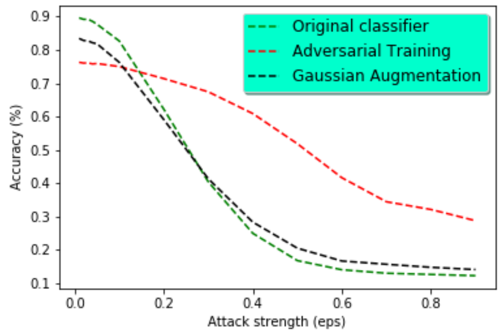
4.5 Discussion

Several observations could be drawn from the obtained results. The first observation concerns the result of the Original Model against attacks. The common remark for all attacks is that the accuracy decreases with the increase of attack strength. For FGSM and BIM, the behavior is similar. Indeed, for a small attack strength ($eps < 0.05$), the model maintains its overall accuracy. However, it loses quickly its performance for a moderate strength attack ($0.1 < eps < 0.6$). Taken the example of FGSM, the accuracy drops from 78.74% ($eps = 0.1$) to 30.72% ($eps = 0.6$). Then, when the attack strength becomes high ($eps > 0.7$), the accuracy stabilizes about 22%. In the case of DeepFool attack, the decision model has a different behavior: the accuracy drops to 30.05% even for a small attack strength ($eps = 0.01$) and then it remains stable regardless of the attack strength. DeepFool is therefore the most efficient attack capable of attacking the model and dropping its performance. Our first observation leads us to conclude that our decision model accepts an ultrasound sensor perturbation about 5% (i.e. $eps = 0.5$) without losing its initial accuracy.

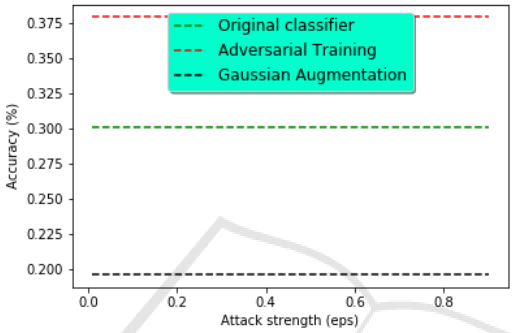
The second observation concerns the impact of defence techniques on the model robustness against adversarial attacks. The expected result is that the model accuracy against attacks is improved by applying defence techniques. However, this expectation is not always guaranteed and the model behaves in different ways depending on the attack type and the defence technique. Regarding FGSM and BIM, Fig.3a and Fig.3b shows that defence techniques improve model robustness. Indeed, this improvement is significant for a moderate attack strength (eps). For an $eps = 0.3$, the adversarial training improved robustness by 20% against BIM and 30% against FGSM. On the other hand, the accuracy of the model is not affected (or is decreased) against attacks of small strength ($eps < 0.1$). Compared the two defence techniques, the contribution of adversarial training technique is more significant than Gaussian augmentation in most cases. Indeed, for an $eps = 0.3$, adversarial training improves accuracy by 30%, while the Gaussian augmentation has practically no impact on the model, in the case of BIM. However, in the case, of



(a) FGSM attack performance



(b) BIM attack performance



(c) DeepFool attack performance

Figure 3: Original model and defence techniques performances.

FGSM, both defence techniques improve significantly accuracy starting from $eps = 0.5$.

The behavior of DeepFool is completely different from FSGM and BIM. Whatever the defence technique, the model accuracy does not depend on the attack strength. Moreover, the accuracy is improved by 8% using adversarial training while it drops by 10% applying a Gaussian augmentation.

Our main conclusion is that defence techniques are important to improve the robustness of the decision model against adversarial attacks. On the other hand, the effectiveness of these approaches depends strongly on the strength of the attack. In a practical case, having a decision model, the expert has to set the strength of the attack against which we would like our model to be effective.

5 CONCLUSION AND PERSPECTIVES

In this paper, we examined the robustness of decision model against adversarial attacks. In our studied use case, the decision model is based on Deep Neural Network and allows the navigation of a robot in a smart room. In this paper, we proposed an experimental pipeline to investigate the behaviour of our decision model against adversarial attacks of neural network. Moreover, we investigated the impact of defence techniques to improve model robustness against attacks. In the experiment stage, our study is achieved on a public robotic dataset. Our results show that model maintains its overall accuracy for a small attack strength and loses quickly its performance for a moderate strength attack. Regarding defence techniques, its contribution depends on attack strength. It is more effective for attacks of moderate strength than small strength.

In future work, we plan to study the behavior of our decision model against more complex attacks. The goal is to imagine any possible attacks that may put the decision model in difficulty. Moreover, we plan to investigate more defence techniques. The selected defence technique should be effective against the most likely attacks.

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