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Safety mechanisms for vision-based object localization for robot grasping

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Preface

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Acronyms

AI artificial intelligence. 2, 3, 5

CNN convolutional neural network. 5, 6

CV computer vision. 2

DNN deep neural network. 5, 6

MC Monte Carlo. 9

NN neural network. 7, 8, 9

Chapter 1

Introduction

1.1 Positioning

We are living in a world where automation is adopted at a rapidly increasing pace. Luggage gets sorted and autonomously transported across an airport, autonomous vacuum cleaners are being used daily, medicines are being produced with extreme cleanliness, etc. This also applies to robotics, where robots are slowly becoming more apparent in factory's and warehouses, improving efficiency, quality, and safety.

These robots need systems to operate properly, now more then ever, these systems are often based on artificial intelligence (AI). More precisely, computer vision (CV), a subdomain of AI which specialises in enabling computers to interpret and make decisions based on visual data via camera's, can be used to detect and localize objects, making it possible for the robot to process them. But also a more general AI could be used to plan the robot's actions and control its actuators to perform the desired tasks. Furthermore, some systems are trained to monitor certain processes, detect defects to finished products, or even predict maintenance needs. Its use thus does not only bring more efficiency, but also some gains in quality and enables for much more complex tasks for a robot to excecute.

These real world scenarios require the AI systems to be robust and reliable. However, AI systems often struggle when faced with situations that differ from their training data, leading to unreliable predictions. Systems should therefore be able to express their uncertainty about their predictions, enabling safety mechanisms to prevent the robot from taking actions based on uncertain predictions. Uncertainty-aware AI models are able to do this, by not only outputting a prediction, but also an uncertainty score about this prediction.

1.2 Problem statement

While an AI system has many advantages in a factory setting, it also introduces new problems that need taken care of. The good but mostly bad thing, in such a setting, with such systems

is that it will always output something, even when it is not sure about its output. Meaning that when it were to be unsure about what it should output, it will not inform the user about this and continue operating as normal. This could be good, because it will sometimes be able to make the right decision even when unsure, increasing efficiency compared to a human worker which would need to inspect and learn the new situation. But it will most probably be bad, since it can do things wrong, which could lead to defects to the products, damage to the robot or its environment, or even worse, harm to humans working nearby.

One example of why a system could be unsure about its output is when it needs to infer something from data that is not seen during training. Most training data is gathered in controlled environments, where all conditions are optimal. However, when used in real-world scenarios with conditions different from the training environment, like different lighting conditions, some dust on the camera lens causing some distortion, someone turning the lights off, etc. the system could become a lot worese at its task. Other unexpected events, like a human operator placing the wrong object for the robot to pick up or a sudden movement of an already placed object, can also throw of the AI system.

1.3 Objectives

This thesis aims to adress these issues by developing and evaluating uncertainty-aware object localization models for a robot arm capable of reliably indicating when their predictions may be unreliable, particularly in challenging real-world conditions. By making the models uncertainty-aware, safety mechanisms that prevent the robot from taking actions based on uncertain predictions can be implemented, thereby reducing the risk of errors and accidents.

The primary research question is: How can we develop uncertainty-aware object localization models for a robot arm that can effectively identify and communicate uncertainty in their predictions, particularly in challenging real-world conditions?

This overarching question is further explored through the following sub-questions:

- What uncertainty aware (object localization) models already exist, and how do they perform in real-world conditions?
- How can we effectively quantify and communicate uncertainty in object localization predictions to ensure safe robot operation?

To address these questions, the following objectives are set:

- Conduct a comprehensive literature review on existing uncertainty-aware models with an emphesis on object localization.
- Create a dataset that simulates real-world conditions, including various challenges such as occlusions, lighting variations, and unexpected object placements.

- Develop, implement and evaluate uncertainty-aware object localization models for our use case.
- Design and implement safety mechanisms that utilize the uncertainty information to prevent the robot from taking actions based on uncertain predictions.

Chapter 2

Literature study

In this chapter, we discuss existing research relevant to uncertainty in AI models and how it can be mapped to real-world scenarios. First, we will elaborate on what uncertainty is and different ways it can sneak in AI models. Next, we will discuss how this uncertainty can be quantified. After that, we will dive into different existing methods to make AI models uncertainty-aware and discuss how their ideas can be applied to object detection. Following that, we will look into ways data is gathered to train and evaluate uncertainty-aware models. To close, we will briefly discuss safety mechanisms that can be implemented to prevent a robot from taking actions based on uncertain predictions.

2.1 Uncertainty in AI

There are lots of complex systems that need to be modeled and understood. These systems can be modelled using AI models as they offer a way can grasp the complexity of these systems and operate them in the most efficient / safe way possible. However, these are, just as humans, not perfect and can make mistakes. When using normal (non uncertainty-aware) AI models, these mistakes are not communicated with the user. For example, when a convolutional neural network (CNN) is used to detect an object on a conveyor belt, it will output the class of the object it thinks is on the conveyor belt, without any indication of how certain it is about this prediction. So if the object is only partially visible, the lighting is bad, or the object is very similar to another object, the model might be very uncertain about its prediction, but it will still output a class as if it is certain about it.

All possible uncertainties regarding deep neural networks (DNNs) can be captured in two groups: aleatoric uncertainty and epistemic uncertainty [1] [2].

2.1.1 Aleatoric uncertainty

Aleatoric uncertainty is the uncertainty that comes from noise in the data. Its nature is irreducible, meaning that no matter how much data we gather, this uncertainty will always

be present in the data.

Measurement errors When gathering data, mistakes can be made when measuring. These can come from limitations of the measurement devices or incorrect / inprecise labeling of the data. An important note to make is that these mistakes can be a way to regulize a network, if it stays subtle.

Let's take a regression problem as an example, where a model needs to predict a pair of x and y values for the center of an object. It could be that the camera used for the capturing of data has a low resolution. This could lead to an object, which needed to be detected, getting lost because of the lack of pixels in the image. Even more, it could lead to inaccurate annotation of the center of the object, as its center is labeled as (x_1, y_1), when it is in fact $(x_1 + \delta, y_1 + \epsilon)$ (δ and ϵ being small errors in the measurement).

2.1.2 Epistemic uncertainty

Epistemic uncertainty is the uncertainty that comes from noise in the model or its training process. This can have many different causes like the architecture of the model, the training procedure, etc. Its nature is reducible, meaning that by gathering more data, using a better model architecture, etc., this uncertainty can be reduced.

Variability in real world situations The real world changes constantly, resulting in different settings where objects can behave / look differently. All situations should be covered sufficiently by the training set. If not, the network trained on the data can not garentee a good output for every new real world situation. A distribition shift occurs when real world situations differ from the training set. These shifts are very hard for a DNN to grasp, causing its performence to change significantly.

Continueing the example of of the regression problem where a model needs to predict the center of an object. When a DNN is trained on a dataset which covers the objects with great lighting, no occlusions, no other objects covering the view, etc., it will be very good at predicting the center of the object in that specific setting. However, it might happen that, when using the model, the conditions change (e.g., lighting changes, new objects appear, etc.). Because the dataset does not cover the new conditions, the trained DNN fails to addapt to these new conditions, causing its performence to drop.

Architecture specification errors The structure of a network differs from model to model, with each model having its advantages and disadvantages on the performence, and thus the uncertainty of the predictions.

Suppose a factory requires the previously discussed regression model to best fit their need. There are a lot of model architectures available, a fully connected network, a CNN, a U-net,

etc. Each model has its own number of layers, connections, activation functions, etc. All these networks will have its their own capabilities and thus uncertainty.

Training procedure errors During the training of a model, there are much decisions that need to be made. The learning rate, the number of epochs, the way of using the data, the optimizer used, the weight initialization, etc. Each combination of parameters will result in a different model with its own errors and uncertainty.

The dataset for regression of an object center can be split in different batch sizes, ordered in different ways, etc. The chosen model can be trained with these different ways of handeling data, using different parameters to optimize the chosen model. Again leading to different models who are better in sertain things and worse in other.

Errors by unknown data When the model is fully trained, it can happen that, during inference, the model encounters a situation it has not seen before. This situation was not expected in the original scope of the problem, but the model will need to deal with it, causing uncertainty.

In the factory example, the model is trained for a sertain enviorment and objective: detecting the center of objects in a factory setting. If an object that was not expected to be in the enviorment, a bird for example, enters the camera's viewpoint, it can cause the model to be uncertain on what to do, since it has never seen a bird before. This is not because the enviorment was insufficiently specified, but because of the bird being there unexpectedly.

2.2 Quantifying uncertainty

The uncertainty of a given prediction of a model, also called predictive uncertainty, is depended on two things: the uncertainty of the data (data uncertainty) and the uncertainty of the model (model uncertainty) [1].

2.3 Uncertainty-aware AI models

2.3.1 Bayesian Neural Networks

2.3.2 Deep Ensemble Methods

A deep ensemble method [3] rests on the idea that a combination of (simpler) models can be trained and perform better then a single (complex) model. Not only that, but it also outputs a great uncertainty score about its predictions. A typical ensemble method uses multiple decision trees as their models, a deep ensemble method uses, as the name suggests, uses deep neural networks (NNs) as its models. Creating a deep ensemble method contains 3 main steps:

- A proper scoring rule, which is used as a way to train the models in the ensemble.
- Adversarial training, which is used to make the models in the ensemble more robust.
- The actual ensembling, which combines the outputs of the different models to create a final output and uncertainty score.

The scoring rule A scoring rule is a way to measure the quality of a model's probabilistic predictions. It should encourage the model to generate outputs which are accurate and are capable of telling when it is uncertain about its output. To make this a bit more concrete, in a setting where a model needs to predict if there is a disk in frame or not, a great scoring rule should punish the model hard if it predicts a disk to be in frame with a high probability, when in fact the groud truth states there is no disk in frame. The model should be encouraged to predict a low probability for the disk being in frame, if it is not sure if there is a disk in frame. It should result in a model which is rightfully confident about its predictions when it is sertain about its predictions, while also being able to express its uncertainty when it is not confident in its predictions.

Fortunately, for classification tasks, the loss functions, which are commonly used to train NNs, such as the softmax cross entropy loss, are proper scoring rules.

Adversarial training Adversarial training is a technique which is used to make NNs more robust against small changes who can drastically change the output of the model. Usually these changes are so small a human can not observe the difference, but the model is fooled to think it is something completely different. For example, when classifying images of disks and cubes, when an image is classified as a disk with a high probability, it could be that with a very small change in pixel value, the network all of a sudden thinks it is a cube with high confidence. This is something we want to avoid at all cost, since this big swing eliminates any notion of uncertainty the model could have had.

Adverserial training tries to fix these big swings by generating new training samples which are very close to some original data (for example a few pixels tweaked) and classified as some other output-class. Using the example, this means it gets an image of a disk, tweaks a few pixels so the model thinks it is a cube, and adds this new image to the training set with the correct label (disk). By doing this, the model learns to be more robust against these small changes, and the big swings in output are reduced.

Ensembling The final step in creating a deep ensemble method is the actual ensembling. The paper [3] suggests to create an ensemble of deep NNs to predict an output with an uncertainty score. Each model in the ensemble should be trained independently, however this does not mean they should be different model architectures. In fact, when randomly initializing the NN parameters, along with shuffeling the training data, the networks where different enough to obtain good results. This makes that no methods like bagging or boosting

are needed to create diversity in the ensemble. Which means all the training data can be used for the training of the models in the ensemble, which is benefitial for the deep NNs which need more data to train properly.

To get the final output and uncertainty score, the outputs of the different models are combined. Each model in the ensemble outputs a probability distribution over the different classes. These probability distributions are then averaged to get the final output distribution. The label with the highest probability in this final distribution is taken as the final output with the uncertainty belonging to it. Lets continue the example of classifying images of disks and cubes to make this more concrete. Assuming we have an ensemble of 3 models, and they output the following probability distributions for a given input image:

- Model 1: [0.7 (disk), 0.3 (cube)]
- Model 2: [0.4 (disk), 0.6 (cube)]
- Model 3: [0.9 (disk), 0.1 (cube)]

Averaging these distributions results in the final output distribution: [0.67 (disk), 0.33 (cube)]. The final output is thus 'disk' with an uncertainty score of 0.67.

2.3.3 Monte Carlo dropout

Dropout is a regularization technique commonly used in the training of NNs to prevent overfitting. The idea is to randomly drop some neurons in the network during the training phase. This forces the model to use all the available neurons and not rely too much on a small subset of them. When the model is fully trained and ready for inference, dropout is usually turned off, using all the neurons to make predictions.

Monte Carlo (MC) dropout [4] expands on this idea by keeping dropout turned on during inference. Every time a set of neurons is dropped, the network changes a bit, which can result in different outputs for the same input. Each alteration of the network can be seen as a different model in an ensemble. By letting the model make multiple forward passes with dropout turned on, we can gather a set of different outputs for the same input with their own predicted probability distributions. These outputs can then be combined in a similar way as the deep ensemble method in Section 2.3.2 to get a final output and uncertainty score.

Reusing the example of classifying images of disks and cubes, assuming we make 3 forward passes with MC dropout, we could get the following outputs:

- Forward pass 1: [0.8 (disk), 0.2 (cube)]
- Forward pass 2: [0.5 (disk), 0.5 (cube)]
- Forward pass 3: [0.6 (disk), 0.4 (cube)]

Averaging these distributions results in the final output distribution: [0.63 (disk), 0.37 (cube)]. The final output is thus 'disk' with an uncertainty score of 0.63.

2.4 Datasets for uncertainty-aware models

2.5 Safety mechanisms for uncertain predictions

Chapter 3

Dataset

In this chapter, we will discuss the dataset created for training and evaluating the uncertainty-aware object localization models. We will outline the requirements for the dataset based on the problem statement and objectives defined in Chapter 1. Furthermore, we will describe the data collection process, including the setup and annotation used.

Chapter 4

Models for uncertainty aware object detection

In this chapter, we will discuss the different uncertainty-aware models discussed in Chapter 2 and compare their adaptability to a real-world scenario.

Chapter 5

Safety mechanisms for uncertain predictions

In this chapter, we will explore various safety mechanisms that can be implemented to turn the outputs of an uncertainty-aware object detection model into safe and reliable actions for a robot arm.

Chapter 6

Conclusion

6.1 Future work

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Chapter 7

GenAI code of conduct for students

Generative AI (GenAI) assistance tools can be used to generate text, image, code, video, music, or combinations of these. It includes typical tools like (but this list is not limited to): ChatGPT, Google Gemini, MS Copilot, Midjourney, Claude.ai, Perplexity.ai, Dall-E, etc.

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☐ Literature search

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☐ Generating programming code

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Code of Conduct for Different Uses

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- The output may not be entirely correct and is limited due to the databases it uses. Knowledge evolves and may change over time, and it may be that the database of the GenAI tool is not up to date.

Literature Search

This use is comparable to a Google Scholar search. Be careful:

- Be aware that the output is restricted to the database it is built on. After this initial search, look for scientific sources and conduct your own analysis.
- GenAI tools (like ChatGPT) may output no or wrong references. As a student, you are responsible for further checking and verifying the accuracy of references.

Short-form Input Assistance

This use is similar to Google Docs powered by generative language models.

Generating Programming Code

The use of GenAI for coding should be explicitly allowed by the teacher. If used for coding, correctly mention the use of GenAI assistance and cite it.

Generating New Research Ideas

Further verify whether the idea is novel or not. It is likely that it is related to existing work, which should be referenced.

Generating Blocks of Text

Inserting blocks of text without quotes and a reference to GenAI assistance in your report or thesis is not allowed. Be careful:

- When you literally copy elements from a conversation with a GenAI tool, quote them between quotation marks and refer to them according to the specified reference style.
- Describe the use of the GenAI tool (tool name, version, date, etc.) in the method section and optionally add the full conversation as an attachment.

Other

Contact the professor of the course or the promoter of the thesis. Inform also the program director. Motivate how you comply with Article 84 of the exam regulations. Explain the use and added value of ChatGPT or another AI tool.

Further Important Guidelines and Remarks

- GenAI assistance cannot be used related to data or subjects under Non-Disclosure Agreement.
- GenAI assistance cannot be used related to sensitive or personal data due to privacy issues.
- Take a scientific and critical attitude when interacting with GenAI assistance and interpreting its output.
- As a student, you are responsible for complying with Article 84 of the exam regulations: your report or thesis should reflect your own knowledge, understanding, and skills.

Exam Regulations Article 84

"Every conduct individual students display with which they (partially) inhibit or attempt to inhibit a correct judgement of their own knowledge, understanding and/or skills or those of other students, is considered an irregularity which may result in a suitable penalty. A special type of irregularity is plagiarism, i.e., copying the work (ideas, texts, structures, designs, images, plans, codes, ...) of others or prior personal work in an exact or slightly modified way without adequately acknowledging the sources."

Additional Reading

More information about being transparent on the use of GenAI assistance and about citing and referencing GenAI can be found on the student website.

A Few Final Words

If you are uncertain whether or not you should declare your use of AI tools, discuss the matter with your teacher or promoter. It is safer to declare AI use when it is not needed than to withhold that declaration when it is required.

Finally, remember that advanced AI tools are new and that they can do things they could not do until recently. It is important to follow up on the most recent developments in AI technologies and communicate openly with your teachers, assistants, supervisors, and peers.