Introduction to Intelligent Vehicles
Final Report

Safe distance detect system by camera

and

ethical dilemma in fail situation

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contests

1. Introduction

Reason for select this problem:

The problem of car accidents caused by distracted and fatigued drivers is often seen in the news, so we want to implement an assistance system that can warn the driver when the vehicle is too close to other objects, to avoid car accidents the occurrence of the accident.

Problem defined :

Goal : Use single camera as sensor to warn when getting too close

Input : The picture taken by the camera

Output : The type of object and its distance which in the picture

We will introduce:

Theory :

What is needed for this implement? How to get data?

What is the estimated deviation rate of this system?

Implement :

Is goal be reached?

Discussion :

Does there have any disadvantage? Is there any room for improvement?

Why do we choose a camera to be the sensor?

2. Theory

What is needed for this implement? How to get data?

If we want to know what this implementation needs, we can first see from the distance formula used this time :

$$\boxed{\frac{\text{focal length} * (\text{real[height or width]})}{\text{pixel[height or width]}}}$$

As the formula, we need to get 3 data, which are:

1. Focal length
2. Real [height or width] of the object :
3. Pixel [height or width] of the object :

(In the following, we will use height as a parameter. reason: taking a car (Fig. 2.1) as an example, it can be found that the difference between the length and width of the front and the side of the car is quite large(about 2.695m), and the maximum difference in height can be found to be smaller than the former in the subsequent calculation. Thus using height as the distance calculate parameter.)

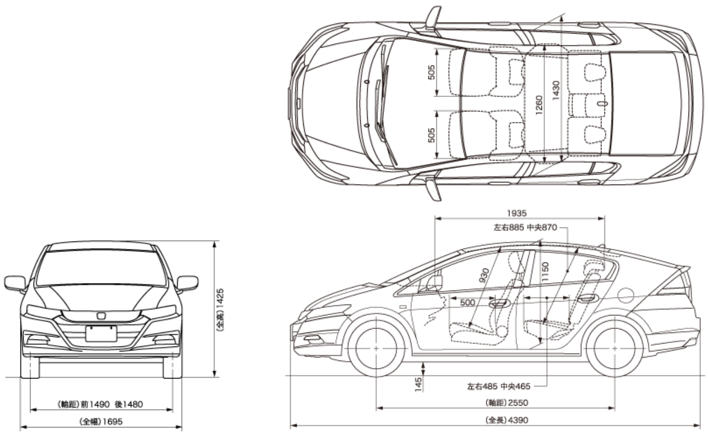

Fig. 2.1

We can know in advance the focal length, but how can we know the real height of the object? Before we start to think about this problem, there is another problem we should deal with at first, that is : what is the object that we want to know the height of? This is a simple question for humans, but what about the computer? Computer not like a human which can detect the object just by “seeing”, thus if we want to know how to get the height of the object, first we should know is how can we let a computer can “see” the object.

At this time, we chose to use yolov5 to let the computer can see the object,

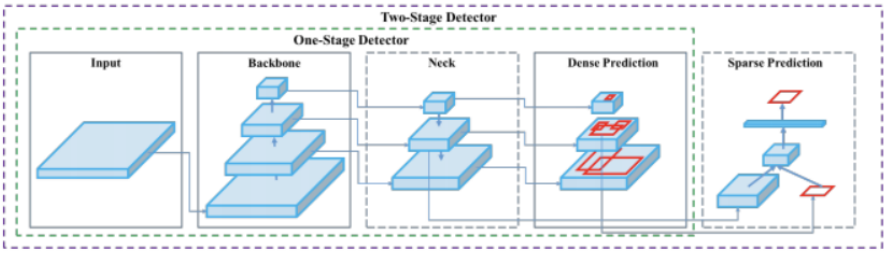

Fig. 2.2

The image (Fig. 2.2) above shows the network of yolov5, there consist of four main parts :

Input : The image which we want to detect.

Backbone : A convolutional neural network that aggregates and forms image features at different granularities.

Neck : A series of layers to mix and combine image features to pass them forward to prediction.

Head : Consists of tow prediction part consumes features from the neck and takes box and class prediction steps.

Through these main parts, as shown in the figure below, yolov5 can extract and classify the objects in the image. We can see in (Fig. 2.4) any object be detected has one string and one number in the upper of the box, string means the type of object, and the number means the credibility of detect type correct.

Fig. 2.3

Fig. 2.4

We can detect objects which we want to detect now, turn back to the problem of how can we know the real height of the object, we want to get the precise height of the object, a good method is to find a reference, which we already know its size and always around the object, take the car as an example, the license plan seems to be a good reference, it has the same size and same position on the all different types of car, but there has a big problem is what if the car turns to the side? can we still see the license plan? the answer is no, thus we need to find another reference, but unfortunately, we can not find a reference that can be seen anywhere and have the same size and is in the same position.

Then we consider a B-plan, it is just "guess" the height of the object, this plan seems not a good plan at all, but what if we can guess more accurately? by using average formula (Fig. 2.6) to calculate average data, we can get an average height of different types cars, then use deviation rate formula (Fig. 2.6) to determine its deviation rate, for example (Fig. 2.5), we chose 10 different types of car's height to calculate as table shows below :

(The Height-low and Height-high means the same type of the car but in the different countries, it will cause the car to have different height so we count separately)

Cars Name	Height-low	Height-high	two plus	average	low bound deviation	Higher bound deviation	average deviation	low deviation rate	high deviation rate	deviation rate
Urban Cars	1.5	1.7	3.2	1.6	0.06	0.14	0.1	0.038461538	0.08974359	0.064102564
Small Size Cars	1.5	1.8	3.3	1.65	0.06	0.24	0.15	0.038461538	0.153846154	0.096153846
Compact Cars	1.4	1.5	2.9	1.45	0.16	0.06	0.11	0.102564103	0.038461538	0.070512821
Porsche Cars	1.3	1.5	2.8	1.4	0.26	0.06	0.16	0.166666667	0.038461538	0.102564103
Sports Cars	1.2	1.3	2.5	1.25	0.36	0.26	0.31	0.230769231	0.166666667	0.198717949
Multipurpose Vehicles	1.5	1.8	3.3	1.65	0.06	0.24	0.15	0.038461538	0.153846154	0.096153846
Small SUVs	1.5	1.7	3.2	1.6	0.06	0.14	0.1	0.038461538	0.08974359	0.064102564
Compact Crossovers	1.5	1.7	3.2	1.6	0.06	0.14	0.1	0.038461538	0.08974359	0.064102564
Big Sports Utility Vehicle	1.5	1.7	3.2	1.6	0.06	0.14	0.1	0.038461538	0.08974359	0.064102564
Pickup Trucks	1.7	1.9	3.6	1.8	0.14	0.34	0.24	0.08974359	0.217948718	0.153846154
Total	14.6	16.6	31.2	15.6	1.28	1.76	1.52	0.820512821	1.128205128	0.974358974
Avg	1.46	1.66	3.12	1.56	0.128	0.176	0.152	0.082051282	0.112820513	0.097435897

Fig. 2.5

L_i : lower bound of same type
H_i : upper bound of same type
n : sample number
Avg : Average height

Average formula : $\frac{\sum_{i=1}^{n}(L_i + H_i)}{2n}$

Deviation rate formula : $\frac{\sum_{i=1}^{n}(|Avg - L_i| + |Avg - H_i|)}{2n * Avg}$

Fig. 2.6

From the above table, if there are only these 10 kinds of cars on the road, and the average height of these cars is 1.56m, we will get an average deviation of about ±9.7% (±0.15m), with a maximum of -21.8% (-0.34m), +23.0%(+0.36m) boundary deviation, maximum deviation is not optimistic, but considering the feasibility and the average deviation seems acceptable, we still choose this method, then use the same estimation method for other objects, there has a point that we take bus and car be two different types of the object because that the bus and the cars have a big difference in height if we take they being the same type will cause higher deviation rate, so we separate measurements this time.

Now we got the real height, the last parameter we need to get is pixel height, but it already got when yolov5 detect the objects (Fig. 2.7), it is the height of the box, so we got all parameters for the distance formula shown in the following table (Fig. 2.8), we can start to test the system now.

Fig. 2.7

- Danger distance : 5m
- Focal length : 760
- Average height: car(1.56 m), people(1.665m), bus(2.875m)
- Pixel height : YOLOv5 detect
- Deviation rate: car(±9.74%), people(±3.90%), bus(±4.34%)

Fig. 2.8

3. Implement

The results of our implementation are shown in the figure below, the distance will display on second number, after credibility, the unit is meters.

The implementation site is: No. 79, Section 1, Heping E Rd, Da'an District, Taipei City, 106.

Fig. 3.1

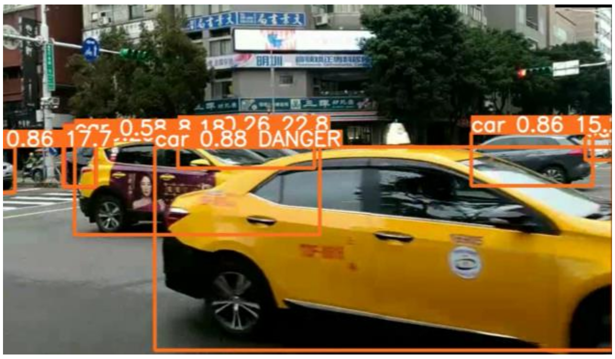

Fig. 3.2

It can be seen that the deviation rate is actually lower than the average deviation, the reason is that the vehicle models on the road will have high repetition in a road section.

According to this experiment (Fig. 3.1 & Fig. 3.2), the result distances & warn when getting too close all work as expected and are within the estimated deviation rate, can we say that this implementation has achieved its goals? considering that most of the road sections except specific road sections have similar conditions, the results of this experiment should also be applied to most road sections, thus we can say that the goal has been achieved.

Fig. 3.3

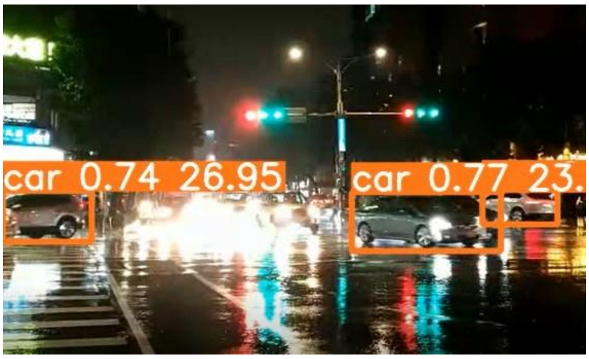

Fig. 3.4

But when turns to the night, our detection (Fig. 3.3 & Fig. 3.4) seems not good as the day, what is the difference between these two situation? how can we improve?

4. Discussion

If we want to improve, the first step is to know what are disadvantages of this system are,

1. Although this distance detection is feasible for most of the road sections, we must also consider specific road sections too.
2. Even in the designated road section, our distance detects still have the deviation.
3. If we got bad weather like fog (Fig. 4.1) or in the night, we can not even detect the object.
4. If object become too close (Fig. 4.2), because pixel height will be reduced, real distance will be closer than our calculate.

Fig. 4.1

Fig. 4.2

The above four points are the disadvantages of this system, and these problems are also the problems that everyone will encounter when using cameras for distance detection, so why we do not use other sensors like lidar doing distance detection? there have three reasons:

1. In 2019, NVIDIA proposed a solution by using deep learning to replace traditional distance measurement formulas for distance detection (Fig. 4.3), although it does not release actual measurement data, I think the above four points have been improved, so those disadvantages is can be solved.
2. Cameras have the advantage of being high-information. For example (Fig. 4.4), in the picture below, in addition to pedestrians, objects such as traffic lights and bicycles can also be identified. This advantage can increase its scope of use, like in the subsequent trolley problem, have an is idea is mentioned that to kill animals instead of humans. At this case, you can use the camera to what object type is and make corresponding choices.
3. Other sensors such as lidar, which is not everyone has, but everyone has a phone that can take a picture, so the camera sensor also has the advantage of high versatility, for example, this system can be used directly on the phone, and it can be used only need to change the danger warning to a prompt tone.

Based on the above three reasons, I think that using the camera as a sensor is a good option.

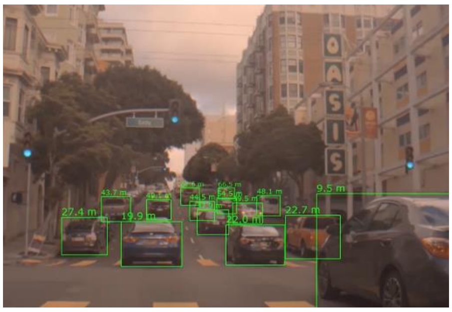

Fig. 4.3

Fig. 4.4

5. Trolley Problem

i. Background

The self-driving car will be the main transportation in the coming future. Maybe 30 years later, there will be thousands of self-driving cars riding on Roosevelt Rd. Then here comes a problem, what if a mischievous children run in the middle of the road, and the oncoming self-driving car can't brake successfully. This situation lets the self-driving car only can make two choices, one is to collide on the wall to save the naughty boy, or do nothing but the children might be injured. This is the standard trolley problem, and now we will discuss how self-driving cars solve this kind of problem.

ii. Introduction

The **trolley problem** is a series of thought experiments in ethics and psychology, involving stylized ethical dilemmas of whether to sacrifice one person to save a larger number. The series usually begins with a scenario in which a runaway tram or trolley is on course to collide with and kill several people down the track, but a driver or bystander can intervene and divert the vehicle to kill just one person on a different track. These thought experiments discuss that people should or should not sacrifice fewer people to save more people. Then other variations of the runaway vehicle, and analogous life-and-death dilemmas are posed, each containing the option to either do nothing, in which case several people will be killed, or intervene and sacrifice one initially "safe" person to save them.

iii. Reaction vs. Decision

There are many differences between reaction and decision. When people face an emergency, they only have less time to decide what they can do. Unfortunately, people do not have enough time to consider the result and determine their actions, so they only depend on their intuition. Most of the time, people can not choose the best solution, and we call it reaction. Otherwise, if people can have enough time to consider the result, determine their actions and choose the best solution, we call it decision.

The main point is that in a car accident, reactions and decisions will take different responsibilities. It is true that a human driver would be acting unlawfully if he killed a person in an emergency to save the lives of one or more other persons, but he would not necessarily be acting culpably. However, if the self-driving car can calculate the best result in a limited time but still injure or kill people, then the driver and the self-driving car company might take responsibility, so how does self-driving car decide what to do when human life is at an inevitable risk will be a serious issue.

6. People Decisions

i. The Moral Machine Experiment

Moral Machine is an online platform, developed by Iyad Rahwan's Scalable Cooperation group at the Massachusetts Institute of Technology, that generates moral dilemmas and collects information on the decisions that people make between two destructive outcomes. The platform is the idea of Iyad Rahwan and social psychologists Azim Shariff and Jean-François Bonnefon, who conceived the idea ahead of the publication of their article about the ethics of self-driving cars. The key contributors to building the platform were MIT Media Lab graduate students Edmond Awad and Sohan Dsouza.

The presented scenarios are often variations of the trolley problem, and the information collected would be used for further research regarding the decisions that machine intelligence must make in the future. For example, as artificial intelligence plays an increasingly significant role in autonomous driving technology, research projects like Moral Machine help to find solutions for challenging life-and-death decisions that will face self-driving vehicles.

Analysis of the data collected through Moral Machine showed broad differences in relative preferences among different countries and correlations between these preferences and various national metrics.

ii. Methods

MIT Media Lab deployed the Moral Machine, an online experimental platform designed to explore the moral dilemmas faced by autonomous vehicles. This platform gathered 40 million decisions in ten languages from millions of people in 233 countries and territories. The Moral Machine website was designed to collect data on the moral acceptability of decisions made by autonomous vehicles in situations of unavoidable accidents, in which they must decide who is spared and who is sacrificed. The only task of the user is to choose between the two outcomes, as a response to the question "What should the self-driving car do?" Users have the option to click on a button labelled 'see description' to display a complete text description of the characters in the two groups, together with their fate in each outcome.

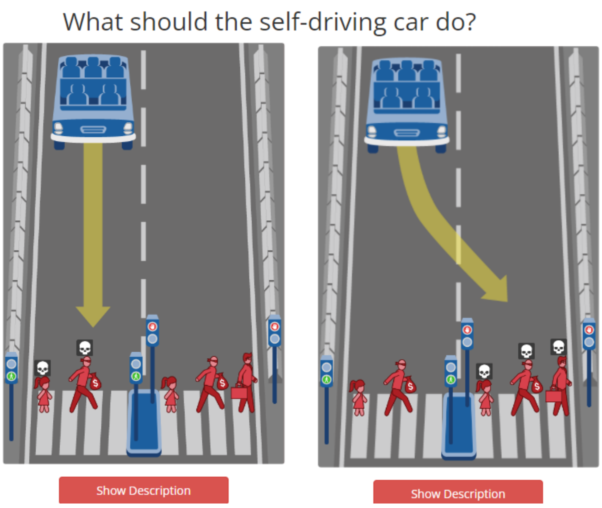

Fig. 6.1 | Example

A simple moral dilemmas in the Moral Machine Experiment

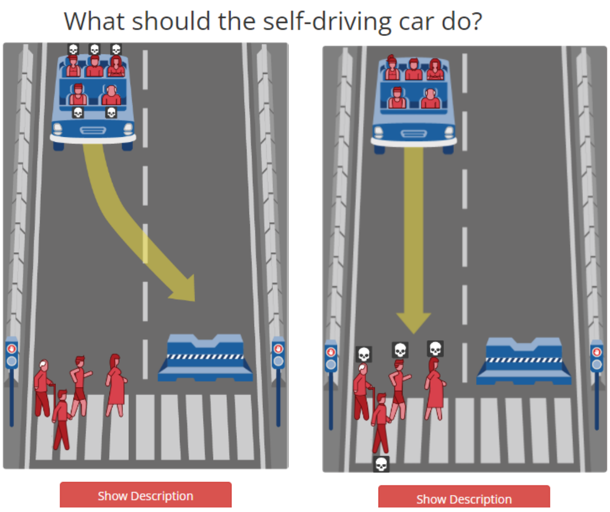

Fig. 6.2 | Example

Another simple moral dilemmas in the Moral Machine Experiment

There are two dilemmas within each session that focus on each of six dimensions of moral preferences: character gender, character age, character physical fitness, character social status, character species, and character number. Furthermore, each dilemma simultaneously randomizes three additional attributes: which group of characters will be spared if the car does nothing; whether the two groups are pedestrians, or whether one group is in the car; and whether the pedestrian characters are crossing legally or illegally. This exploration strategy is supported by a dilemma generation algorithm.

After completing a session of 13 dilemmas, users are presented with a summary of their decisions: which character they spared the most; which character they sacrificed the most; and the relative importance of the nine target moral dimensions in their decisions, compared to their importance to the average of all other users so far.

iii. Results

As shown in Fig. 6.3 and Fig. 6.4, the strongest preferences are observed for sparing humans over animals, sparing more lives, and sparing young lives. We can surmise that different types of characters have a distinctive value, so people prefer to save a baby or a woman for an uncertain reason.

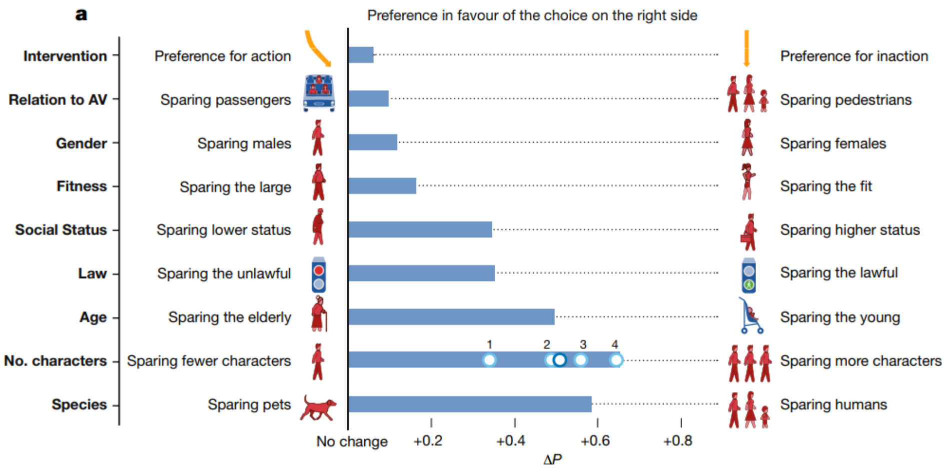

Fig. 6.3 | Global preferences

In each row, ΔP is the difference between the probability of sparing characters possessing the attribute on the right, and the probability of sparing characters possessing the attribute on the left, aggregated over all other attributes. ΔP means the different preferences between two counter situations. For example, for the attribute age, the probability of sparing young characters is 0.49 greater than the probability of sparing.

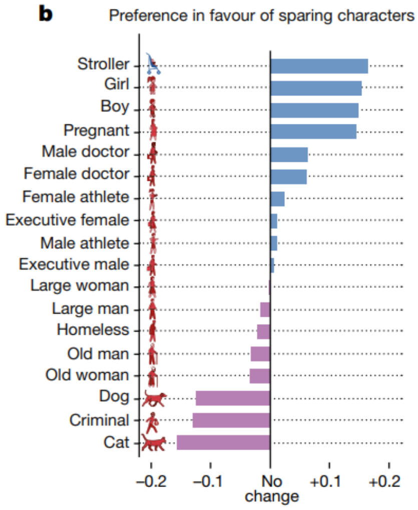

Fig. 6.4 | Global preferences

Relative advantage or penalty for each character. For each character, ΔP is the difference between the probability of sparing this character (when presented alone) and the probability of sparing one adult man or woman.

One possible reason is that different cultures will exhibit disparate reactions. The author identified three distinct “moral clusters” of countries. The first cluster, which is labeled the Western cluster, contains North America as well as many European countries of Protestant, Catholic, and Orthodox Christian cultural groups. The second cluster (which we call the Eastern cluster) contains many far eastern countries such as Japan and Taiwan that belong to the Confucianist cultural group, and Islamic countries such as Indonesia, Pakistan, and Saudi Arabia. The third cluster (a broadly Southern cluster) consists of the Latin American countries of Central and South America, in addition to some countries that are characterized in part by French influence.

As shown in Fig. 6.5, clusters largely differ in the weight they give to some preferences. For example, the preference to spare younger characters rather than older characters is much less pronounced for countries in the Eastern cluster and much higher for countries in the Southern cluster. The same is true for the preference for sparing higher-status characters. However, Between-cluster differences, though, may pose greater problems, which means that the same action will cause different adoption in the distinctive country. Manufacturers and policymakers should be at least cognizant of moral preferences in the countries in which they design artificial intelligence systems and policies.

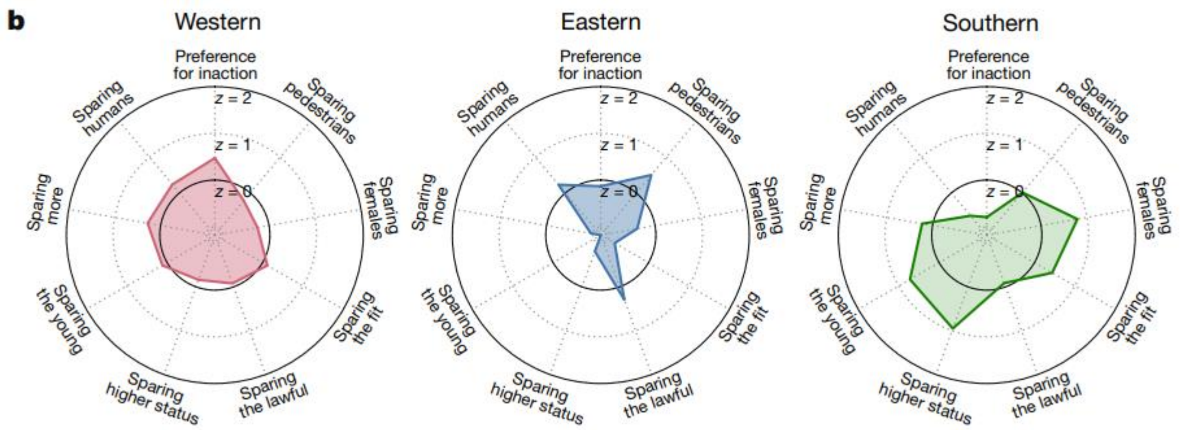

Fig. 6.3|Country-level clusters

Mean AMCE z-scores of the three major clusters.
Radar plot of the mean AMCE z-scores of three clusters reveals a striking pattern of differences between the clusters along the nine attributes. For example, countries belonging to the Southern cluster show a strong preference for sparing females compared to countries in other clusters.

iv. Controversy

Here are several debates on this experiment.

1. The system is too comical to be serious, people will not take too much time to consider the result before making the choice. Maybe using virtual reality to simulate traffic collisions will be a better way, people can truly experience the damage of the traffic collision and realize the consequence in every choice.

2. Otherwise, the feature of characters and the effect of the car accident are too simplified that the experiment can not reflect a true car accident in real life. There is only death and save in the experiment, but in real life, there will occur different kind of injuring. For example, slightly injured, badly injured, paralyzed and fracture, etc.

7. Government's Policy

i. Ethics Commission – AUTOMATED AND CONNECTED DRIVING

In 2017, Federal Ministry of Transport and Digital Infrastructure in Germany publish German report ethics commission. The Commission was instated by the Federal Government in September 2018. It has to explore ethical standards, guidelines and legal recommendations for action regarding the use of data as well as algorithmic systems in a digital society. The Commission's proposal comes in the wake of the EU Commission's launch of a pilot project intended to test draft rules for developing and applying artificial intelligence technologies. Here introduce several ethical rules mention in the report.

ii. Ethical rules for automated and connected vehicular traffic

- The protection of individuals takes precedence over all other utilitarian considerations. The objective is to reduce the level of harm until it is completely prevented. The licensing of automated systems is not justifiable unless it promises to produce at least a diminution in harm compared with human driving, in other words, a positive balance of risks.

  In this rule, the commission clearly illustrates the government's standpoint, the goal of automated driving is to save more lives and let the traffic be more safety. Furthermore, in this case, this rule can be explained that it is okay to save a human life by sacrificing an animal.

- In the event of unavoidable accident situations, any distinction based on personal features (age, gender, physical or mental constitution) is strictly prohibited. It is also prohibited to offset victims against one another. General programming to reduce the number of personal injuries may be justifiable. Those parties involved in the generation of mobility risks must not sacrifice non-involved parties.

  According to the rule, the commission undoubtedly highlights the main restraint in the decision rule, which means that the algorithm in a self-driving car can not use any personal features to decide who will be sacrificed.

- Liability for damage caused by activated automated driving systems is governed by the same principles as in other product liability. From this, it follows that manufacturers or operators are obliged to continuously optimize their systems and also to observe systems they have already delivered and to improve them where this is technologically possible and reasonable.

  The commission defines the duty of manufacturers and operators. They need to upgrade their system to avoid any miscues. If the system causes any non-artificial damage, then manufacturers and operators might shoulder the blame.

8. Company Design

Nowadays, the self-driving car become trendy transportation. For example, Waymo, a self-driving technology development company that operates a commercial self-driving taxi service in Arizona, is the first company that serves the first autonomous service worldwide operating without safety drivers in the car. We want to know how they solve the trolley problem.

i. Waymo - Deontology

Waymo choose deontology to be their core ideology, which is the normative ethical theory that the morality of an action should be based on whether that action itself is right or wrong under a series of rules, rather than based on the consequences of the action. In other words, Waymo is not to calculate the best plan to save most lives, but try to follow the preset rule, which is always hit the smallest object no matter what.

ii. Tesla – Accountability

In contrast, Tesla uses another way to face the trolley problem. They collect human driving data all around the world and mimic human driving behaviors. This includes speeding, swerving, and sometimes breaking the law. Furthermore, Tesla can recreate a synthetic world during driving that Tesla's autopilot system can simulate different situations and seek the best way. For instance, the system can simulate the emergency that a reindeer walking on the road or let people run on the highway, and figure out the best solution.

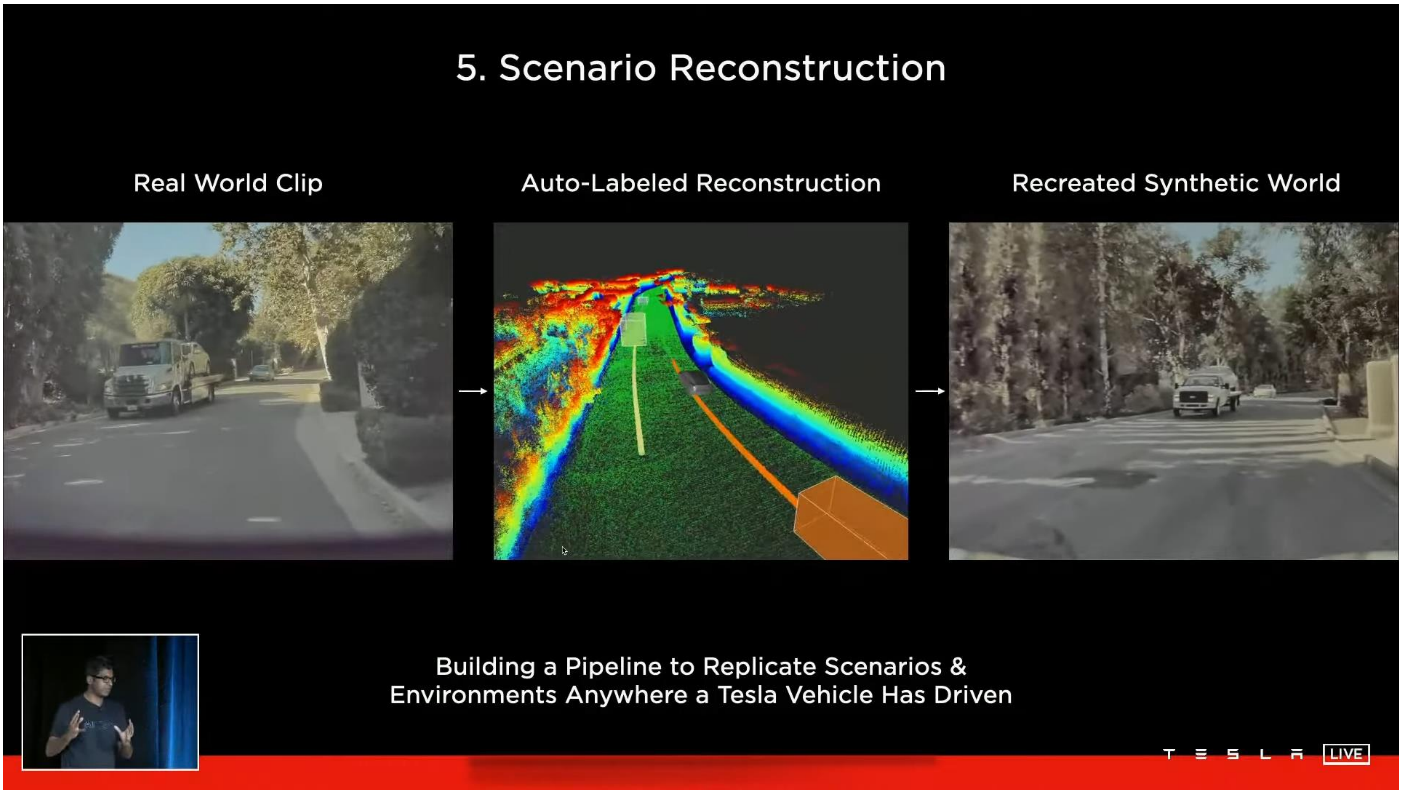

Fig. 8.1 | Tesla's simulation technique

Tesla uses the camera to capture the scene and the system absorbs the data from the clip, labels the object, and recreates a synthetic world in the system.

9. Conclusion

Never in the history of humanity have we allowed a machine to autonomously decide who should live and who should die, in a fraction of a second, without real-time supervision. We are going to cross that bridge any time now, and it will not happen in a distant theatre of military operations; it will happen in that most mundane aspect of our lives, everyday transportation. Before we allow our cars to make ethical decisions, we need to have a global conversation to express our preferences to the companies that will design moral algorithms, and to the policymakers that will regulate them.

Even self-driving system seems can handle most of the problems during driving, there are still have several difficulties that need to be solved.

First, companies cannot commonly get extreme emergency data, so it is hard to train deep learning by using such insufficient data. For example, the world's first death caused by a self-driving car happen in 2018, the system could not identify Herzberg, who are the victim in this car accident, as a pedestrian being on the road, nor did it accurately predict her path. The NTSB report said that Uber's "inadequate safety risk assessment procedures" were contributing factors. As you can see, several companies try various ways to solve this problem, just like Tesla, they try to build a synthetic during driving, that they can do a simulation in a virtual world.

Second, do the self-driving car companies need to public their algorithm to prove that they truly follow the law. I think it is illegal that a self-driving car's algorithm is designed to protect the passengers in the car and prefer to sacrifice pedestrians on the road, so the governments need to design a method to certificate the legitimacy of the algorithm, but still maintain confidentiality.

10. Contribution

We split our presentation in half by two topics, which is the object detecting implementation and the survey of Trolley Problem. YuXuan Chou is in charge of the implementation and YuMing Chou is in charge of the survey of Trolley Problem. We made the slide and the report jointly and discussed the presentation with each other. The leader of each topic needs to decide the architecture, when someone got a problem then we will deal with the problem unitedly.

<table>
<tr><td rowspan="3">YuXuan Chou
(Use single camera to determine the distance)</td><td>Leader of Implement</td></tr>
<tr><td>Making the slide</td></tr>
<tr><td>Making final report</td></tr>
<tr><td rowspan="3">YuMing Chou
(The Solution of Trolley Problem)</td><td>Leader of Survey</td></tr>
<tr><td>Making the slide</td></tr>
<tr><td>Making final report</td></tr>
</table>

Contribution of report:

<table>
<tr><td rowspan="4">YuXuan Chou
(Use single camera to determine the distance)</td><td>Introduction</td></tr>
<tr><td>Theory</td></tr>
<tr><td>Implement</td></tr>
<tr><td>Discussion</td></tr>
<tr><td rowspan="4">YuMing Chou
(The Solution of Trolley Problem)</td><td>Trolley Problem</td></tr>
<tr><td>People Decisions</td></tr>
<tr><td>Government’s Policy</td></tr>
<tr><td>Company Design</td></tr>
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11. Reference

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