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Methodology for ADAS validation: Potential Contribution of other Scientific Fields which have already answered the Same Questions

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Abstract: Since the 80's, the building of learn and test data bases for learning-based systems (i.e. neural networks) had to cope with problems of picking representative examples and measuring the generalization / the score of the system. And of course, real open world applications cannot be fully tested.

It seems that artificial vision-based ADAS now discover the same question, and then, may use the same solutions, involving the same methodology (A.G.E.N.D.A.), using design of experiments and data analysis tools.

Keywords: factors of variability, testing, open world systems, methodology AGENDA, design of experiments, data abalysis, efficiency, testing, validation

1. Introduction

Advanced Driver Assistance Systems implement general sensors, such as cameras , for instance, creating multidimensional signals. Each dimension , or measurement channel into an image, is called a pixel. Each pixel is a light sensor (brightness and color) . This sensor is sensitive to all light emission in a given range of wavelengths . By comparing the output of thousands of sensors (forming the image) one can transform this multidimensional light sensor in an ADAS sensor (for exemple : a "pedestrian detector"). Then it is a computer program that is responsible for extracting the information sought by comparison of measurement channels (pixels) , which allows decide 'absence' or 'presence' of a pedestrian.

This computer program applies algorithms and heuristics that are tested in a number of cases that are supposed to be important in order to validate their effectiveness. The Automotive Industry use to aplly the so called "One Million Kilometers" validation test.

The problem of the formal validation of these algorithms and heuristics (" image processing", " pattern recognition " methods) is that it is difficult to predict their performance in all possible cases. Indeed, if you consider an image of 1 million 8 bits pixels, then there are 2,561,000,000 possible images. This huge number of possible messages (as defined in the information theory [1]) is the cardinal of the population of images. A complete validation should test the processing system for every possible message. So one can notice that the "one million km" validation procedure doesn't make sense regarding this huge number of possible messages.

Engineers use to test the system on cases deemed interesting. This leads then to create a validation/test database of several hundreds or several thousands or even maybe several millions images. Whatever, this number of cases used for test and validation is very small compared to the number of possible messages. So you see that yhe validation of a system using cameras in an open world (such as ADAS) is then a complex issue.

This paper presents other sectors or other types of applications for which the validation poses the same kind of problems, and where solutions have been developed.

We describe those solutions and see how to build from there a draft methodological validation for ADAS.

2. Learn and test data bases for Learning-Based Systems

Learning-Based Systems need only ONE thing to be tuned perfectly : "the" examples. But in general you only have "some" examples plus knowledge (about how these example could change for different situations). The question was "how to use this knowledge" in order to build a good learn data base (the data base that allows the sytem to learn properly) and to build the good test base (the data base that allows to validate the system).

It has been shown that it is possible to use desing of experiment on factors of experiments {2] using the methodology AGENDA [3].

Ths methodoly builds every possible crossing of every factors of variability.

Then rare facts are as well represented than usual facts : this is not true if you take your example in a complete random way. But keep in mind that road safety must take into account rare facts as they may be the cause of accidents.

So, for neural networks validation as for ADAS validation, taking "many" examples in a random way is not a good idea at all.

3. Application to ADAS validation

3.1 List of factors of variability

Bulding a validation data base for a vision based ADAS sould then consist in :

. listing the factors of variability (the knowledge that you have on the problem).

. building a complete design of experiments to sample this variability factors space

. building factional orthogonal designs of experiments [4] to decrease the number of examples to keep into the validation data base.

Let us do this work for a camera-based "road detection" system (as an example).

Factors of variability may be structured in several kinds :

. sensor variability

- Internal parameters of the camera
- External parameters of the camera settings
- Spatial resolution
- s/n ratio
- black threshold level
- gain
- white level light
- number of bits

NB : you may consider that these parameters may be constant values ... but beware, in industrial projects, there are releases among time (with possible new generation camera), and industrial processes are not always precise (exemple : precise location of the camera into the car).

. global scene variability

- kind of light (cloudy day, sunny day, sunny dawn/evening/sunrise, night in the city, night in countryside, ...)
- kind of scene (urban, road, highway, ...)
- weather (dry, rain, fog, snow, ...)
- traffic (no one, average, heavy)
- road signs (no white lines, exhausted white line, regular white lines, ...)
- road shape (curve, straight, ...)
- color of the road (grey/blue, red, ...)
- texture of the road (exhausted, new, ...)

. special characteristics

- presence of obstacles (pedestrian, construction work, ...)
- etc ...

Then one can see that even if only consider 10 factors that may take 3 positions, then you should build a data base with 3^{10} examples.

Of course, it is possible to take less examples using factional designs of experiments.

3.2 How to take those examples

In many applications, the combination of some factors of variability may not be encountered while driving, even millions and millions of kilometres.

The solution may be :

. filter big data bases (using human beings, or off-line automatic detection systems)

. change the context during measurement (send water on the car, on a sunny afternoon, in a curve. etc ...)

. use computer simulation

The key is that you must know the combinations that you never tested.

Whatever the method, it is a very tough job. and this should be done in a systematic way.

NB : The score of your adas must use statistical estimators (and not invented ratios that are usually biased) :

. Khi-2 if your output is a classification [5]

. correlation if your output is a quantitative variable (a score) [6]

You may also add "automatics" quality estimators such as "distances" (and there are many candidates).

All the efficiency scores are computed on the same validation data base (for every application).

You may ponderate the crossings of variability factors if you consider that your system must be qualified for a number of kilometers without failure or for a given time without failure.

4. Data analysis and online confidence estimation

Because the validation is an orthogonal sample of every known factors of variability, it makes sense to analyse the data base of inputs of your ADAS :

. statistics : average values and standard deviations

. factorial analysis : eigen vectors of the data base and eigen values [7].

These computed elements let you build a multidimensional "shape" of the input data base. If you are able to compare the onboard inputs to this recorded shape, then you know :

. if the current image corresponds to already seen cases

. if the current image is completely new.

And of course, you can compute a score.

Than it is possible to give a confidence measurement of the system in the open real world, depending on the closeness to validation data base shape.

And because the desing of experiments is orthogonal, rare events are as well represented by the shape that ordinary events.

4. Conclusion

This paper has provided some ideas that consist in using methodology and statistical tools developed for neural networks, because the problems of validation are quite similar.
The use of such a methodology should be implemented in a system that would allow :
. real time recorded images and signals replay system
. simulation system : computer simulation, and also "car in the loop" simulation systems
We think that car manufacturers should gather with data analysis and validation teams, in order to mutualise this tough work that may lead to official validation for ADAS and maybe for autonomous vehicles too.
Such a work is possible but may take 2 or 3 years to build the proper design of experiment and to chose the proper statistical estimators for efficiency measurement.

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6. Glossary

ADAS: Advanced Driver Assistance Systems

s/n ration : signal/noise ratio