KTH VETENSKAP OCH KONST

KTH ROYAL INSTITUTE OF TECHNOLOGY

GNSS Position Error Estimated by Machine Learning Techniques with Environmental Information Input

M. Sc. In Engineering Design: Mechatronics Master Thesis

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Agenda

1. Introduction
2. State of The Art
3. Development of Positioning Error Estimator with Machine Learning
4. Results & Discussion
5. Conclusion and Future Work

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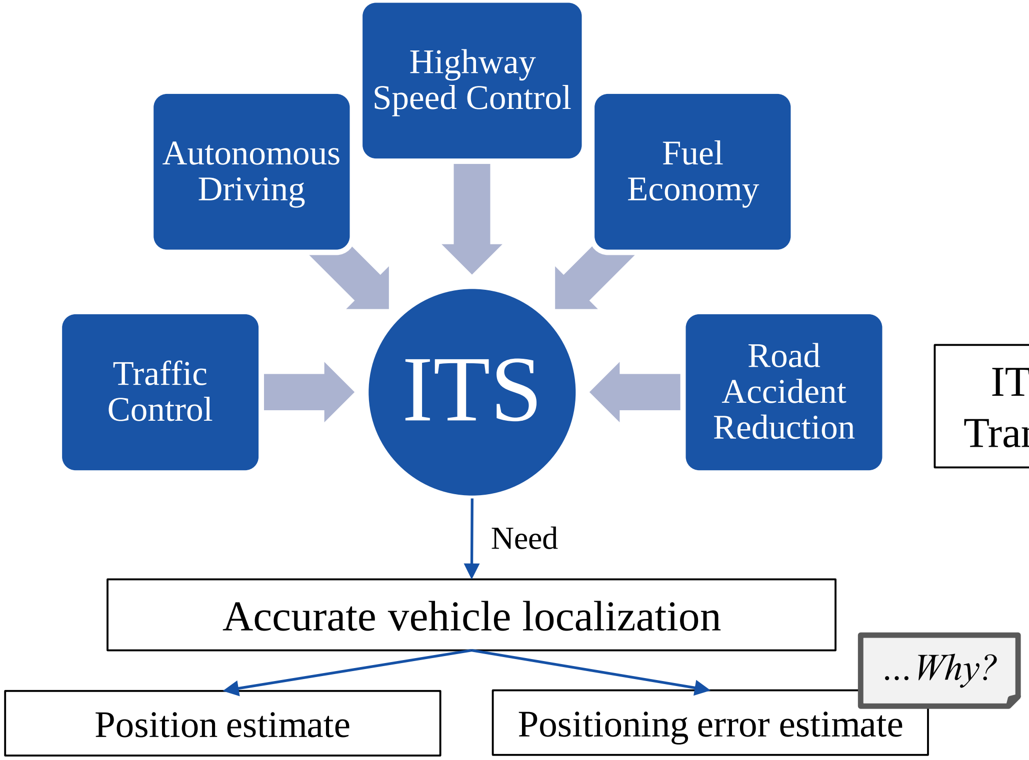
1. Introduction

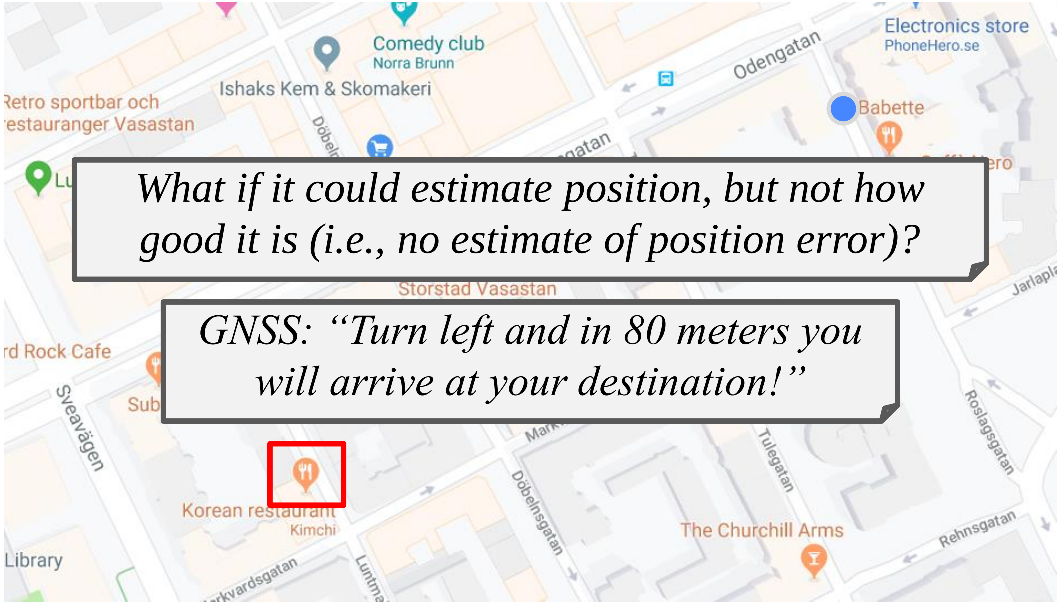


ITS: Intelligent Transport Systems

1. Introduction

Positioning Error estimate is **as** important as the Position estimate itself.

Estimate Position: Global Navigation Satellite Systems (GNSS)



Stanford Diagram

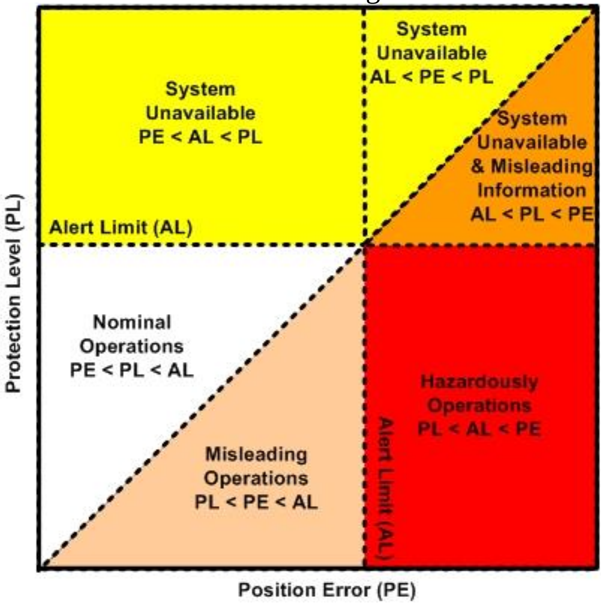


Image available at: *European Space Agency: https://gssc.esa.int/navipedia/index.php/Integrity*

1. Introduction

How to measure positioning error then?

ANSWER: Use Reference Position Systems with higher accuracy than GNSS

Reference Position Systems

1. *Cameras*: Complex arrange, high cost: 150.000 EUR.
2. *IR beacon based triangulation*: limited range.
3. *Total Stations*: High accuracy, limited range, high cost.

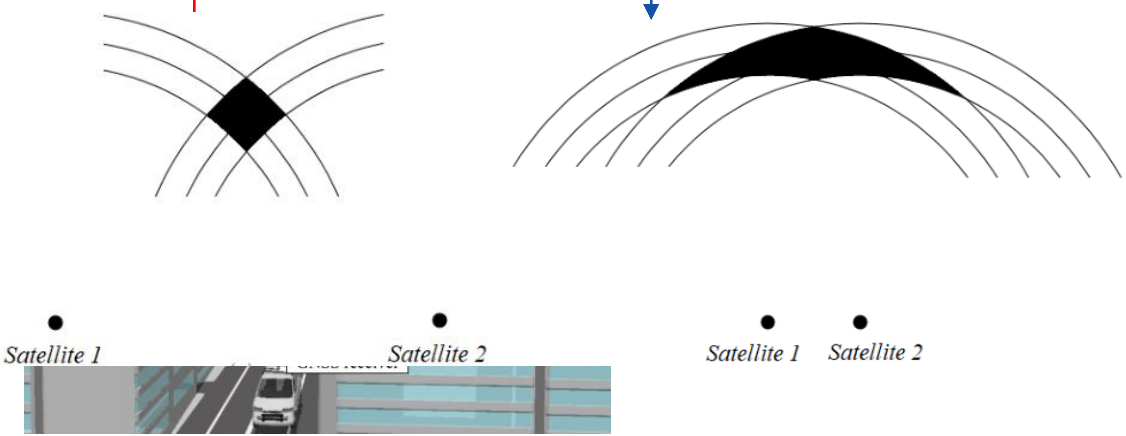
Possible Solution: *Estimate such errors with Machine Learning using GNSS and environmental information.*

1. Introduction

Error Sources and Estimation

GNSS Total Error

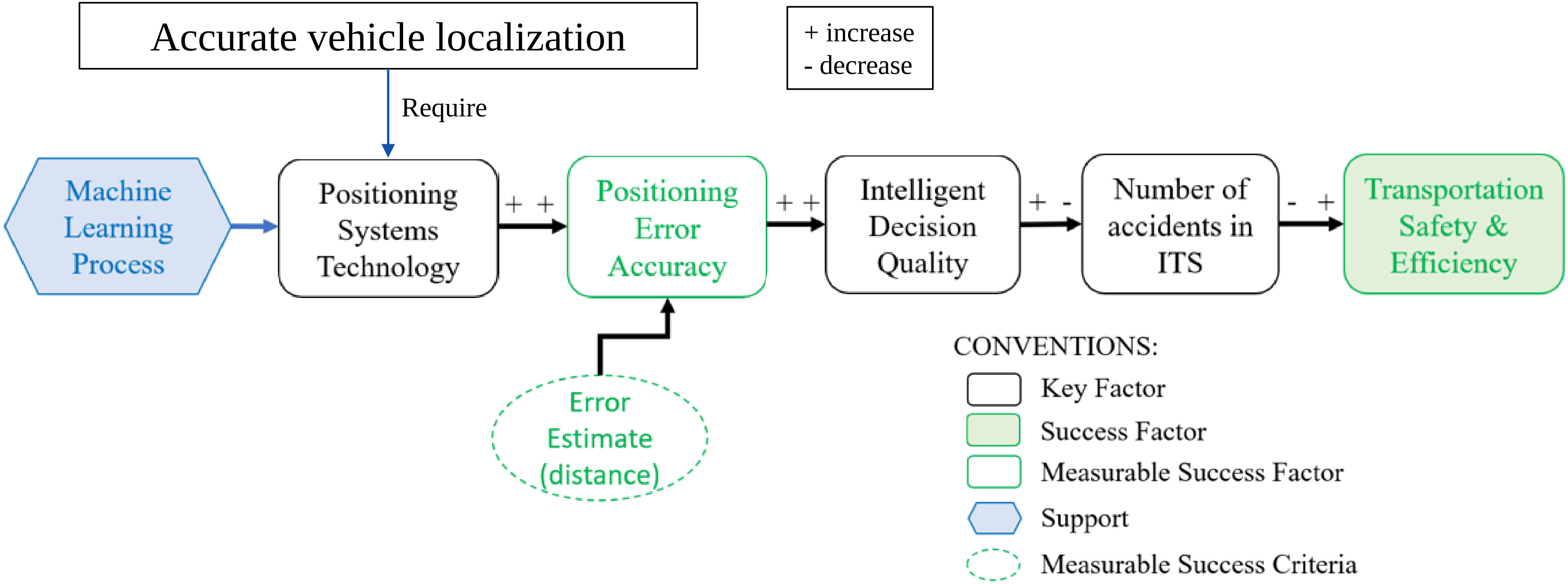
- User Equivalent Range Error (UERE)
  - Multipath Error
  - Satellite Clock Error
  - Ionospheric Error
  - Tropospheric Error
  - Receiver Error
  - Ephemeris Error
- Dilution of Precision (DOP)



Dezhang Tang, Debiao Lu, Baigen Cai, and Jian Wang. GNSS Localization Propagation Error Estimation Considering Environmental Conditions. 2018 16th International Conference on Intelligent Transportation Systems Telecommunications (ITST), pages 1–7

1. Introduction

Methodology: Impact Model



1. Introduction

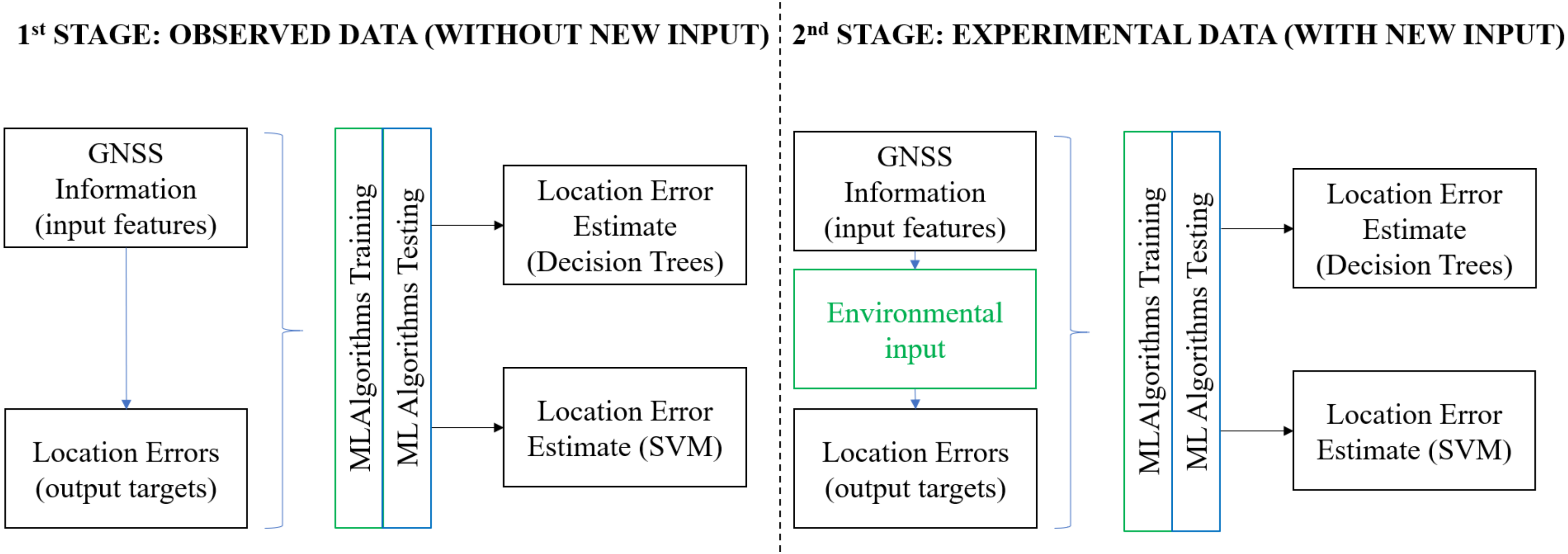
Research Questions

1. Which set of input data and corresponding sensors, related to GNSS and environmental conditions in an autonomous driving situation, can be used for a Machine Learning algorithm, to estimate GNSS positioning errors with an acceptable quality?

2. Based on previous studies of the environment surrounding a vehicle by using additional sensors and their respective inputs so as to autonomously identify possible multipath errors in positioning, which alternative configuration of the previously built Machine Learning algorithms will provide similar or better positioning error estimates?

1. Introduction

Methodology: Case Studies Design



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2. State of The Art

Machine Learning in GNSS

ϵ = Position error.

Can Machine Learning help estimate $\boldsymbol{\epsilon}$*?*

ϵ is greatly affected by *Multipath* phenomena:

- Hardest error to model / predict [2][4][5].
- High impact in position error: up to 100 meters impact [3].
- LiDAR, Monocular and Infrared **cameras** with **computer vision algorithms** have been tried to estimate / reduce it [6][7][8].

Possible part of the solution: *Add camera to input surroundings information*

2. State of The Art

Machine Learning in GNSS

Can Machine Learning help estimate ϵ?

Machine Learning Algorithm comparison					
Feature	ANN / DNN	Decision Trees	Naive Bayes	SVM	EL (Boosting)
Outliers Consideration	Black box inherent nature	Not good for outliers	Good for outliers	Good overfitting control	Not good for outliers
Irrelevant inputs	Black box inherent nature	Good for irrelevant inputs	Not good for irrelevant inputs	Not good for irrelevant inputs	Not good for irrelevant inputs
Type of data and amount	Requires large amount of data	Good for any type of data	Good for continuous data uncorrelated data	Good for binary data	Good for continuous data only
Computational load	Computationally demanding and time demanding	Not computationally demanding	Computationally demanding	Not computationally demanding	Computationally demanding
Predictive power	High predictive power			No local minima	High predictive power

2. State of The Art

Computer Vision

- Useful to extract information from images and videos.
- **Thresholding** is a segmentation technique that makes image features differentiable from others or background [14]

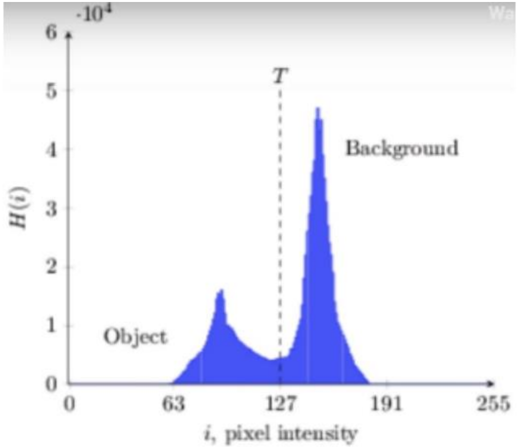

Image from [14]

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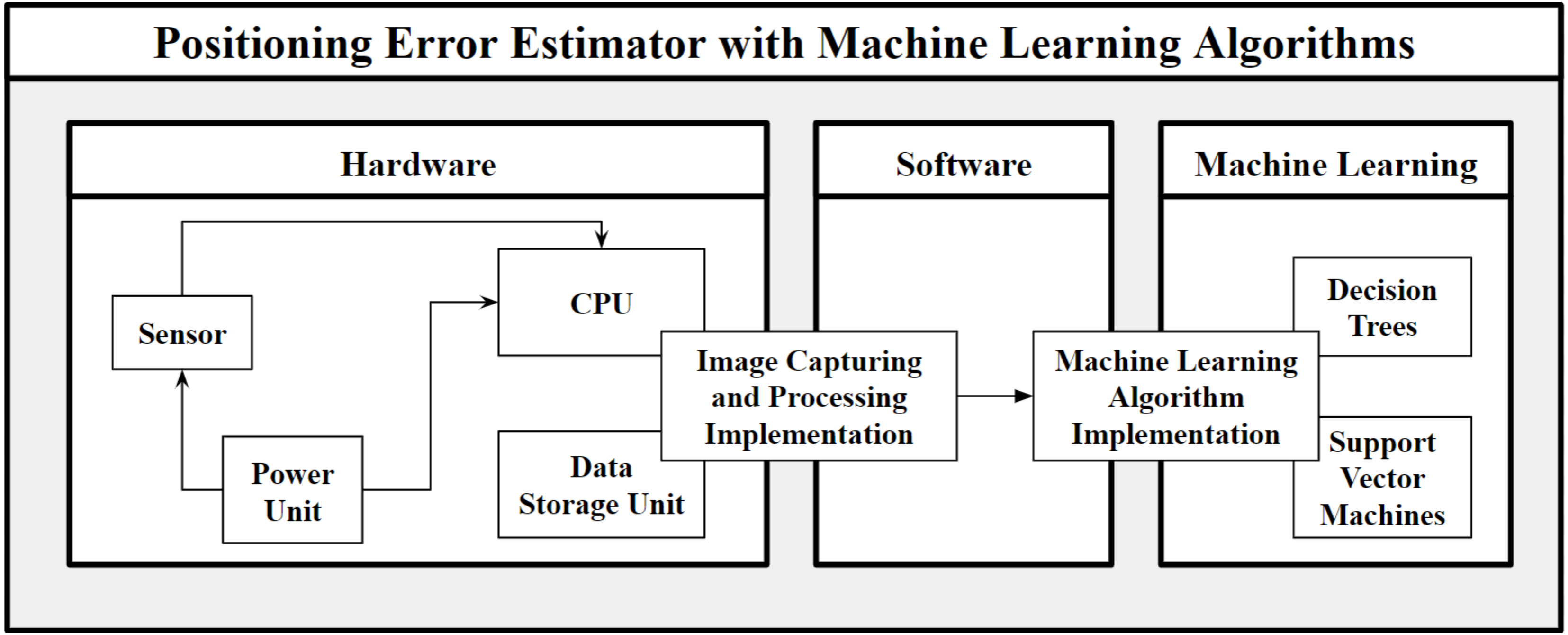
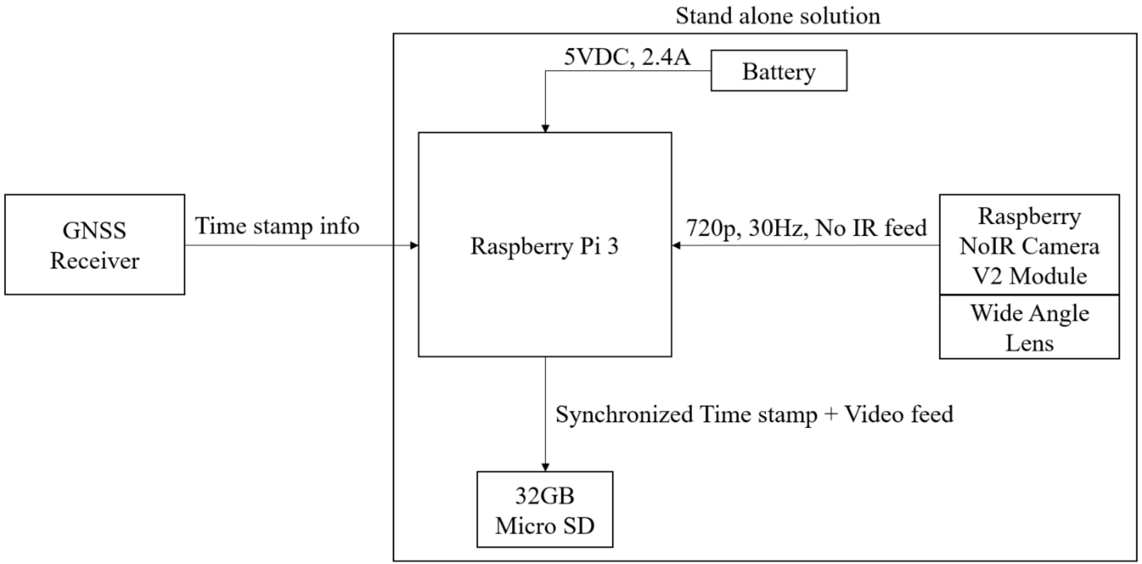
3. Development of Positioning Error Estimator with Machine Learning



3. Development of Positioning Error Estimator with Machine Learning

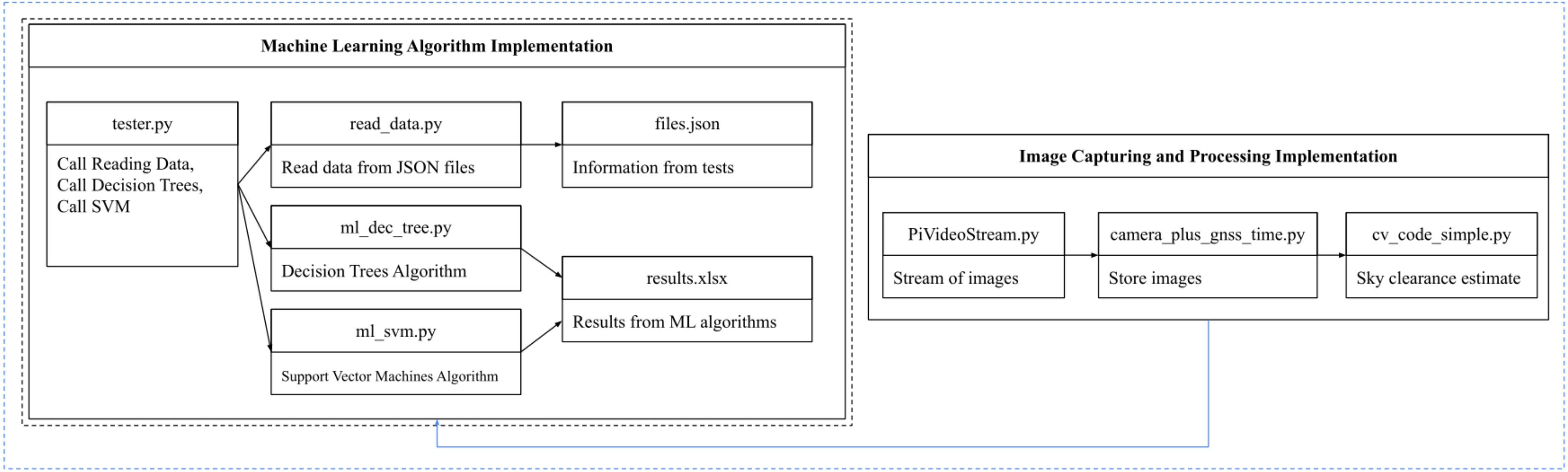
Hardware



- Hardware developed will be adapted and installed onto a moving testing platform

3. Development of Positioning Error Estimator with Machine Learning

Software



First Stage files
Second Stage files

- Python language and Spyder IDE.
- Scikit & OpenCV packages

3. Development of Positioning Error Estimator with Machine Learning

Machine Learning

Countless Machine Learning algorithms.

Decision Trees and **Support Vector Machines** have:

1. Direct answer to research questions: feature relevance based on Information Gain.
2. Interpretability: Less “black box” behavior.

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4. Results & Discussion

Performance Metrics

Metric	Decision Trees	Support Vector Machine
$RMSE = \sqrt{\frac{1}{n}\sum(x_i - \mathrm{T})^2}$	Used	Used
Classification Error: Instances wrongly classified (%)	Used	Not used
Interval Accuracy: Instances inside the bin range values for each leaf (%)	Used	Not used

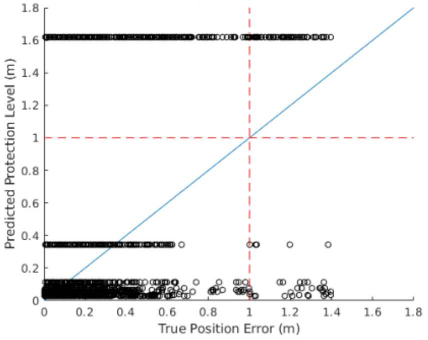
4. Results & Discussion

Results: 1st STAGE TRAINING AND TESTING ON OBSERVED DATA

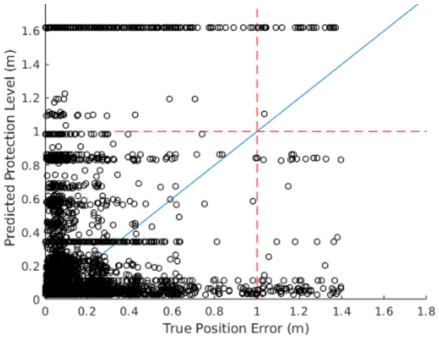
1st step: Decision Trees with all data:

Test Number	Classification Error (%)	Interval Accuracy (%)	RMSE (m)
1	70.94	$\boxed{59.91}$	$\boxed{0.081}$
2	$\boxed{64.16}$	55.87	0.112
3	91.95	16.58	0.084
4	81.81	15.26	0.112

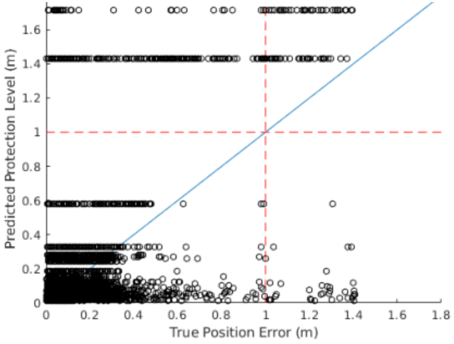
Test 1



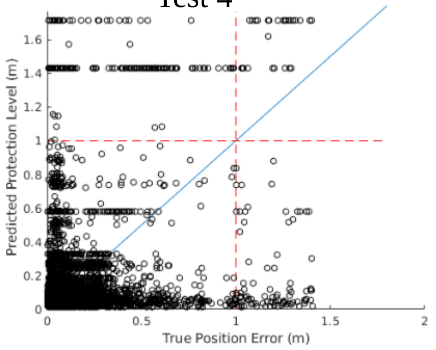
Test 2



Test 3



Test 4



4. Results & Discussion

Results: 1st STAGE TRAINING AND TESTING ON OBSERVED DATA

2nd step: Obtain input feature relevance:

Ranking	Features
1	Cno
2	Nr. Used Measures
3	Elevation
4	Difference ENU
5	Lsq. Residuals
6	Azimuth
7	Innovation ENU
8	PDOP
9	Constellation
10	NDOP

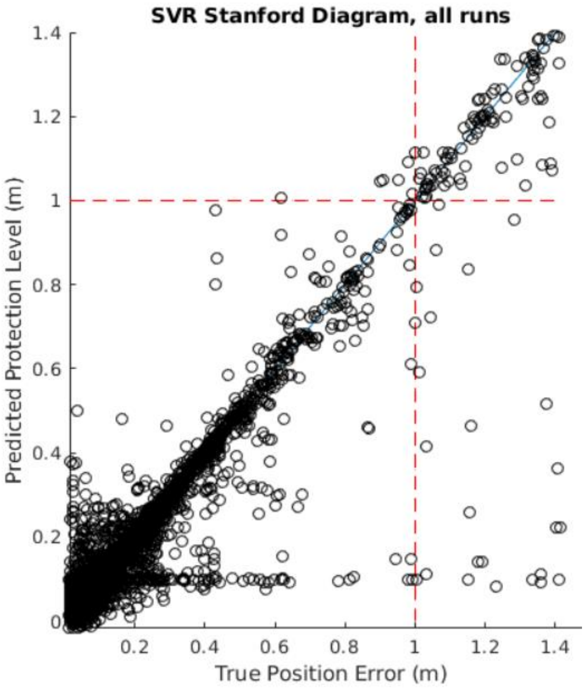
Decision Trees	Relevant Features →	SVM
Not good for outliers		Good overfitting control
Good for irrelevant inputs		
Good for any type of data		Good for binary data
Not computationally demanding		Not computationally demanding
		No local minima

4. Results & Discussion

Results: 1st STAGE TRAINING AND TESTING ON OBSERVED DATA

3rd step: SVM with all data:

Test	Features	RMSE (m)
Average Ranking	7	0.03541
Average Ranking	8	0.03576



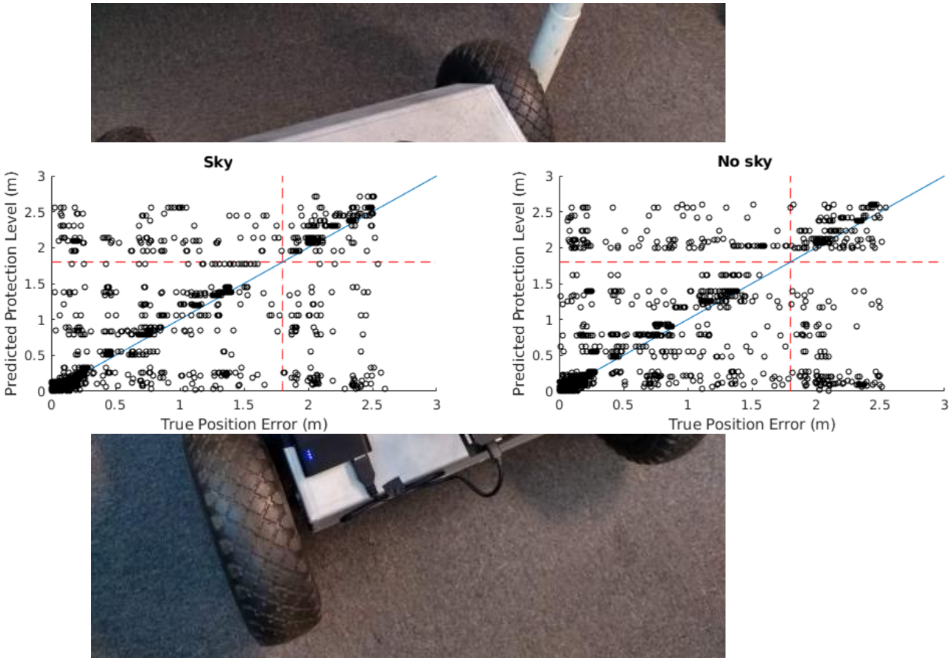
Best result:

- Support Vector Machines
- Average ranking from Decision Trees
- 7 features

4. Results & Discussion

Results: 2nd STAGE TRAINING AND TESTING ON EXPERIMENTAL DATA

1st step: Decision Trees with all data:



Ranking	2nd Stage (no sky)	2nd Stage (sky)
1	Difference ENU	Difference ENU
2	Elevation	Nr. Used Measures
3	Nr. Used Measures	Cno
4	Cno	Elevation
5	Lsq. Residuals	Innovation ENU
6	Azimuth	Sky
7	Innovation ENU	Constellation
8	Constellation	Azimuth

Classification Error Interval Accuracy RMSE without sky RMSE with sky
Performance measure Performance measure

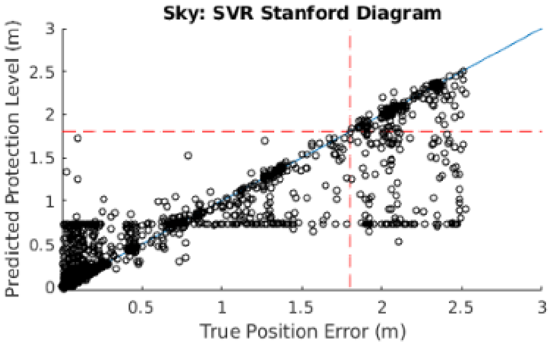
(b) Segmentation by 6 tests results.

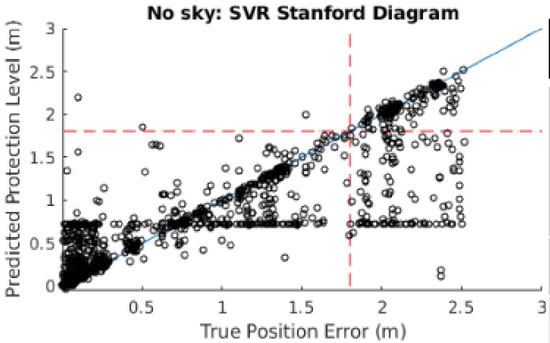
4. Results & Discussion

Results: 2nd STAGE TRAINING AND TESTING ON EXPERIMENTAL DATA

2nd step: Support Vector Machines with all data:

Test	Features	RMSE no sky (m)	RMSE with sky (m)
New Ranking	7	0.2878	0.3416
New Ranking	8	0.2872	0.2875





Student's T test showed **NO** significant difference between sky and no sky clearance

2nd Stage	α	P-Value
Student's T Test, 2 tailed, n = 5	0.05	0.1637
	Average (m)	**Std. Dev. (m)**
Sky RMSE	0.2816	0.0088
No Sky RMSE	0.2887	0.0041

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5. Conclusion and Future Work

Answers to Research Questions:

1. Which set of input data and corresponding sensors, related to GNSS and environmental conditions in an autonomous driving situation, can be used for a Machine Learning algorithm, to estimate GNSS positioning errors with an acceptable quality?

Answer: With a RMSE of 29 cm with SVM inside the range presented in [16] (10 to 30 cm error in position error), the input features relevant for position error estimation are obtained from the GNSS receiver data and are:

Ranking	1st Stage	2nd Stage (no sky)	2nd Stage (sky)
1	Cno	Difference ENU	Difference ENU
2	Nr. Used Measures	Elevation	Nr. Used Measures
3	Elevation	Nr. Used Measures	Cno
4	Difference ENU	Cno	Elevation
5	Lsq. Residuals	Lsq. Residuals	Innovation ENU
6	Azimuth	Azimuth	Sky
7	Innovation ENU	Innovation ENU	Constellation
8	PDOP	Constellation	Azimuth

5. Conclusion and Future Work

Answers to Research Questions:

2. Based on previous studies of the environment surrounding a vehicle by using additional sensors and their respective inputs so as to autonomously identify possible multipath errors in positioning, which alternative configuration of the previously built Machine Learning algorithms will provide similar or better positioning error estimates?

Answer: After obtaining sky clearance as a relevant input, and retraining and testing the machine learning algorithms with the new data, *there is no statistical difference between adding and not adding the sky clearance input*. As shown in Student's T test of mean's difference for small sized samples with 5 runs each, there is no evidence that sky clearance provides a better or worse positioning error estimate.

2nd Stage	α	P-Value
Student's T Test, 2 tailed, n = 5	0.05	0.1637
	Average (m)	**Std. Dev. (m)**
Sky RMSE	0.2816	0.0088
No Sky RMSE	0.2887	0.0041

5. Conclusion and Future Work

Future Work

- Other algorithms would be interesting to try:
    1. DNN are less interpretable and more complex, but more accurate.
    2. Variations of the algorithms tried to investigate errors obtained.
- Additional input features may be included:
    - Time (sudden loss of single carrier phase signal at a given time).
    - Test platform states (velocity, acceleration).
    - Surrounding object detection.
    - Real time satellite line of sight obstruction [17][18].
- With desired accuracy attained: real time implementation.

5. Conclusion and Future Work

Summary:

- The positioning error estimate is as important as the position estimate itself.
- There is a need to improve positioning error estimation.
- This project investigated Machine Learning algorithms application to positioning error estimation by:
  1. Assessing relevant features from GNSS.
  2. Adding environmental information from a camera.
- The relevant features obtained from the Machine Learning algorithms are presented.
- There is no statistical evidence to conclude that the tested environmental input increases or decreases positioning error estimation accuracy with the built Machine Learning models.
- Future work is presented, mainly on ML algorithms and more inputs to be researched.

THANK YOU

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