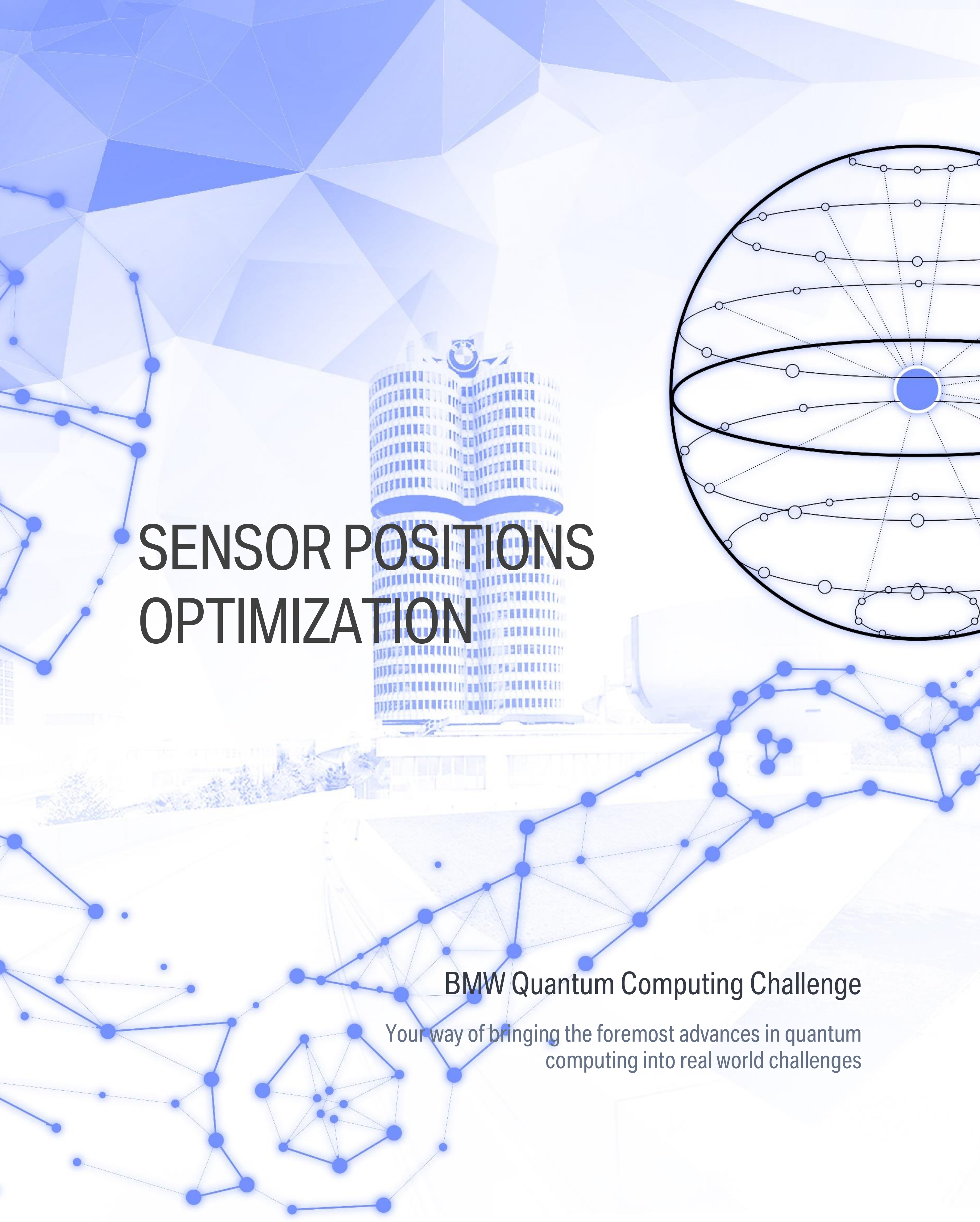


SENSOR POSITIONS OPTIMIZATION

BMW Quantum Computing Challenge

Your way of bringing the foremost advances in quantum computing into real world challenges

BMW GROUP

ROLLS-ROYCE MOTOR CARS LTD

Motivation & Business Value

Vehicles with functionalities of automated driving need a large number of sensors to observe the vehicle's surroundings. These sensors are a crucial factor in advancing automated driving and increasing the security for humans inside and outside the vehicle. However, sensors like Lidar, radar, to name a few, are complex systems and, therefore, very expensive. Thus, the sensors for driver assistance systems and automated cars are considered a large cost factor. Therefore, it is essential to minimize the cost of sensor setup for every individual car during development.

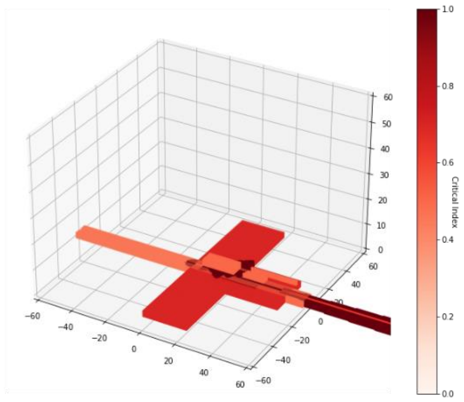


FIGURE 1 VISUALISATION OF REGIONS OF INTEREST WHICH NEED TO BE COVERED BY A SENSOR CONFIGURATION IN THREE-DIMENSIONAL GRID. EACH GRID POINT REPRESENTS THE CRITICAL INDEX (ci) AS A FUNCTION OF THREE SPACE COORDINATES.

The problem presented in this document thus consists in finding an optimal configuration of sensors and can be mainly defined by two aspects:

- an optimal configuration demands a specific sensor positioning: every important area/object of the vehicle's surroundings must be detected with the highest possible certainty. Some regions may even require a redundant cover (i.e. two sensors of different types covering the same part);
- the cost of optimal configuration must be reduced to a minimum.

Advancing the BMW Group's automated driving activities, it is essential to have a robust and efficient technology to identify the optimal number, type, and position of sensors covering the relevant areas around the vehicle, thus ensuring the optimal sensor configuration at a minimal cost.

Problem Formulation

The numerical challenge of finding an optimal sensor configuration raises mainly from the following reasons:

- huge search space: placement of sensors in a continuous space on vehicle surface; different types of sensors available; different placement angles (i.e. one specific sensor at one specific position can yield different coverage);
- expensive evaluation of sensor or sensors setup: it requires comparison of the coverage obtained from the configuration with the regions of interest and their critical index (ci), which leads to solving the geometric equations or, after discretization, multiplication of large three-dimensional matrices.

Sensor configuration

The problem solution represents one specific sensor configuration that the algorithm evaluates as optimal. A sensor configuration is defined by a number of n sensors placed on the vehicle surface, where n is bound by a given maximum allowed number of sensors K.

$$n \in [0, K] \tag{1}$$

For each of the n sensors multiple variables (degrees of freedom) must be set:

- T: sensor's characteristic (i.e. type, range, field of view, price);
- P: sensor's position;
- O: sensor's orientation.

Sensor characteristics

In a simplified way, one individual sensor can be defined by three characteristics: type, geometry of its field of view, price.

$$S_i = \{t_i, fov_i, p_i\} \tag{2}$$

Sensor Type

Modern vehicles are equipped with sensors based on various technologies, such as, for example, Lidar, radar, camera and ultrasound (see the corresponding variable definition below):

$$\mathrm{t} = \begin{cases} 0 & \text{if sensor based of Lidar} - \text{type} \\ 1 & \text{if sensor based of radar} - \text{type} \\ 2 & \text{if sensor based of camera} - \text{type} \\ 3 & \text{if sensor based of ultrasound} - \text{type} \end{cases} \tag{3}$$

Each type has its pros and cons compared to others. In a realistic scenario, it might therefore be necessary to use a mix of two and more sensors of different types to cover the specific regions of interest (RoIs). While building mathematical formulation, latter can be considered as an additional option to a minimal geometrical requirement to cover a given RoI by any of the sensors. However, a simple way to handle such additional constraint is to set a threshold on the critical index of a region. For example, all regions of interest with a critical index above $ci \geq 0.7$ need to be covered by at least two sensors of a different type.

Range & field of view

As mentioned in the previous section, sensors are defined by multiple characteristics which might differ from one technology to another, and from one provider to another. In a simplified way, one may only consider the angles of view (α_V - vertical, α_H - horizontal) and the range (R):

$$fov_i = \{\alpha_{V_i}, \alpha_{H_i}, R\} \tag{4}$$

These two parameters enable to obtain a geometrical description of the region covered by a sensor (see figure 2). Since the actual values for sensor configuration parameters change over time due to new models and technologies available, it is important that the new numerical approach takes these basic α_V, α_H and R parameters into account.

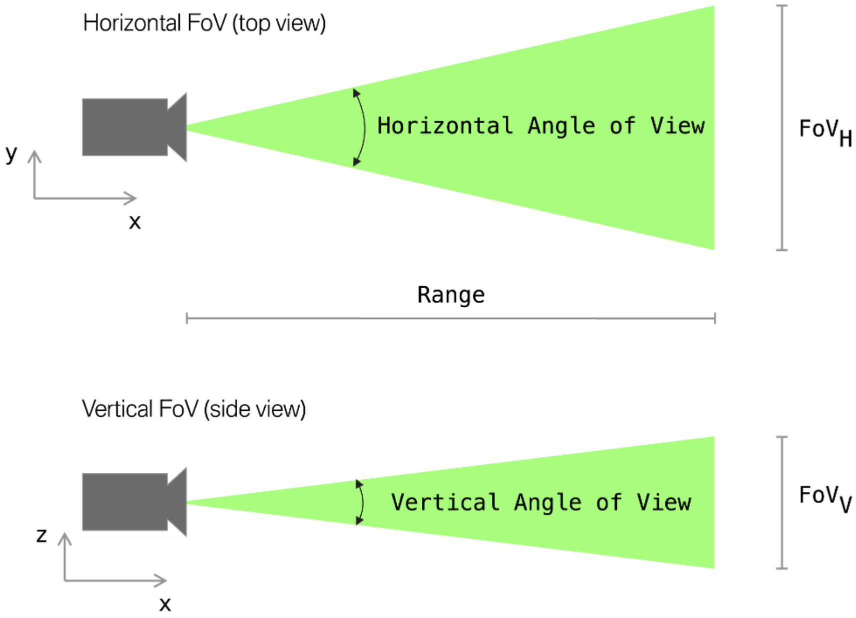


FIGURE 2 SIMPLIFIED REPRESENTATION OF A RECTANGULAR SHAPED FIELD OF VIEW OF A SENSOR DEFINED BY THE HORIZONTAL AND VERTICAL ANGLE OF VIEW AND THE RANGE.

Price

The last but not least important characteristic to consider while developing a new numerical model for optimal sensor configuration is the sensor price p. In the simplified formulation, the principal cost function C of the problem can be described as a sum of prizes of the sensors.

$$C = \sum_i p_i \tag{5}$$

Sensor position

Sensor position is mainly constrained by the vehicle's surface geometry, as it must be positioned directly on the vehicle's body (except its specific parts such as windows, lights, etc.). Furthermore, some external factors can be considered as well. For example, due to the risk of the sensor getting covered by dirt or snow, a minimum height for sensor position should be defined. To simplify the definition of possible sensor position, one or multiple

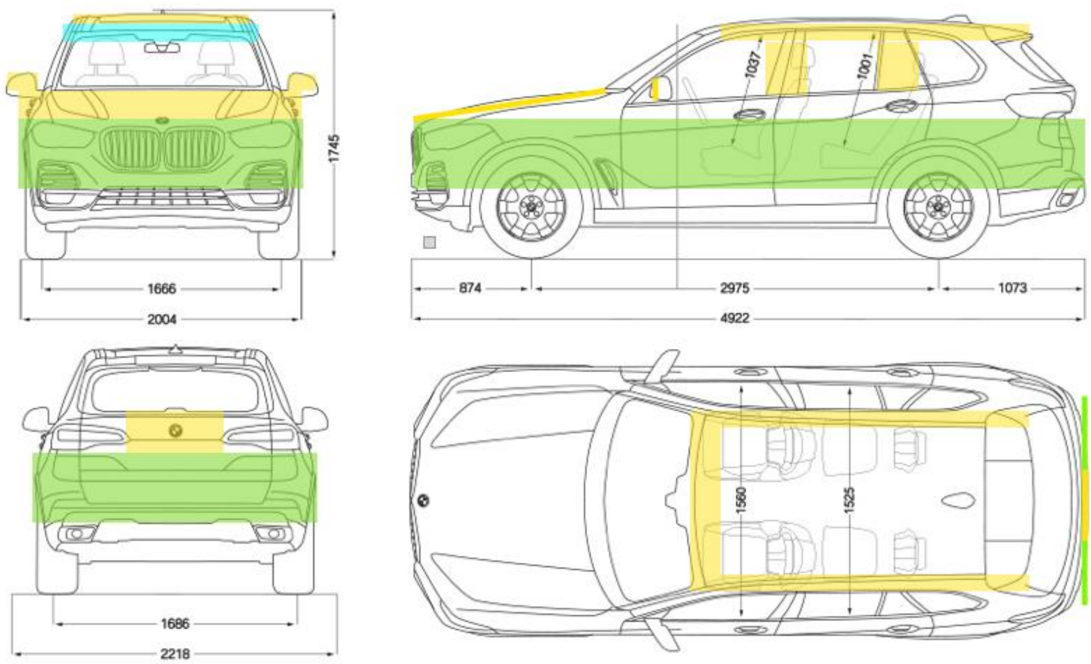


FIGURE 3 SIMPLIFIED VISUALISATION OF POSSIBLE SENSOR POSITION (GREEN: ALL SENSORS, YELLOW: LIDAR \& CAMERA, CYAN: CAMERA). ADAPTED FROM **[5]**

polygons can be drawn over the surface area in the vehicle's front, side, and back view. As a first approximation, these rectangles can be used as flat surfaces for sensor placement.

The rectangles are set by their four corners and the allowed sensor types. The regions visualised in figure 3 are defined similarly to those from the provided test data.

```
Front : [[0;1000;1000], [0;-1000;1000], [0;-1000;500], [0;1000;5000]]; Lidar, Camera, Ultrasound, Radar
```

LISTING 1 EXTRACT FROM THE EXAMPLE SURFACES DEFINED FOR THE SENSOR POSITIONS.

Note. In the test data, the information is provided in tabular form (.csv file); the listing above is only intended to visualize the data.

Sensor Orientation

The installation of sensors depends on different orientation angles, which are constrained, in particular, by the geometry of the vehicle body, thus challenging to model. The minimal requirement for a numerical model would be to consider only the orientations pointed towards the surface's exterior. For this purpose, an occlusion geometry limiting the field of view is provided in the test data and can be optionally used.

Resolution

One may consider resolution as another optimization criterion that may also impact sensor configuration's efficiency. Integration of an additional parameter will increase the complexity of formulation, thus can be considered as an optional on top of mentioned above minimal requirements.

Evaluation of a sensor setup

The evaluation of one specific sensor configuration is quite expensive because one would need to perform several simulations to estimate the performance in multiple scenarios. Practically, it can be done by using specific software tools for simulating different driving scenarios. In the case of an optimal sensor configuration problem, this amount of simulations must be multiplied by the number of different configurations in order to compare them. To overcome this numerical challenge, one may map a vehicle's surrounding area onto a grid of 3D points and assign specific importance (critical index) of being observed to each grid point. The values for each point are collected through all scenarios, which allows validating an optimal sensor setup by comparing its resulting field of view.

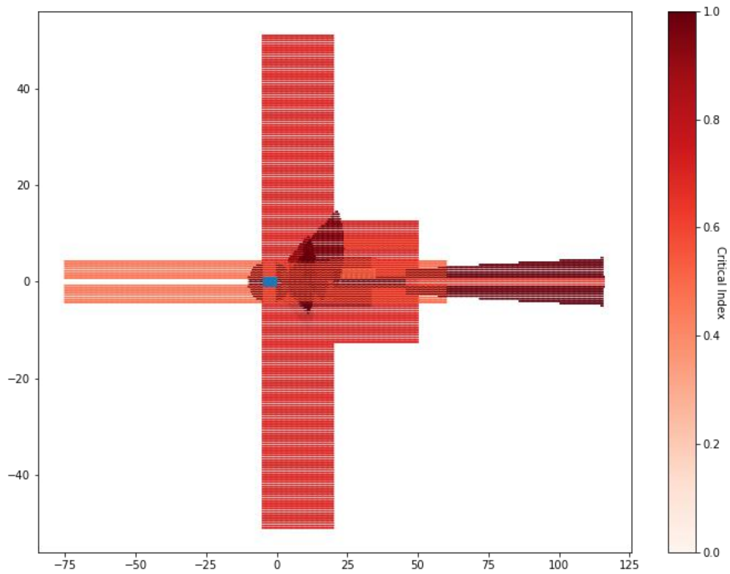


FIGURE 4 VISUALIZATION OF THE CRITICAL INDEX GRID FROM ABOVE. THE X- AND Y-COORDINATES ARE SHOWN ON THE HORIZONTAL AND VERTICAL AXIS RESPECTIVELY. THE COLOR OF A POINT REPRESENTS ITS CRITICAL INDEX

Regions of interest

To identify the critical index with respect to the different regions of interest (RoI)s, one must consider typical and critical driving scenarios. In the 2D model example, each RoI is described by either cubical or a circle segment shape (see figure 5). A three-dimensional model can be obtained by fixing the height parameter in the z-direction.

In the example above the cubical regions are defined by their start and end coordinates and the critical index for the full region. The circle segments are defined by the minimum and maximum radius in combination with the heading angle, angle of view and the center of the circle. The heading angle defines the direction of the central angle (i.e. the ray in the middle of the field of view). The angle of view describes the total angle covered by the region.

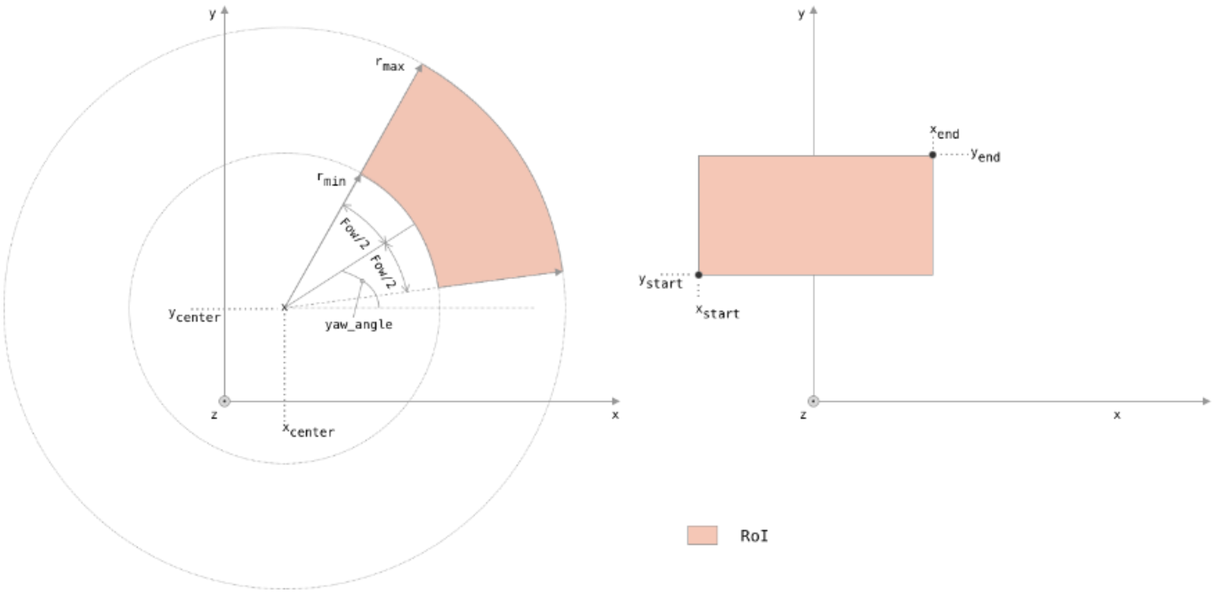


FIGURE 5 GEOMETRICAL DEFINITIONS OF THE REGIONS OF INTEREST IN FORM OF AN EXTRUDED CIRCLE SECTOR (LEFT) OR CUBE (RIGHT)

Evaluating the covered regions of interest

As mentioned in the section above, evaluating a particular sensor configuration consists of computing and comparing the RoI grid covered by the sensor setup. It can be done by assigning to RoI grid points R a boolean variable C (1 - grid point is covered by sensor setup, 0 - otherwise). Such discrete coverage model can be computed based on the field of view characteristics (see equation (4)). Computing the sum over the resulting array and dividing it by the sum of the RoI grid points gives a measurement of how good the setup covers the full set of RoIs.

$$V_{\text{cover}} = \frac{\sum_{i=x_{min}}^{x_{max}} \sum_{j=y_{min}}^{y_{max}} \sum_{k=z_{min}}^{z_{max}} r_{ijk} \cdot c_{ijk}}{\sum_{i=x_{min}}^{x_{max}} \sum_{j=y_{min}}^{y_{max}} \sum_{k=z_{min}}^{z_{max}} r_{ijk}} \tag{6}$$

<u>Note.</u> The proposed formulation is not the only possible way to estimate the efficiency of sensor configuration coverage. The approximation choice stays an open option.

Summary of the optimization problem

To summarize the statements above, the optimization problem of finding the maximum RoIs coverage with minimal cost can be described by following objective function:

$$\underset{T,P,O}{\arg\min}(-A \cdot V_{cover} + B \cdot C)$$

where

- V_{cover} is a value measuring the efficiency of RoIs coverage as defined in (6);
- C represents the cost of the sensor setup as defined in (5);
- A and B are positive-valued weights.

Possible simplifications

Simplification approaches / search space reduction

To approach the optimal sensor configuration problem numerically, finding an efficient way to reduce the complex search space is essential. Fortunately, some scenarios provide already substantial boundings regarding the minimum number of sensors and their positions. Even preliminary empirical evaluation of different scenarios by experts (in [1] authors consider the impact of sensor height on overall efficiency) should restrict the search space drastically. Further improvements can be achieved by evaluating one sensor independently from all other sensors. These independent locally optimized positions should provide good starting points for subsequent optimizations.

Pre-calculation of all covers

The genetic algorithm approach currently used in BMW simplifies the evaluation by determining the performance only based on a weighted set of observed positions in space. This approach yields a considerable performance gain but still requires a simulation of the physical behavior of the sensor. Calculating and caching all possible sensor covers would be a way to speed up this calculation, but this is only feasible if simplifications reduce the number of possible positions for each sensor significantly. Restrictions similar to [2] would result in up to 30k sensor positions, which should be reasonable to pre-calculate.

Given all those pre-calculated sensor coverages, the problem can also be formulated as a (weighted) Maximum Set Coverage[1]:

- all grid points define a set with weights for each point;
- each possible sensor position covers a specific subset of the grid points.

The weighted maximum coverage problem is to find those k subsets, that maximize the covered weights (each covered point only counts once). Testing for different k will yield the overall optimal solution.

The maximum coverage problem is a famous optimization problem due to its in-approximability but can easily be formulated as a linear program (or Mixed Integer Linear Program (MILP) in case of the weighted maximum coverage problem). Modern MILP solver should be able to solve large instances of the problem and, even though good results are not guaranteed, greedy approximations tend to provide good results [3].

If a fixed coverage model for the sensors is proven to be simple enough, an approach similar to [4] using gradient descent with a probabilistic coverage function might be considered. At each step of the algorithm, the analytical derivatives of the coverage function are calculated with respect to the position and orientation of each sensor. They are used to move the sensors in a way that maximizes the overall coverage. It is not clear if this approach is usable because the strong positional restrictions might make the derived gradients useless and prevent convergence.

---

[1] https://en.wikipedia.org/wiki/Maximum_coverage_problem

Research Proposal

The proposed use-case represents a high strategic potential for BMW Group, as obtaining an optimal sensor configuration implies higher security and quality standards and a reduced production cost.

Research Focus

Regarding the computational complexity of the sensor configuration problem, the main goal is to develop a new efficient and robust numerical model to approach it by means of quantum or hybrid quantum-classical computing. Regarding the computational complexity of the sensor configuration problem, the main goal is to develop an efficient and robust numerical model and to approach it by means of quantum or hybrid quantum-classical computing. The principal metrics for the algorithm evaluation will be the quality of approximation (number of different characteristics taking into account, potential to scale) and the level of innovation with respect to the established classical/quantum techniques.

Minimal requirements for the new model consist of including the following constraints:

- sensor configuration:
  - geometries of the field of view (see (4));
  - orientation angles;
  - price;
- evaluation of covered regions as in (6).

The following characteristics are optional, but can be beneficial for a more accurate numerical model:

- sensor configuration:
  - sensor types;
  - sensor resolution;
- alternative methods to (6) to evaluate the RoIs coverage.

Test Data

The following data can be used for the new algorithm development and validation:

- a list of cubical RoIs and their defining parameters (figure 6);
- a list of segment RoIs and their defining parameters (7);
- a 3D grid with the assigned critical indices for the regions of interest;
- a list coordinates for surface geometry representing the possible areas for sensor positioning;
- a list of polygon coordinates representing the occlusion geometry;

Note. The initial problem and the proposed mathematical formulation is a very general approximation that can be expanded and reviewed in a different manner. This choice is open and not restricted by the organizers.

Acknowledgement

The document was created with the support of Deloitte Consulting and Amazon Web Services.

Appendix

Visualization of RoIs

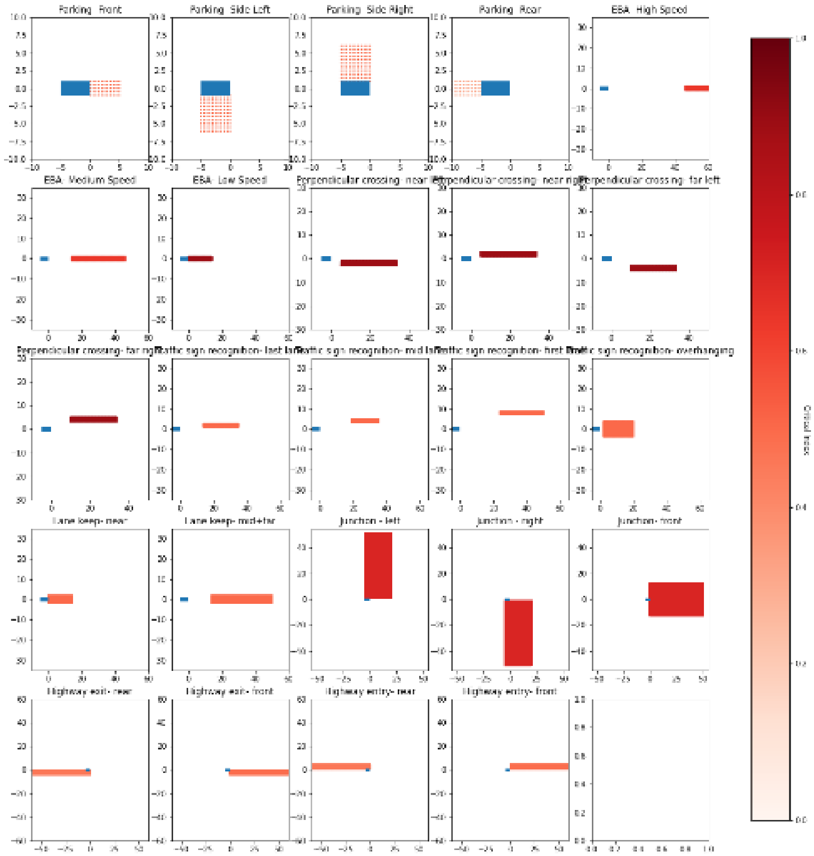


FIGURE 6 VISUALISATION OF THE CUBIC RoIs

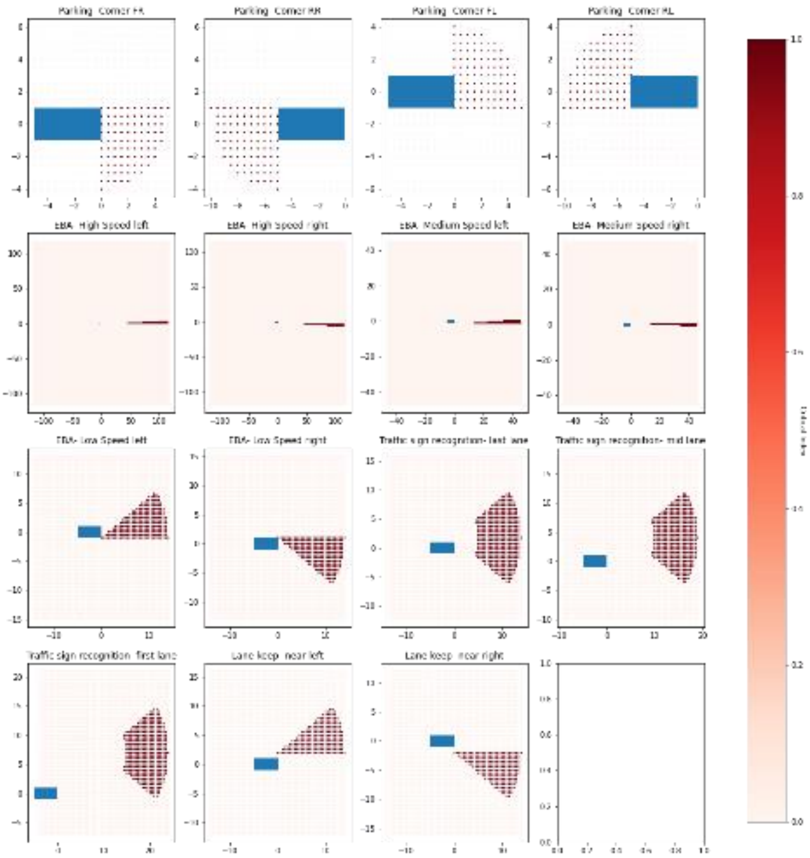
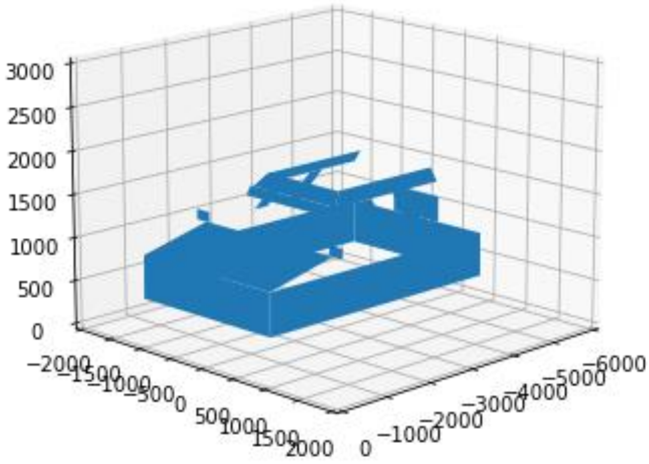
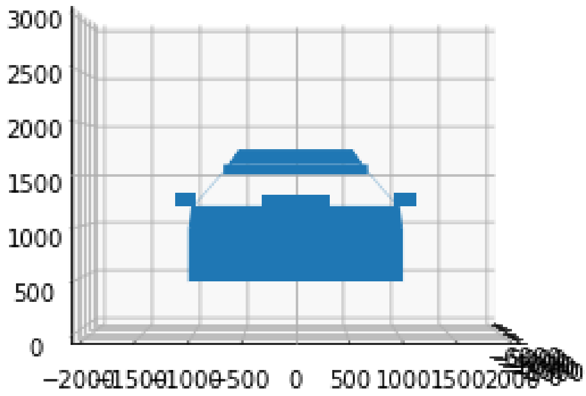


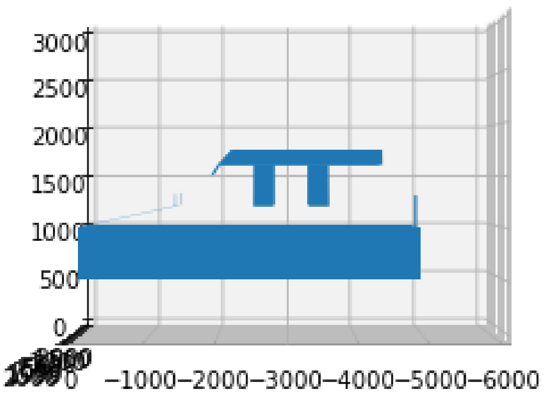
FIGURE 7 VISUALISATION OF THE ROIS IN EXTRUDED CIRCLE SECTOR SHAPE.



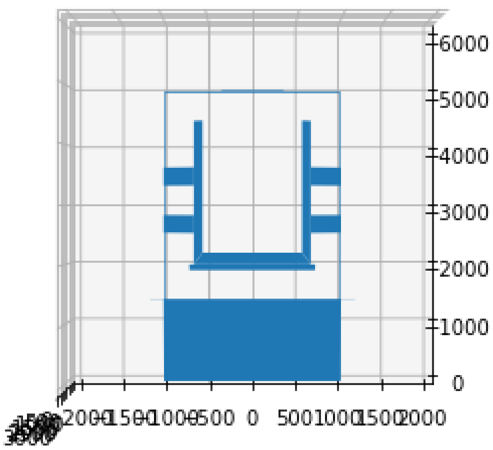
(A) ISOMETRIC VIEW.



(B) FRONT VIEW.



(C) SIDE VIEW.

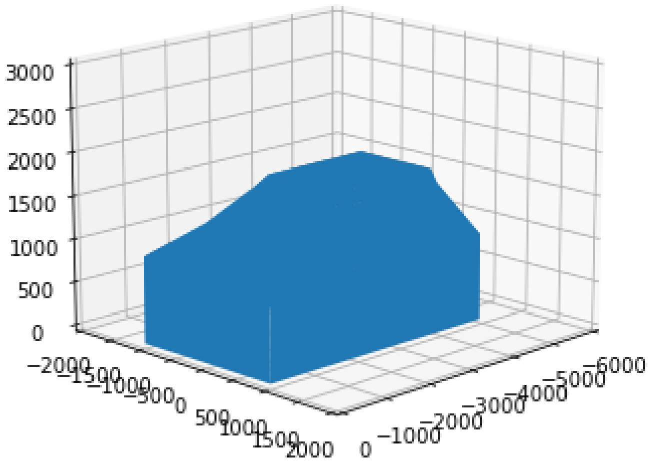


(D) TOP VIEW.

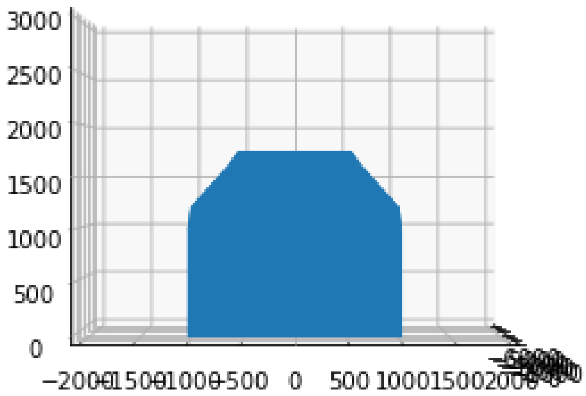
FIGURE 8 VISUALIZATION OF THE PROVIDED DATA OF A SIMPLE OCCLUSION GEOMETRY.

BMW GROUP

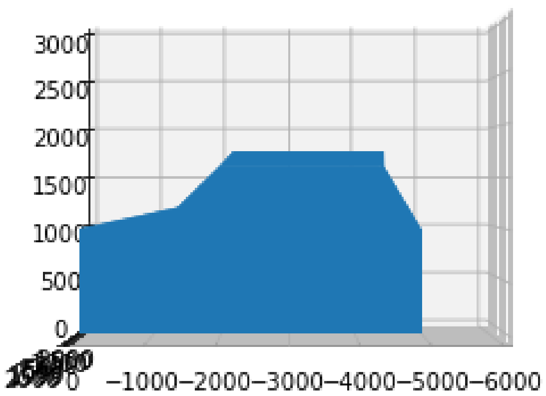
Visualization of a simple occlusion geometry



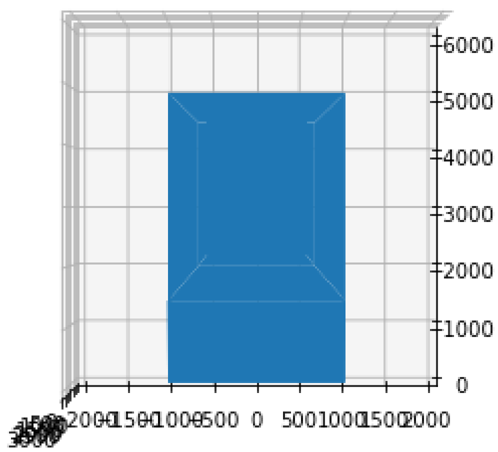
(A) ISOMETRIC VIEW.



(B) FRONT VIEW.



(C) SIDE VIEW.



(D) TOP VIEW.

FIGURE 9 VISUALIZATION OF THE PROVIDED DATA OF A SIMPLE OCCLUSION GEOMETRY

References

[1] M. Hartstcrn, V. Rack and W. Stork, "Conceptual Design of Automotive Sensor Systems: Analyzing the impact of different sensor positions on surround-view coverage," 2020 IEEE Sensors, 2020.

[2] J. Dey, W. Taylor and S. Pasricha, "VESPA: A Framework for Optimizing Heterogeneous Sensor Placement and Orientation for Autonomous Vehicles," IEEE Consumer Electronics Magazine, 2020.

[3] A. A. Ageev and M. I. Sviridenko, "Approximation algorithms for maximum coverage and max cut with given sizes of parts," in International Conference on Integer Programming and Combinatorial Optimization., Springer, 1999, pp. 17-30.

[4] V. Akbarzadeh et. al, "Efficient Sensor Placement Optimization Using Gradient Descent and Probabilistic Coverage," Sensors, vol. 14, pp. 15525-15552, 2014.

[5] BMW Austria, "BMW X5 Technical Data," https://www.bmw.at/content/dam/bmw/marketAT/common/technicaldata/G05_BMW_X5_2019_v2_CM/images/bmw_x5_xdrive40i/bmw-x5-technical-data-sp-sketch.jpg, Accessed July-2021.