Shader-based Automatic Camera Layout Optimization for Mobile Robots using Genetic Algorithm

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Abstract: Given a mobile robot and a certain number of cameras, this paper addresses the problem of finding locations and orientations of the cameras relative to the robot such that an optimality criteria is maximized. The optimality criteria designed in this paper emphasizes the trade-off between the coverage of area of interest around the robot by the cameras subject to occlusion constraints and the proximity of cameras to the robot structure. Real coded genetic algorithm is employed to search for such optimal layout and the optimality criteria serves as the fitness function. The computation intensive parts, namely the coverage and proximity analysis, are adapted to such a form that GPU with programmable shader can be accommodated to accelerate them. A graphical user interface tool is constructed to allow observation and checks during the optimization process. Promising results are displayed in an experiment concerning a truck with seven cameras. The optimization framework outlined in this paper can also be extended to optimize layout of scanning sensors like LiDAR and Radar mounted on arbitrary structures.

1 INTRODUCTION

Mobile robots often use cameras to perceive their surroundings, as is shown in the case of autonomous vehicles with a vision system consisting of cameras, LiDARs and Radars. As camera sensors become more affordable and effective, an increasing number of daily driven cars and utility vehicles are adopting camera systems to improve driving safety. For instance, a garbage truck operator needs a vision system to secure loading and unloading of the garbage at the rear of the truck. Another example comes from the field of mining truck. Huge mining trucks up to date can be 10 meters tall and 20 meters long; as a result, it is necessary for them to have a monitoring system in order to avoid accidents with other small vehicles. These mobile vehicles with such vision assistants are also categorized as mobile robots in terms of the problem domain concerned in this paper.

Efficiency and effectiveness are crucial in such camera systems: the limited power supply and space resources on mobile robots restrict the camera amount, while desirable effects of image processing algorithms demand extensive and detailed perception. Therefore, an optimal layout of cameras is significantly important. However there has been little research effort towards this problem in field of mobile robots so far. The work presented in this paper is thus motivated to fill this gap, i.e. to address the problem of camera layout optimization for mobile robots.

Without loss of generality, given a mobile robot R, certain area of interest A around R, a fixed number N of cameras C and a bounded continuous design space P from which the locations and orientations of cameras are chosen; we are focusing on finding a set of camera parameters $P_{optimal}$ that can maximize an objective function F_N implying the trade-off between the coverage of the camera system over A and the proximity of cameras to the robot structure. Equation (1) gives a mathematical expression of the problem. In terms of evaluation of a certain layout, coverage calculation and the computation of proximity of cameras to the robot structure are two key issues among others. We adapt the coverage analysis and proximity computation to such a form that GPU with shader can be adopted to enhance the computation. Genetic algorithm (GA) is employed as optimization method. Our solution framework can also be applied to hybrid sensor system consisting of cameras, LiDARs and Radars.

$$P_{optimal} = \underset{P' \in P}{\arg\max} F_N(P',\ R,\ A) \quad (1)$$

With problem definition stated above, main contributions of our work are as follows:

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(1) First attempt to take into account in camera layout optimization the proximity of the cameras to the structure on which they are mounted and to transform the problem in a way that shader can be employed to enhance the optimization process.

(2) Detailed presentation of a GUI Tool framework allowing observations and checks in optimization process.

(3) First attempt to adopt real coded GA to search for the optimal layout of a camera system in the context of mobile robot over a continuous design space, as opposed to using preselected camera candidates with discrete location and orientation values presented in works in other contexts such as security monitoring system.

The remaining of this paper is organized as follows: in Section 2 a review of related work is illustrated and our approach is justified in comparison with them. In Section 3 the methodology with respect to coverage and proximity analysis is presented. In Section 4 the instantiation of the methodology using shader are described in detail. After that, GA optimization overview and implementation details are presented in Section 5. Section 6 depicts the GUI Tool. The experiment and related results about camera layout optimization for a truck are presented in Section 7. Section 8 contains a conclusion of this work and directions of future work.

2 RELATED WORK

Research in the area of camera layout optimization has roots in the Art Gallery Problem (AGP), an extensively studied topic in the field of computational geometry. The purpose of AGP is to find the positions of a minimum number of guards such that every point in a polygon is within sight of at least one guard. Extensive reviews about AGP and its variants can be found in (O'Rourke, 1987),(Erdem and Sclaroff, 2006),(Murray et al., 2007). In short, the determination of exact solution for AGP is NP-hard, while many efficient algorithms and heuristics are available to ensure a suboptimal decision; theoretical results concerning AGP are based on unrealistic assumptions such as infinite Field Of View (FOV) for cameras and therefore they cannot provide effective approaches to real world problems.

Consequently, a large majority of research related to optimization of camera configuration with more realistic assumptions has emerged and most of it is set in the context of in- or outdoor surveillance and monitoring system, where video camera systems are widely employed and an optimal arrangement of cameras is crucial.

In (David et al., 2007) a sensor placement approach was proposed for monitoring human activities in indoor scenes. Their goal is to determine a subset of preselected sensor samples such that the sensor cost is minimized and the required scene is covered. Firstly, the polygons in the scene are sampled into a list of points and the points covered by each sensor candidate are determined via a ray tracing algorithm from Matlab. Then branch and bound algorithm and GA are implemented respectively for an optimal solution. The approach is exemplified with cameras while the authors stated that it also applies to other camera-like sensors.

With the same basic idea as (David et al., 2007), (Erdem and Sclaroff, 2006) proposed a radial sweep visibility algorithm to handle holes in the floor during ray tracing rendering in order to consider the occlusions caused by them. In terms of optimization method, it was asserted that the optimality of the final result would depend on the density of the preselected camera samples with discrete location and orientation values.

Although it was stated in (David et al., 2007) and (Erdem and Sclaroff, 2006) within their methodology that the problems are set in a 3D context, yet the implementations were carried out in simplified 2D versions.

A framework was developed in (Murray et al., 2007) to optimize video sensor placement for security monitoring in an urban area. They employed Geographical Information System (GIS) to implement visibility analysis(i.e. coverage analysis) and adopted a commercial optimization software to search for the optimal solution. They focused on illustrating the effects of various trade-offs among different areas of interest via implementing the optimization framework.

Research in (Becker et al., 2009) focused on camera layout optimization for detection of human beings. Instead of a planar area of interest, a 3D volume of interest extruded from horizontal surfaces up to the height of a human being is taken as the target space. The 3D volume is sampled into a series of points and the coverage is computed by a ray tracing algorithm. A greedy heuristic is followed in the selection of cameras.

An automatic approach is proposed in (Fleishman et al., 2000) for choosing camera positions that can guarantee an image-based modeling of high quality. In addition to the coverage requirements, the rendered images should be qualified for the 3D scene modelling task. Correspondingly, the coverage quality is stressed. They mentioned that they employ 3D hardware to speed up the visibility analysis; thus our visibility analysis method might be similar to theirs in scope.

A wireless sensor network optimization using multi-objective GA(MOGA) is described in (Jourdan and de Weck, 2004). Besides horizontal and vertical coordinates of the sensors, they also introduce the sensor number into the design vector. The MOGA provides the end-user with a set of Pareto-optimal layouts illustrating the trade-off between different objectives, one of which is the number of deployed sensors.

To conclude, the methodology and implementation presented in our work suits very well to the context of mobile robots. Firstly, in contrast to the huge amount of sensors and quite large area of interest in contexts of surveillance system mentioned above, the number of sensors mounted on a robot is very limited and thus the area of interest of such a camera system is relatively small. Consequently, a more accurate coverage analysis considering occlusion constraints imposed by the robot body itself is necessary and tractable in terms of time consumption. Secondly, mobile robots are always in dynamic states due to motion and suffer from frequent contact with its surroundings, thus it is better to place the sensors close to the robot body for the sake of compactness. As a result, the proximity between the cameras and the robot body should be considered in the evaluation of a camera layout. Lastly, as the design space of the optimization problem in the case of mobile robot is much smaller than that of in-or outdoor surveillance systems, we do not need to preselect sensor candidates; instead, we use GA to search over a continuous design space with bounding limits defined by the robot body structure and the target area, which is otherwise computationally prohibitive in terms of surveillance systems involving large areas.

3 METHODOLOGY

The evaluation of a given layout according to the optimality criteria that emphasize the trade-off between coverage and proximity is the most computation intensive part in the problem focused in this paper. We formulate the coverage and proximity analysis in such a way that rasterization based rendering technique can be employed to enhance the computation via the use of GPU. The programmable shader in the rendering pipeline is designed to record the information we need.

3.1 Coverage Analysis

As the FOV of a camera can be represented as a frustum, the coverage analysis within the scope of this paper can be formulated in the following way: given several frustums , a set of primitives like points, lines and polygons serving as area of interest to be covered and another set of such primitives imposing occlusions, the problem is to calculate the intersection area of the frustums and the area of interest subject to the occlusions. It is almost intractable in terms of computational intensity to obtain accurate results for such problems when the primitives and the frustums are in a large amount and positioned irregularly, which is just the case as presented in this paper. As a result, the coverage analysis algorithm designed in this paper implies a trade-off between the accuracy and the time consumption and is based on the parallel computation architecture of GPU and the flexibility of the programmable shader. The corresponding method is presented in the following:

(1) The set of primitives composing the area of interest is discretized into small entities, with each assigned a specific identity number. All the primitives producing occlusions are assigned one common identity number.

(2) While normally the rendering result of the frustum by GPU is an image of pixels with each containing color information of the targeted entity(i.e, the entity that lies within FOV of the frustum and is used to provide information for that specific pixel during image rasterization), a specific shader can be designed to record the identity number of the entity rather than the color information in the pixel.

(3) After all the frustums are rendered, the coverage is calculated according to the set of entities belonging to the area of interest recorded in the images. The fact that an entity would appear more than once means that some part of the covered areas of different frustums are overlapped, so in such case only one instance of the entity should be considered. Weights can be assigned to the entities to indicate their various degrees of importance.

3.2 Proximity Analysis

Proximity analysis can be reduced to finding the shortest euclidean distance between a point and a set of primitives in 3D space (i.e., the robot in our case). Such problem is faced with the same challenge as the coverage analysis. The common method to deal with it is to make use of a bounding box comprising the set of primitives and calculate the shortest distance of the point to the bounding box. As the body structure of a mobile robot is complicated and irregular, the bounding box solution would result in a large discrepancy between the real distance and the approximated one.

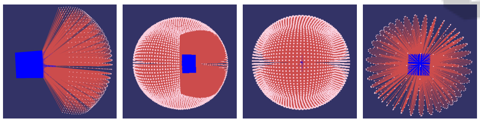
The method proposed in this paper can yield a more accurate proximity calculation with the extra computation cost incurred being discounted to some extent by leveraging the parallel computation architecture of GPU. The resulted method is in principle similar to that of coverage analysis. The following is applied to each camera separately:

(1) A certain amount of frustums with origins at the position of one camera are constructed and oriented in such a way that they can together cover the 3D space around that camera.

(2) The shader for each frustum rendering is designed to record in each pixel the identity number of the targeted entity as well as its distance to the origin of the frustum (i.e.,the location of the camera).

(3) The shortest distance (i.e., the proximity) can be obtained by comparing the distance values saved in all the pixels with the identity number of the robot in the images rendered by all the frustums.

Finally, the largest proximity among the member cameras is assigned to be the proximity of the camera system. Figure 1 demonstrates the effect of proximity analysis instantiated with 6 frustums for one camera.



(a) (b) (c) (d)

Figure 1: One camera location with 6 frustums: $\psi = 0°, \theta = 0°, 90°, 180°, 270°$ respectively; $\theta = 0°, \psi = 90°$ and $270°$ respectively. $\phi = 0°$ for all. (a): 1 frustum; (b): the other 5 frustums; (c): 6 frustums with high resolution images; (d): 6 frustums with low resolution images.

4 INSTANTIATION

In this section, the implementation details with regard to the methodology presented in Section 3 are described. As the coverage and proximity analysis are similar in principle with main differences lying in the information recorded in shader, we only emphasize the coverage analysis here. The instantiation is set in the scenario of camera system layout optimization for a truck. As is pointed out earlier, a truck with a camera system is also regarded as a mobile robot within the scope of this paper.

4.1 Mobile Robot Modelling

The mobile robot model is a 3D mesh composed of geometric primitives like points, lines and polygons. It has two roles in the scenario: cameras accommodation and camera view occlusion. In terms of genetic algorithm implementation, we specify a bounding box on the robot as the location design space for the cameras. With regard to coverage and proximity analysis, we assign an identity number *IDR* to the robot as a common property for all its vertices such that it can be differentiated from the area of interest.

4.2 Area of Interest Modelling

As surroundings of the mobile robot always change, it is hard to define a universal target space. As a result, we specify a planar area around the robot as the area of interest. While this is a a naive assumption, it can be adapted to more complex versions as long as more detailed information about the environment is available.

The planar area is discretized into a grid to facilitate coverage calculation and thus the calculation accuracy depends in part on the resolution of the grid. Two arrays, $WeightArray(WA)$ of float type and $OccupancyArray(OA)$ of binary type with each of size $ArraySize(AS)$, are allocated in shared memory to store weights and states of coverage of the grid cells respectively. Each grid cell is assigned a specific identity number *IndexID* identical to its index in the arrays to communicate if any cell is covered by any camera FOV. It should be noted that the robot identity number *IDR* must be outside the scope of the array index and that the weights are determined according to specific requirements from the area of interest. The element in *OA* is set to the value of 1 if the grid cell related to it is covered; thus the coverage can be represented in the form of (2). R and A are implicitly included in (2) because they have influences on the values of $WA(i)$ and $OA(i)$.

$$C_N(P,R,A) = \frac{\sum_{i=0}^{AS-1}(WA(i) \times OA(i))}{\sum_{i=0}^{AS-1}(WA(i))} \quad (2)$$

In combination with the proximity, the objective function F_N in (1) can be formulated as (3), where the value of α implies the trade-off between coverage and proximity. The range of the fitness function is $[0,1]$.

$$F_N(P,R,A) = C_N \times \frac{C_N}{\alpha Proximity_N + C_N} \quad (3)$$

4.3 Camera Modelling

The camera, namely the frustum, is modelled by the camera node specified in OpenSceneGraph(OSG). More details can be found in (Wang et al., 2012), where the simulated Radar works in a similar way to the frustums for coverage analysis while the main function of simulated LiDAR corresponds to the role of frustums for proximity analysis. Cameras have intrinsic and extrinsic properties. The intrinsic ones concerned in this paper include mainly depth of field bounded by *Near* and *Far* values, vertical FOV, horizontal FOV, vertical resolution and horizontal resolution; the first three define the frustum which in turn determines the transformation matrix from camera coordinates to the 2D image arrangement, while the last two specify the image resolution. The extrinsic ones contain location (x, y, z) and orientation $(yaw(\psi), pitch(\theta), roll(\phi))$ which specify the transformation matrix from world coordinates to the camera coordinates. In our work only the extrinsic parameters are taken as design variables while the intrinsic ones embodying the camera type remain unchanged during the optimization.

As we evaluate the coordinated performance of all the cameras in the camera system, we construct a class *MultiCameraModel* comprising both intrinsic and extrinsic properties necessary in the modelling of one set of N cameras. The counterpart of *MultiCameraModel* with respect to GA is another class *MulticameraIndividual* involving only the extrinsic properties. There is only one instance of *MultiCameraModel* in shared memory, whereas the number of *MulticameraIndividual* instances remain consistent with the *population size* specified for GA optimization. During the coverage analysis, *a MulticameraIndividual* would substitute for extrinsic properties of *the MultiCameraModel* such that the camera system would be remodelled and the corresponding coverage would be calculated. In addition, three variables, *AllImageProcessed*, *TotalImages* and *ProcessedImages*, are allocated in shared memory to assist the coverage analysis; *TotalImages* is of value N while *ProcessedImages* changes in value on the fly. The coverage analysis framework is elaborated in subsection 4.4.

A vertex shader and a fragment shader serve in the rendering pipeline of the camera model such that the identity number of the objects within the camera view can be recorded during the rendering stage and analysed thereafter. Related shader programming is illustrated in Figure 2. The targeted position of each pixel is also recorded for displaying of the vision system effect. As each of the four elements composing one fragment ranges from 0 to 1, the identity number and position must be divided by certain *ScaleFactor*s before assigned to the *FragData*(pixel). More details about shader application in camera-like sensor modelling are available in (Wang et al., 2012).

A class *PostRenderingAnalysis* is attached to the camera model for image analysis implemented for each camera during coverage analysis. The pseudo code of this procedure is shown in Algorithm.1, where the letter M indicates the index of the element that stores *IndexID* of targeted entity in *FragData*.

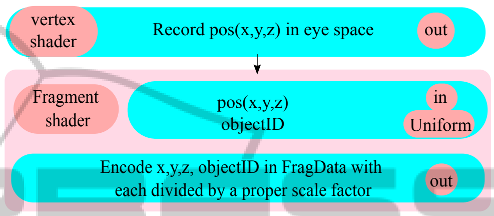


Figure 2: Vertex and fragment shader programming.

Algorithm 1: Image analysis for one camera.

```
function POSTRENDERINGANALYSIS( )
    if !AllImageProcessed then
        for Frag ← all frags in current image do
            ObjectID ← Frag[M] × ScaleFactor
            if 0 ≤ ObjectID < ArraySize then
                OccupancyArray[ObjectID] ← 1
            end if
        end for
        ProcessedImages ← ProcessedImages + 1
        if ProcessedImages == TotalImages then
            AllImageProcessed ← true
        end if
    end if
end function
```

4.4 Coverage Analysis

Coverage analysis serves as part of fitness evaluation in GA. There are three modules involved in coverage analysis: GA, shared memory and simulator (camera modelling and rendering). GA and simulator communicate with each other via shared memory. Basically, individuals of GA iteratively substitute for the extrinsic parameters of the *MultiCameraModel*, leading to reconstructions of the camera models. After images in the frame buffer are refreshed and analysed, GA summarizes the fitness value in terms of coverage according to (2). Figure 3 displays a detailed implementation.

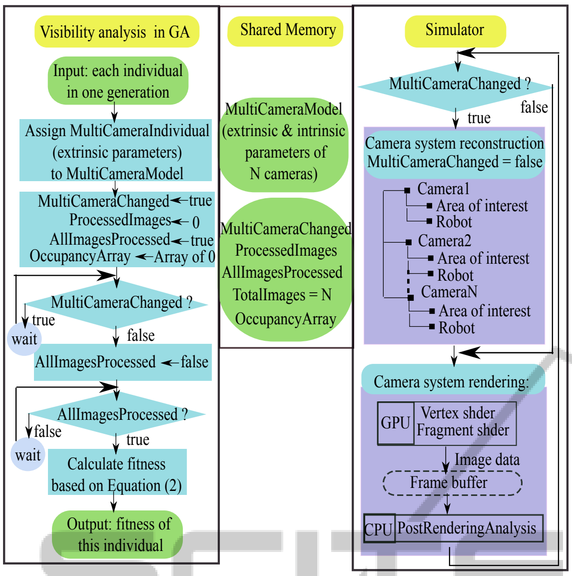


Figure 3: Coverage analysis implementation.

5 GENETIC ALGORITHM IMPLEMENTATION

5.1 Justification for Applying GA

The main characteristics of the optimization problem defined in this work are as follows:

- It is hard to present the objective in terms of the design variables: expression of the intersection of the ground with one single frustum in terms of design parameters is already very difficult, not to mention the case where the overlapping area of every two intersections and the occlusions of the mobile robot are considered.
- The quantitative and qualitative relationship between each design variable and the objective is also difficult to determine. Due to the two reasons mentioned above, classical slope based optimization algorithm is not applicable for our task.
- The design space is continuous and multi-dimensional. As the time complexity grows exponentially with the number of design parameters, it would be computationally intractable to simply discretize the design space and perform a brute force algorithm.

As a result, GA, an efficient tool in handling optimization problems involving functions intractable by classical optimization methods(Sharapov and Lapshin, 2006), is chosen for resolving our problem.

5.2 Optimization Framework

GA imitates natural selection process in search of a better solution (Holland, 1992). Therefore its basic idea is to iteratively reproduce a new generation of individuals through operating on the old one; these operations should be designed in such a way that the new generation in general adapts to the environment at least as well as, if not better than, the old one. Common operations are selection, crossover and mutation (Goldberg, 1989). As operations on the individuals are probabilistic, GA optimization is also a stochastic process which cannot ensure that a solution can be found. In (Sharapov and Lapshin, 2006) some proofs on the convergence of several genetic algorithm variants in the mean are provided. In general, the probability of operations and the design of operations themselves are crucial in terms of search efficiency and global optimality of the converged solution. Our GA optimization framework is shown in Figure 4.

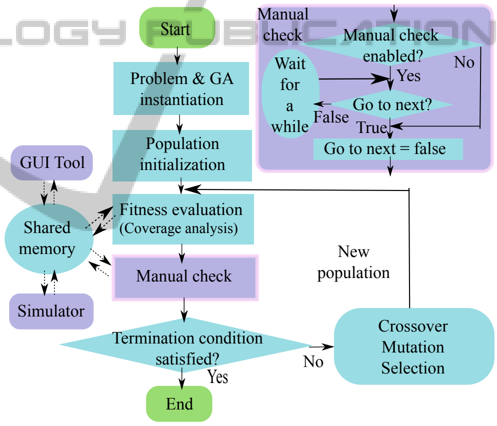


Figure 4: GA optimization flow chart.

5.3 Implementation Details

The following describes the adaptations of GA for solving the problem defined in this paper.

- Individual: *MultiCameraIndividual* containing design variables of N cameras, as mentioned in Section 4, is represented in the following way:

$$[x1, y1, z1, \psi 1, \theta 1, \phi 1, x2, y2, ..., \phi N] \quad (4)$$

- Population: The population size is empirically set to be around 10 times the number of design variables of the individual. The initial population is generated by pseudo random number generator.
- Selection: Detailed discussion of selection methods are available in (Sivaraj and Ravichandran, 2011). Traditional Roulette Wheel selection is

utilized in this work and thus the probability for each individual to get involved in *crossover* is proportionate to their fitness. Elitist selection is also applied to ensure that individual with the highest fitness is always passed to the next generation.

- Crossover and mutation: One-point and two-point crossover are undertaken respectively, each with two crossover strategies: crossover per camera, crossover per design variable. The results turned out to be almost the same, though. Mutation is applied on one stochastically chosen parameter of each camera of randomly selected individual camera system.
- Random number generator: Pseudo random number generator proposed in (Matsumoto and Nishimura, 1998) is adopted in this work. We observe that random number is crucial to the success of the optimization.

6 GUI TOOL

The GUI Tool contains a display for observation and a GUI control panel facilitating observation and checks of the optimization progress and result. The GUI Tool functionalities and framework is presented in Figure 5 while a snapshot of the GUI Tool is shown in Figure 6. Via the manual check, the GA pauses while the user can check the performance of any individual in current generation via GUI Tool. The user can also modify the individual and GA parameters to influence the GA process if necessary.

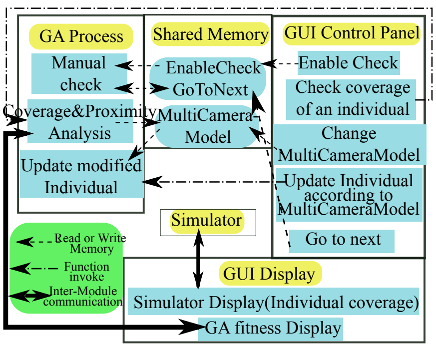


Figure 5: GUI Tool functionalities and framework.

7 EXPERIMENT AND RESULTS

In the experiment we consider the problem of a truck and its vision system of 7 cameras. The scenario is shown in Figure 6. The experiment is carried out on a computer with 4 core-Intel i5 CPU and GeForce GT 330 with 1024MB memory.

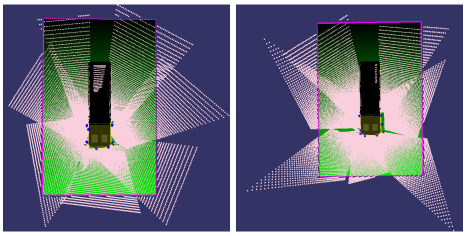
Figure 6: Problem instantiation and part of GUI Tool.

7.1 Problem Modelling

- Design variable constraints: The yellow bounding box in Figure 6 suggests the design space of camera locations(indicated by the blue box) while the orientations are bounded within $\psi : [0°, 360°]$, $\theta : [50°, 65°]$, $\phi : [0°, 90°]$. The red frustum displays the camera modelling. The white points on the floor and the truck represent the coverage of camera view and the occlusion effect imposed by the truck respectively. Image resolution of each camera is 75×48 for coverage analysis and 180×180 for proximity analysis.
- Area of interest: A grid of 2280 cells represents an area with $5m$ offset surrounding a truck with length of $8m$ and width of $2.5m$, as is shown in Figure 6 with each cell drawn in a random colour. Weights of all the cells are set equally to 1.
- GA: Population size is 480; crossover rate is 0.99; mutation rate is 0.1; elitism rate is 1%; it terminates at the 120th iteration.
- Fitness function: refer to (3). We demonstrate two cases in the following with α equal to 0 and 1 respectively.

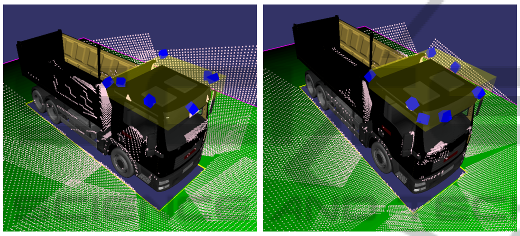
7.2 Results

The performance of the camera system after 120 iterations is shown in Figure 7 and Figure 8. Figure 9 displays the corresponding evolution processes of 120 iterations in terms of best (green), average (blue) and worst (red) fitness , and also of proximity (yellow) and coverage(magenta) for the individual with the best fitness when α is not 0 in the fitness function. It takes about 80 minutes in average for optimization without proximity analysis while those with proximity analysis last about 600 minutes.



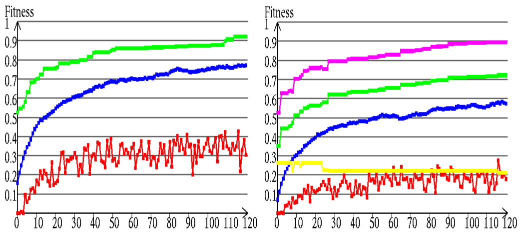
(a) $\alpha = 0$ (b) $\alpha = 1$

Figure 7: Coverage performance of the optimal layouts: (a) coverage = 0.92, (b) coverage = 0.89.



(a) $\alpha = 0$ (b) $\alpha = 1$

Figure 8: Camera locations of the optimal layouts: (a) Proximity = 0.39(m), (b) Proximity = 0.21(m).



(a) $\alpha = 0$ (b) $\alpha = 1$

Figure 9: Fitness evolution of 120 iterations.

8 CONCLUSIONS AND FUTURE WORK

In this paper, we formulate the camera layout optimization problem for a mobile robot and propose an automatic approach using real coded GA. Coverage and proximity analysis are accelerated by GPU with shader. A GUI Tool for observation and checks in GA process is depicted. The result demonstrated in the experiment concerning a truck is promising. As future work, we will focus on following aspects: (1) modify the fitness function to consider the requirements from the image-processing stage, e.g. distance of neighbouring targeted points on the planar area (2) investigate into the practical guidelines in choosing the parameters of genetic algorithm.

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