# The K-Framed Quadtrees approach for path planning through a known environment 

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#### Abstract

One of the most important tasks for a mobile robot is to navigate in an environment. The path planning is required to design the trajectory that generates useful motions from the original to the desired position. There are several methodologies to perform the path planning. In this paper, a new method of approximate cells decomposition, called K-Framed Quadtrees is present, to which the algorithm $\mathrm{A} \star$ is applied to determine trajectories between two points. To validate the new approach, we made a comparative analysis between the present method, the grid decomposition, quadtree decomposition and framed quadtree decomposition. Results and implementation specifications of the four methods are presented.


Keywords: Path Planning, K-Framed Quadtree, Approximate Cells Decomposition

## 1 Introduction

Mobile robots have inspired a number of studies in complex environments, where path planning and control of robotic systems is a concern. They must be agile, efficient and fast, avoiding collisions and situations that could endanger human who are in the same environment.

Given the current location and a destination, path planning algorithms determine a path to reach the desired position. Initially, it is necessary to define the configuration space, which represent all possible system configurations. This consists of two zones, the space free of an obstacle, which may belong to the trajectory to be defined for the robot, and the space occupied by obstacles. Often, a reduction of the configuration space is applied, reducing the robot to a single point [1]. To do this, all obstacles must be expanded, so the trajectory to be defined is free of robot obstacle collisions.

There are several techniques for determining the path between two points. Methods based on Roadmap involve the creation of nodes representing locations, and links between them, that represent possible paths between nodes. Examples of Roadmap techniques are the Visibility graph [6], which generates trajectories
in which the robot can move very close to obstacles, or Voronoi diagram [7], which generates a Roadmap where the distance between the robot and the obstacles is maximized. In this technique, the generated trajectory commonly do not correspond to the smallest possible path [2], and the probabilistic roadmap consists of the random distribution of nodes along the free space. Therefore, trajectories with narrow passages are not determined, even if they exist [3]. The algorithm Bug is the simplest algorithm in terms of implementation, which is used when without knowledge of the environment. However, it does not generate optimal trajectories [4]. The use of potential fields in path planning is based on the use of electrical potentials of physics as a heuristic to find the trajectory. However, this method has important limitations such as local minimums, which block the robot, and when the robot is in front of concave obstacles, there are several possible minimum distances, which results in oscillations between the points closest to the target. The problem of local minima may be solved by forcing local potential extremes to lie on the boundaries of obstacles through the use of harmonic potentials [8]. The cell decomposition consists of the decomposition of the space into cells and subsequent division into occupied or free cells. ells decomposition can be effected through exact cells, where each cell has only two possible states, totally free or fully occupied, or in approximate cells, where each cell can be free, occupied or partially free. There are several techniques to implement this method, decomposition, where the map is decomposed into fixed-size cells, decomposition into quadtrees, and decomposition into framed quadtrees [5]. The approximate cell decomposition is one of the most used techniques in the path planning of mobile robots [1].

In this paper, we present a new approximate cell decomposition method called K-Framed Quadtrees which generates a graph to $A$-star $(A \star)$ that is applied to determine the best trajectory. In order to validate the new decomposition, a comparative analysis is done with the most used methods of approximate cells decomposition: grid decomposition, Quadtrees decomposition and Framed Quadtrees decomposition, that also use $\mathrm{A} \star$.

## 2 Approximate Cells Decomposition

Initially, an expansion of the obstacle area is performed with the dimensions of the robot, to allow a free of collisions path. This allows the robot to be considered as a point in space.

### 2.1 Grid Decomposition

Grid decomposition consists of dividing the map into cells of equal size, each representing a node containing information about the state of the space, i.e. free or occupied. This size varies according to the type of environment and the expected results. If a small portion of an obstacle is intersected by a cell, the cell is filled as occupied, so large cells have associated greater loss of information,
and consequently, there are more areas of the map considered to be wrongly occupied.

The size of the cells affects the performance of graph search algorithm subsequently applied, since the smaller the cell size, the greater the number of cells to analyze. This increases processing time, but the defined path will be closer to the optimal. The chosen cell size should be enough to maximize the speed of search algorithms, while allowing the access to most areas of the map.

In this work, the neighbor cells are determined through a search with connectivity 8 around the current cell, where the state of each is stored in a state vector in the position $x+y \times$ numberOfCellsPerLine, where $x$ and $y$ correspond to the Cell indexes in $X X$ and $Y Y$.

### 2.2 Quadtree Decomposition (QD)

Quadtree decomposition uses cells of variable size to represent the environment. The cells are successively divided into four children cells recursively, until a cell is located in a completely occupied or completely free zone or until a threshold resolution is achieved.

Quadtree is a tree data structure in which each inner node has exactly four children nodes, and each one represents a quadrant (Northwest-NW, NortheastNE, Southwest-SW and Southeast-SE). Each cell is represented by a structure that contains the following information:

1. Initial cell position in $X X$ and $Y Y$
2. Size of the cell in $X X$ and $Y Y$
3. State of the cell: totally occupied, totally free or to be subdivided
4. Division level to which the cell belongs
5. Pointers to the 4 children cells (NW, NE, SW and SE)

This method provides great precision in areas close to obstacles. The limit resolution determines the loss of map information, i.e. a higher limit resolution allows cells of smaller size, so it will be possible to access more zones of the map, in relation to a lower limit resolution. Cells are considered neighbor cells if they share an edge and / or a vertex. Thus, if a neighbor cell is free of obstacles, the union between them may belong to a path.

### 2.3 Framed Quadtree Decomposition (FQD)

Framed quadtree decomposition results of an enhancement of the previous method. This algorithm consists in the addition of higher resolution cells near the perimeter of each quadtree region. Each resulting cell is represented by a structure that contains the following information:

1. Cell's central point position in $X X$ and $Y Y$
2. Pointer to the quadtree cell to which the cell belongs

In this algorithm, when determining the neighbors of the cells generated through QD, it is necessary to store the information on the side to which the neighbor cell belongs, that is, if the neighbor cell is located North (N), South (S), west (W), east (E), northeast (NE), northwest (NW), southeast (SE) or southwest (SW) of the current cell. Once the neighbors of a parent cell (cell generated by the QD) are determined, the neighbors of a children cell (cell generated by the FQD) are higher resolution cells belonging to the same parent cell and the children cells of the neighbor cells originated by the QD, if they are within restricted limits. These limits are listed below, where $v$ represents the neighbor cell and $n$ represents the current cell:

1. If $v$ is a neighbor parent cell (cell originated by QD) to N or S

- The children cells (cells originated by FQD) of $v$ are considered neighbor cells if their position in $X X$ is between the parent cell's boundaries in $X X$ of n and if v contains in its $X X$ boundaries the x position of n
- The children cells of $v$ are considered neighbor cells if their position in $Y Y$ is between the parent cell's boundaries in $Y Y+$ size of children cells (S), or $Y Y$ - size of children cells ( N ), and if there are no flaws on the side to which v belongs ( N or S ) and v does not contain in its $X X$ boundaries the x position of n

2. If $v$ is a neighbor parent cell to W or E

- The children cells of $v$ are considered neighbor cells if their position in $Y Y$ is between the parent cell's boundaries in $Y Y$ of n and if v contains in its $Y Y$ boundaries the y position of n
- The children cells of $v$ are considered neighbor cells if their position in $X X$ is between the parent cell's boundaries in $X X+$ size of children cells (E), or $X X$-size of children cells (E), and if there are no flaws on the side to which v belongs ( W or E ) and v does not contain in its $Y Y$ boundaries the y position of n

3. If $v$ is a neighbor parent cell to NW, NE, SW or SE, the children cell closest to the current cell is considered neighbor, if the sides to which it belongs do not exist faults.

## 3 K-Framed Quadtree Decomposition

This method consists of the junction of quadtree decomposition (QD) and framed quadtree decomposition (FQD). In the K-Framed Quadtree algorithm, the QD is performed in a first phase, and subsequently cells of higher resolution are added in the vicinity of the perimeter of each cell with size above the previously established lower limit, $k$. This allows an adjustment between the two algorithms in which at the two extreme points it is possible to have a decomposition very similar to the QD and the FQD.

Figure 1 shows the map represented by the present algorithm. In the first instance, decomposition with $k=2.5 \times 2.5 \mathrm{~m}$ results in a decomposition identical to QD, since there are no cells with size larger than $k$. However, the third case results in decomposition identical to FQD because the coefficient $(k)$ considered
was smaller than the size of the smallest cells. The second case is an intermediate between the QD and the FQD.


Fig. 1: Representation of the map through the algorithm K-Framed Quadtree. It was considered a limit for the cell size of $62 \times 62 \mathrm{~cm}$, the cells of higher resolution have dimensions of $25 \times 25 \mathrm{~cm}$, being applied to cells with dimensions greater than $2.5 \times 2.5 \mathrm{~m}$ (Figure 1a), $1 \times 1 \mathrm{~m}$ (Figure 1b) and $25 \times 25 \mathrm{~cm}$ (Figure 1c).

In the case of the chosen coefficient $k$ being high, and consequently, existing cells that hasn't children cells, if some of those cells belong to the initial point or to the target point, FQD is executed and then deleted. The reason why these children cells should be eliminated is due to the fact that it is desired to maintain the previously selected configurations. If they were not eliminated after executing the graph search algorithm to determine the several trajectories, the map's representation would be even more similar to the FQD. Therefore, they are eliminated after the determination of the trajectory, maintaining the chosen configuration. Figure 2a shows a representation of the map in which none of the cells underwent FQD. However, when performing the search algorithm, cells that contain the beginning and the end point are determined, to which FQD is applied, as represented in Figure 2b.


Fig. 2: Representation of the map using the K-Framed Quadtrees method (Figure 2a. Changing the map representation when executing the graph search algorithm on the cells containing the start point and the destination point (Figure 2b).

When the neighbor cells originated by the QD (parent cells) are determined, is it also determined if there is a fault in the neighbor to the North (N), South (S), West (W) and East (E), that is, if any of the neighbor cells are busy. The following are some of the restrictions for a cell to be considered neighbor of the current cell $n$.

1. If cell $v$ is neighbor at S of cell $n$
(a) If $v$ has children cells (cells from the FQD)
i. Are considered Neighbor cells the children cells of $v$ if cell $v$ has within its limits $X X$ the $x$ of cell $n$
ii. If there are no faults at S of cell $n$ and if $v$ does not contain within the limits of $X X$ the $x$ of cell $n$
A. Neighbor cells are the children cells of $v$ that do not exceed the limits of the parent cell of $n$ in $X X$, and which do not exceed in $Y Y$ the upper limit of $Y Y$ of the parent cell of $n$ plus the size of each children cell
(b) If $v$ does not have children cells
i. If $n$ are a parent cell
A. Cell $v$ is considered a neighbor cell
ii. If $n$ are a children cell
A. $v$ is considered to be a neighbor cell if it contains within its limits $X X$ the $x$ of cell $n$
2. If cell $v$ is neighbor at NW of cell $n$
(a) If $v$ has children cells
i. If there are no failures to N and W of n or if n is a parent cell
A. It is considered neighbor only the children cell of $v$ closest to cell $n$
(b) If $v$ does not have children cells
i. if $n$ is a parent cell or if there are no faults at N and W of $n, v$ is considered a neighbor cell

The remaining restrictions on the other sides follow the same logic.
Considering the path to be obtained, is possible to determine a coefficient that minimizes the processing time, with the application of this algorithm. The cells to be considered for the search of graphs are the cells obtained through the FQD in cells of dimensions greater than $k$ and cells belonging to the QD if they have dimensions equal to or less than $k$.

## 4 Results

In order to evaluate the results of the different methods, processing time ( t ) and distance ( $\mathrm{D)} \mathrm{associated} \mathrm{with} \mathrm{the} \mathrm{path} \mathrm{from} \mathrm{the} \mathrm{start} \mathrm{point} \mathrm{to} \mathrm{the} \mathrm{destination}$ are considered. The tests were carried out on two separate maps, with dimensions of $10 \times 10 \mathrm{~m}$ and $20.1 \times 17.5 \mathrm{~m}$. These tests were done in a simulation environment, where all methods must give access to the same zones, that is, the loss of associated information should be the same for all methods. The graph search algorithm A-star $(A \star)$ is used to determine the path through the graphs that result from the previously described methods. In the tables below, the coefficients $\mathrm{T}, \mathrm{l}, \mathrm{r}$, and K represent the size of the cells upon grid decomposition, the lower limit of imposed parent cell size, the size of the children cells, and the minimum dimensions that the parent cells need so children cells are added in the K-Framed Quadtrees decomposition, respectively.


Fig. 3: Path generated in the first map by $A \star$ applied to the methods of grid decomposition (pink), quadtrees (green), framed quadtrees (blue) and k-framed quadtrees (yellow).

| Algorithm | $T$ or $l[\mathrm{~cm}]$ | $r[\mathrm{~cm}]$ | $k[\mathrm{~cm}]$ | $\mathrm{t}[\mathrm{ms}]$ | $\mathrm{D}[\mathrm{m}]$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Grid | $T=30 \times 30$ | - | - | 40 | 5.5 |
| Quadtrees | $l=30 \times 30$ | - | - | 9 | 6.33 |
| Framed Quadtrees | $l=30 \times 30$ | $30 \times 30$ | - | 126 | 5.4 |
| K-Framed Quadtrees | $l=30 \times 30$ | $30 \times 30$ | $62.5 \times 62.5$ | 61 | 5.42 |

Table 1: Results in the first map of $\mathrm{A} \star$ applied to the grid decomposition, quadtrees decomposition, framed quadtrees decomposition and k-framed quadtrees decomposition.

By interpreting Figure 3 and Table 1, we can verify that the trajectory with a smaller associated distance is generated by the framed quadtrees decomposition (FQD), followed by the K-Framed Quadtrees method, the grid decomposition and finally quadtrees decomposition (QD).

Regarding the processing times presented, all values are less than 200 ms , however, the processing time that stands out refers to the QD being only 9 ms . The remaining methods have an additional processing time cost of $31 \mathrm{~ms}, 52 \mathrm{~ms}$, and 117 ms for the grid decomposition, for the k-Framed Quadtree method, and the FQD, respectively.

Considering a small map, such as the one used for the described test, the algorithm that showed the best results was the grid decomposition, although the processing time is significantly better in quadtrees decomposition, the trajectory associated with this algorithm has a high additional cost in the distance, and, with the remaining algorithms, the grid decomposition algorithm presents a better processing time and a very similar trajectory, having an additional cost of about 10 cm .

The second map is a large map with narrow passages. In order to compare the methods, they must have the same loss of information and allow access to the same zones of the map. Two different paths are considered, where the starting point is equal for the two trajectories, and the destination point is different in location of the map, P1, and P2.

| Algorithm | $T$ or $l[\mathrm{~cm}]$ | $r[\mathrm{~cm}]$ | $k[\mathrm{~cm}]$ | $\mathrm{t}[\mathrm{ms}]$ | $\mathrm{D}[\mathrm{m}]$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Grid | $T=15 \times 15$ | - | - | 1068 | 18.05 |
| Quadtrees | $l=15 \times 12.5$ | - | - | 190 | 18.69 |
| Framed Quadtrees | $l=15 \times 12.5$ | $12.5 \times 12.5$ | - | 10184 | 17.80 |
| K-Framed Quadtrees | $l=15 \times 12.5$ | $30 \times 30$ | $65 \times 62.5$ | 411 | 18.41 |

Table 2: Results in the second map of $A \star$ applied to the grid decomposition, quadtrees decomposition, framed quadtrees decomposition and K-framed quadtrees, to the destination point $P_{1}$.

Taking into consideration the values presented in Table 2 and the trajectories presented in Figure 4, the ideal path is generated through the FQD, having a


Fig. 4: Trajectories generated on the large map, by $\mathrm{A} \star$ applied to the methods of grid decomposition (pink), quadtrees decomposition (green), framed quadtrees decomposition (blue) and k -framed quadtrees decomposition (yellow), to the destination point $P_{1}$.
distance of 17.80 m . The remaining trajectories generated by grid decomposition, K-framed quadtrees decomposition, and QD, have an additional cost in the path distance generated $1.4 \%, 3.4 \%$ and, $5 \%$, respectively.

The QD results in the trajectory with greater distance, being this approximately 0.7 m higher, nevertheless the associated processing time is the most satisfactory, being only 190 ms . The path determined through the FQD is the most optimized of the paths presented, however, this method has a high processing time associated, being approximately 10 s . The grid decomposition gave a trajectory with a distance 25 cm higher than the ideal path and a processing time of 1 s . The new method resulted in a path of $18.41 \mathrm{~m}, 41 \mathrm{~cm}$ higher than the ideal one and a processing time of 411 ms , so there is significant improvement, in temporal terms, in relation to the grid decomposition and FQD.

| Algorithm | $T$ or $l[\mathrm{~cm}]$ | $r[\mathrm{~cm}]$ | $k[\mathrm{~cm}]$ | $\mathrm{t}[\mathrm{ms}]$ | $\mathrm{D}[\mathrm{m}]$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Grid | $T=15 \times 15$ | - | - | 705 | 14.60 |
| Quadtrees | $l=15 \times 12.5$ | - | - | 124 | 14.78 |
| Framed Quadtrees | $l=15 \times 12.5$ | $12.5 \times 12.5$ | - | 4776 | 14.46 |
| K-Framed Quadtrees | $l=15 \times 12.5$ | $30 \times 30$ | $65 \times 62.5$ | 234 | 14.54 |

Table 3: Results in the second map of $\mathrm{A} \star$ applied to the grid decomposition, quadtrees decomposition, framed quadtrees decomposition and K-framed quadtrees, to the destination point $P_{2}$.


Fig. 5: Trajectories generated on the large map, by $A \star$ applied to the methods of grid decomposition (pink), quadtrees decomposition (green), framed quadtrees decomposition (blue) and k -framed quadtrees (yellow), to the destination point $P_{2}$.

Figure 5 and Table 3 show results of the path generated from the initial point to the target point, by the different methods implemented. The shortest path results from the FQD , which is considered the ideal route. The remaining methods, in relation to the ideal path, have an additional distance cost of $0.6 \%, 1.0 \%$, and $2.2 \%$, corresponding to the K-Framed Quadtree method, the grid decomposition, and the QD, respectively. The processing times for grid decomposition and FQD are higher than those associated with the remaining algorithms. The QD has the best processing time, followed by the suggested method.

## 5 Conclusion and Future Work

Taking into account that is desired a good compromise between the distance of the trajectory generated and the time of processing, the developed tests allow us to conclude that, in the presence of a small map, the grid decomposition is the method that presents the most satisfactory results. Only the QD presents a shorter processing time, however, it has associated the path more distant than the ideal one. In the test for the first map, this presents an additional cost of a distance of $17 \%$ and is not applied when a near-ideal path is desired. In a completely different way, the FQD allows a path very close to the ideal. However, the processing time is much higher than the other methods and it is consequently not the best method to apply. The suggested decomposition presents a path very close to the ideal, and a processing time not much higher than that presented by the grid decomposition. However, the increase of processing time is considerable,
in relation to a small decrease in the distance of the path. So, this was not considered the best method for these cases.

For the larger map, the grid decomposition obtains a longer processing time, thus becomes unsuitable for applications where a rapid response is desired. In all the tests, the QD presents very satisfactory values of processing time, however, this one originates paths further away from the considered ideal, having as characteristic the presence of an abrupt change of direction, in relation to the other algorithms. On the other hand, FQD presents the shortest path in most tests, but a very high processing time compared to the other methods implemented. In view of these results, a new decomposition appears, which aims, through an appropriate choice of coefficients, to obtain a compromise between the distance of the trajectory generated and the processing time. In this way, it is concluded that when using large maps with narrow passages, with an adequate choice of the coefficients associated with the k-Framed Quadtrees method, this allows better results than the others, if the objective is to obtain a good compromise between processing time and the distance of the trajectory generated. In addition, if the objective is to obtain a fast response by the algorithm, the new method is a good approach, with the proper choice of coefficients. It allows a very similar decomposition with the QD, also obtaining similar results, with an improvement of the trajectory at the beginning of the path and arrival at the destination.

As future work it would be interesting to test the algorithm in a real robot, as well as consider the orientation of the same and including dynamic obstacles.

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