11.AMCL

11.AMCL
- 11.1 Introduction
- 11.2 Navigation and positioning test
  - 11.2.1 Start
  - 11.2.2 positioning analysis
- 11.2 Topics and Services
- 11.3 parameter configuration
- 11.4 coordinate transformation

11.1 Introduction

The full English name of amcl is adaptive Monte Carlo localization, which is a probabilistic localization system for two-dimensional mobile robots. In fact, it is an upgraded version of the Monte Carlo positioning method, which uses an adaptive KLD method to update particles and uses particle filters to track the robot's pose based on a known map. As currently implemented, this node is only available for laser scans and laser maps. It can be extended to process other sensor data. amcl receives laser-based maps, laser scans, and transformation information, and outputs pose estimates. On startup, amcl initializes its particle filter according to the provided parameters. Note that due to the default settings, if no parameters are set, the initial filter state will be a medium-sized particle cloud centered at(0,0,0).

Monte Carlo

- Monte Carlo method, also known as statistical simulation method and statistical experiment method, is an idea or method. It is a numerical simulation method that takes probability phenomena as the research object. It is sampling survey a calculation method for estimating unknown characteristic quantities by obtaining statistical values
- Example: There is an irregular shape in a rectangle, how to calculate the area of the irregular shape? Not good. But we can approximate. Take a bunch of beans, spread them evenly on the rectangle, and count the number of beans in the irregular shape and the number of beans in the rest. The area of the rectangle is known, so the area of the irregular shape is obtained by estimation. In terms of robot positioning, it is possible to be in any position on the map. How can we express the confidence of a position in this case? We also use particles, and where there are more particles, it means the robot is more likely to be there.

The biggest advantage of Monte Carlo method

- The error is independent of the dimensionality of the problem.
- Problems with statistical properties can be solved directly.
- Discretization is not necessary for continuous problems

Disadvantages of Monte Carlo Method

- Deterministic problems need to be transformed into random problems.
- Errors are probabilistic errors.
- Usually requires more calculation steps N.

particle filter

- The number of particles represents how likely something is. Change the distribution of particles through some evaluation method(evaluate the possibility of this thing). For

example, in robot positioning, for a certain particle A, I think the possibility of this particle at this coordinate(for example, this coordinate belongs to the "this thing" mentioned earlier) is very high, so I will give it a high score. Next time you rearrange the positions of all the particles, place more around this position. After a few more rounds like this, the particles will all be concentrated to the position with a high probability.

Adaptive Monte Carlo

- Solved the robot kidnapping problem, it will re-sprinkle some particles globally when the average score of the particles is suddenly reduced(meaning that the correct particles are discarded in a certain iteration).
- Solved the problem of fixed number of particles, because sometimes when the robot positioning is almost obtained, for example, these particles are concentrated in one piece, it is not necessary to maintain so many particles, and the number of particles can be less at this time.

11.2 Navigation and positioning test

According to different models, you only need to set the purchased model in [.bashrc], X1(ordinary four-wheel drive) X3(Mike wheel) X3plus(Mike wheel mechanical arm) R2(Ackerman differential) and so on, to X3 for example.

Open the [.bashrc] file

```
sudo vim .bashrc
```

Find the [ROBOT_TYPE] parameter and modify the corresponding model

```
export  ROBOT_TYPE=X3    # ROBOT_TYPE: X1 X3 X3plus R2 X7
```

11.2.1 Start

Start the driver(robot side), for the convenience of operation, this section takes [mono + laser + yahboomcar] as an example.

```
#You need to enter docker first, perform this step more
#If running the script to enter docker fails, please refer to 07.Docker-orin/05,
Enter the robot's docker container
~/run_docker.sh
roslaunch  yahboomcar_nav  laser_bringup.launch            # laser + yahboomcar
roslaunch  yahboomcar_nav  laser_usb_bringup.launch        # mono + laser +
yahboomcar
roslaunch  yahboomcar_nav  laser_astrapro_bringup.launch   # Astra + laser +
yahboomcar
```

Start the navigation obstacle avoidance function(robot side), you can set parameters and modify the launch file according to your needs.

<Open another terminal and enter the same docker container

1. In the above steps, a docker container has been opened. You can open another terminal on the host (car) to view:

```
docker ps -a
```

```
jetson@ubuntu:~$ docker ps -a
CONTAINER ID   IMAGE                                COMMAND       CREATED      STATUS       PORTS     NAMES
5b698ea10535   yahboomtechnology/ros-foxy:3.3.9   "/bin/bash"   3 days ago   Up 9 hours             ecstatic_lewin
jetson@ubuntu:~$
```

2. Now enter the docker container in the newly opened terminal:

```
docker exec -it 5b698ea10535 /bin/bash
```

```
jetson@ubuntu:~$ docker ps -a
CONTAINER ID   IMAGE                                COMMAND       CREATED      STATUS       PORTS     NAMES
5b698ea10535   yahboomtechnology/ros-foxy:3.3.9   "/bin/bash"   3 days ago   Up 9 hours             ecstatic_lewin
jetson@ubuntu:~$ docker exec -it 5b698ea10535 /bin/bash
------------------------------------------------------------
my_robot_type: x3 | my_lidar: a1 | my_camera: astrapro
------------------------------------------------------------
root@ubuntu:/#
```

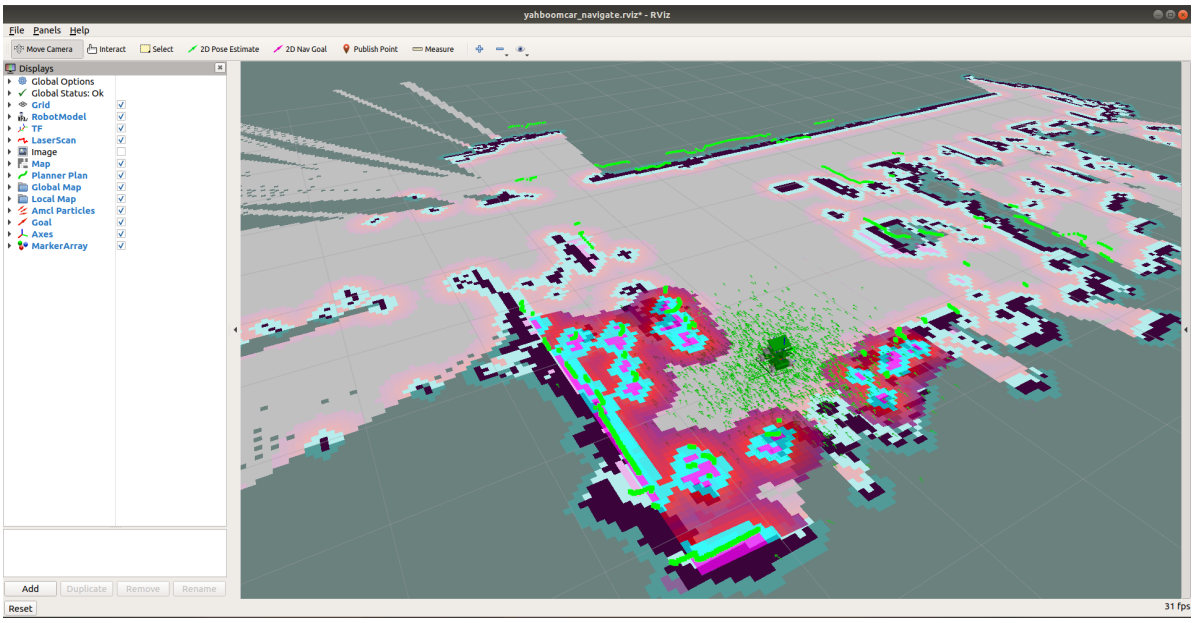
After successfully entering the container, you can open countless terminals to enter the container.

```
roslaunch yahboomcar_nav yahboomcar_navigation.launch use_rviz:=false map:=house
```

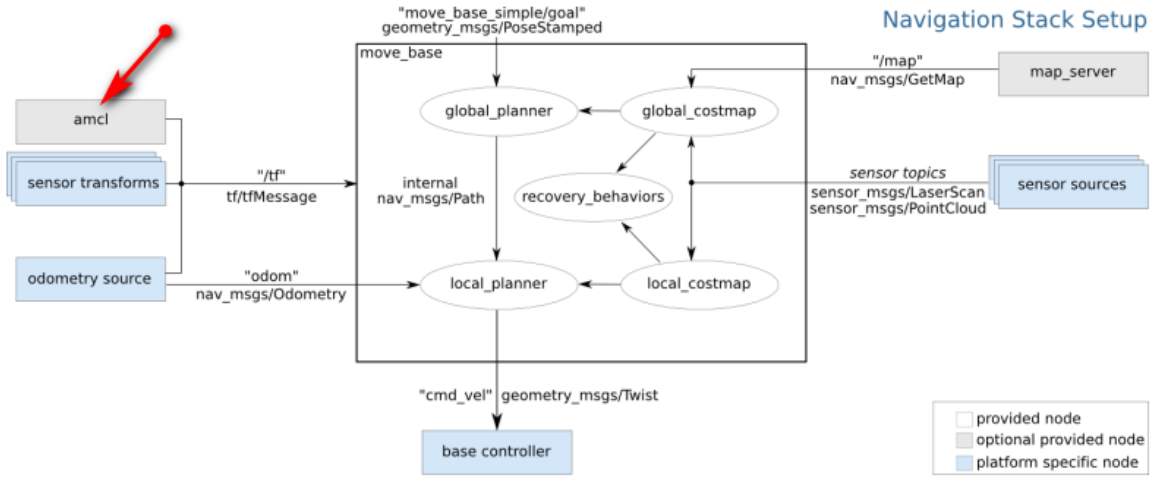
- [use_rviz] parameter: whether to open rviz.
- [map] Parameters: map name, the map to be loaded.

Open the visual interface(virtual machine side)

```
roslaunch yahboomcar_nav view_navigate.launch
```



11.2.2 positioning analysis



The position of amcl in the upper left corner of the navigation frame, its role is to tell the robot where.

After opening it, we can see that a handful of green particles are evenly scattered around the robot. When we randomly move the robot(keyboard or mouse control), all the particles move with it. Use the position of each particle to simulate a sensor information and compare it with the observed sensor information(usually a laser), thereby assigning a probability to each particle. Then, the particles are regenerated according to the generated probability, and the higher the probability, the greater the probability of generation. After such iterations, all the particles will slowly converge together, and the exact position of the robot is calculated.

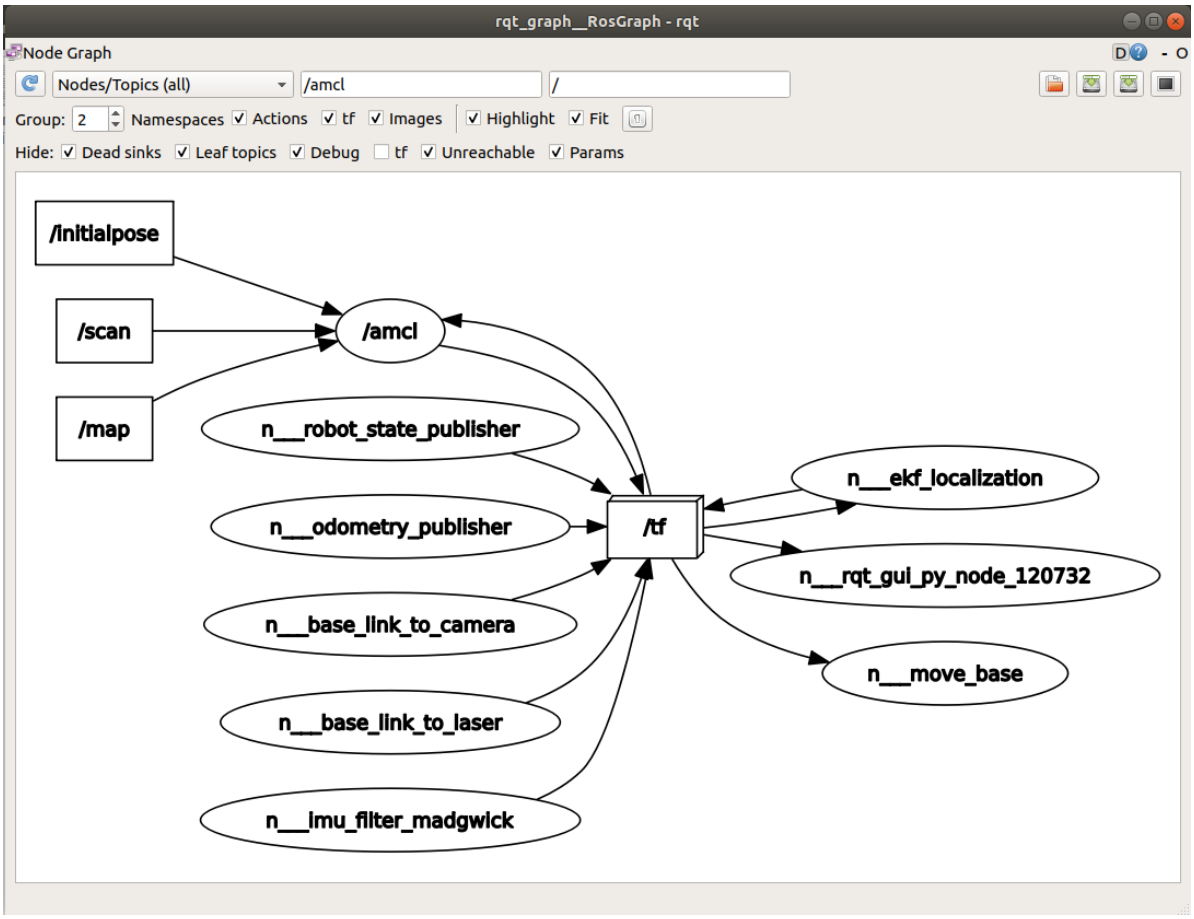
11.2 Topics and Services

Subscribe to topics	**type**	**describe**
scan	sensor_msgs/LaserScan	Lidar data
tf	tf/tfMessage	Coordinate transformation information
initialpose	geometry_msgs/PoseWithCovarianceStamped	Mean and covariance used to(re)initialize the particle filter.
map	nav_msgs/OccupancyGrid	When the use_map_topic parameter is set, AMCL subscribes to this topic to retrieve maps for laser-based positioning. New in Navigation 1.4.2.
Post a topic	**type**	**describe**
amcl_pose	geometry_msgs/PoseWithCovarianceStatmped	Pose estimation of the robot in the map, with covariance information
particlecloud	geometry_msgs/PoseArray	A collection of pose estimates maintained by particle filters
tf	tf/tfMessage	Post the conversion from odom to map
Server	**type**	**describe**
global_localization	std_stvs/Empty	Initialize global positioning, all particles are randomly scattered on the free area on the map
request_normotion_update	std_stvs/Empty	Perform the update manually and publish the updated particles
set_map	nav_msgs/SetMap	A service to manually set up new maps and poses.
client	**type**	**describe**

Subscribe to topics	type	describe
static_map	nav_msgs/GetMap	amcl calls this service to retrieve maps for laser positioning; start prevents maps from being fetched from this service.

View Nodes

```
rosrun rqt_graph rqt_graph
```



11.3 parameter configuration

There are three categories of ROS parameters that can be used to configure amcl nodes: global filters, laser models, and odometer models.

- Overall filter parameters

parameter	type	Defaults	describe
~min_particles	int	100	Minimum number of particles allowed
~max_particles	int	5000	maximum number of particles allowed
~kld_err	double	0.1	Maximum error between true distribution and estimated distribution
~ kld_z	double	0.99	The upper standard normal quantile of(1-p), where p is the probability that the estimated distribution error is less than kld_err
~update_min_d	double	0.2(m)	The translation distance required to perform a filter update
~update_min_a	double	ft/6.0(rad)	Rotational movement required to perform a filter update
~reseample_interval	int	2	number of filter updates before resampling
~transform_tolerance	double	0.1(s)	When to publish the transform to indicate that this transform is valid in the future
~recovery_alpha_slow	double	0.0	Exponential decay rate of the slow average weight filter used to decide when to resume operations by adding random poses, 0.0 disables
~recovery_alpha_fast	double	0.0	Exponential decay rate of the fast average weight filter used to decide when to resume operations by adding random poses, 0.0 disables
~initial_pose_x	double	0.0(m)	Initial pose mean(x), used to initialize the Gaussian filter
~initial_pose_y	double	0.0(m)	Initial pose mean(y), used to initialize the Gaussian filter
~initial_pose_a	double	0.0(m)	Initial pose mean(yaw), used to initialize the Gaussian filter
~ initial_cov_xx	double	0.5*0.5(m)	Initial pose mean(x*x), used to initialize the Gaussian distribution filter
~ initial_cov_yy	double	0.5*0.5(m)	Initial pose mean(y*y), used to initialize the Gaussian filter
~ initial_cov_aa	double	(ft/12)* (ft/12) (rad)	Initial pose mean(yaw*yaw), used to initialize the Gaussian distribution filter

parameter	type	Defaults	describe
~gui_publish_rate	double	-1.0(Hz)	When visualizing, the maximum rate at which information is published, -1.0 means disable
~save_pose_rate	double	0.5(Hz)	the parameter server *and covariance initial_cov* for subsequent initialization filters. -1.0 means disable
~use_map_topic	bool	false	When set to true, amcl will subscribe to the map topic instead of receiving maps via service calls
~first_map_only	bool	false	When set to true, amcl will only use the first map it subscribes to, not the map it receives with each update
~selective_resampling	bool	false	When set to true, will reduce the resampling rate when not needed and help avoid particle deprivation. Resampling occurs only when the effective number of particles(N_eff=1/(sum(k_i^2)) is less than half of the current number of particles.

- Laser Model Parameters

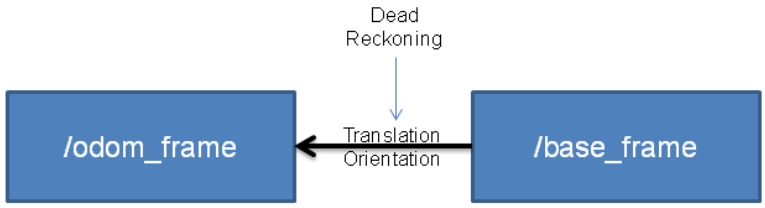
parameter	type	Defaults	describe
~laser_min_range	double	-1.0	Minimum scan range, set -1, the minimum usage range reported by the lidar.
~laser_max_range	double	-1.0	Maximum scan range, set -1, the maximum usage range reported by the lidar.
~laser_max_beams	int	30	How many evenly spaced beams to use in each scan when updating the filter
~ laser_z_bit	double	0.95	Mixed weights for the z_bit part of the model
~laser_z_short	double	0.1	Mixed weights for the z_short part of the model
~laser_z_max	double	0.05	Mixed weights for the z_max part of the model
~laser_z_rand	double	0.05	Mixed weights for the z_rand part of the model
~laser_sigma_hit	double	0.2(m)	Standard deviation of the Gaussian model used in the z_hit part of the model
~laser_lambda_short	double	0.1	Exponential decay parameter for the z_short part of the model
~laser_likelihood_max_dist	double	2.0(m)	Measure the maximum distance on the map that the obstacle swells
~laser_model_type	string	"likelihood_field"	Model selection, bean, likelihood_field or likelihood_field_prob

- Odometer Model Parameters

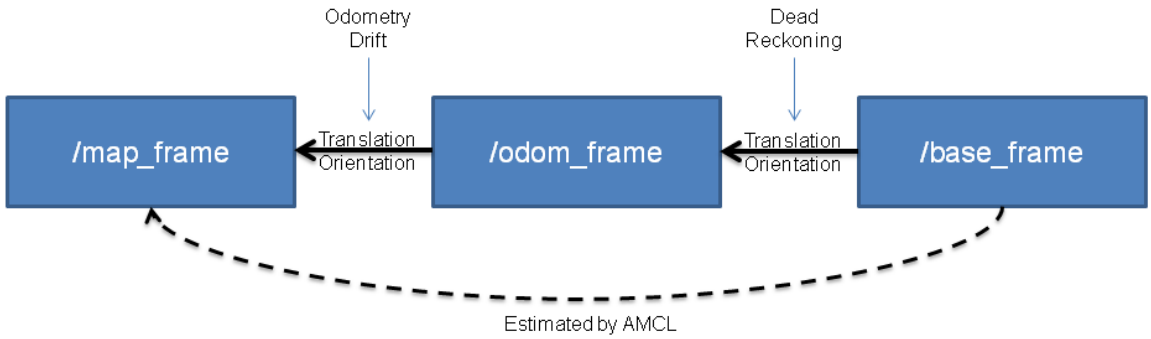
parameter	type	Defaults	describe
~odom_model_type	string	"diff"	Model selection, diff, omni, diff-corrected or omni-corrected
~odom_alpha1	double	0.2	Specifies the expected noise in the odometry rotation estimate based on the rotational component of the robot's motion
~odom_alpha2	double	0.2	Specifies the expected noise in the odometry rotation estimate based on the translational component of the robot's motion
~odom_alpha3	double	0.2	Specifies the expected noise in the odometry translation estimate based on the translational component of the robot's motion
~odom_alpha4	double	0.2	Specifies the expected noise in the odometry translation estimate based on the rotational component of the robot's motion
~odom_alpha5	double	0.2	Translation-dependent noise parameter(only used in model omni)
~odom_frame_id	string	"odom"	The coordinate system of the odometer
~base_frame_id	string	"base_link"	The coordinate system of the robot chassis
~global_frame_id	string	"map"	Coordinate system published by the positioning system
~tf_broadcast	bool	true	When set to false, amcl will not publish the coordinate system transformation between map and odom

11.4 coordinate transformation

Odometry Localization



AMCL Map Localization



Compare the two methods Odometry Localization and AMCL Map Localization:

Odometry Localization: The speed of the wheel can be known through the encoder feedback of the motor, the current speed of the wheel can be obtained according to the radius of the wheel, the overall moving speed of the robot can be obtained according to the forward kinematics model, and the movement can be obtained by integrating according to time. total mileage.

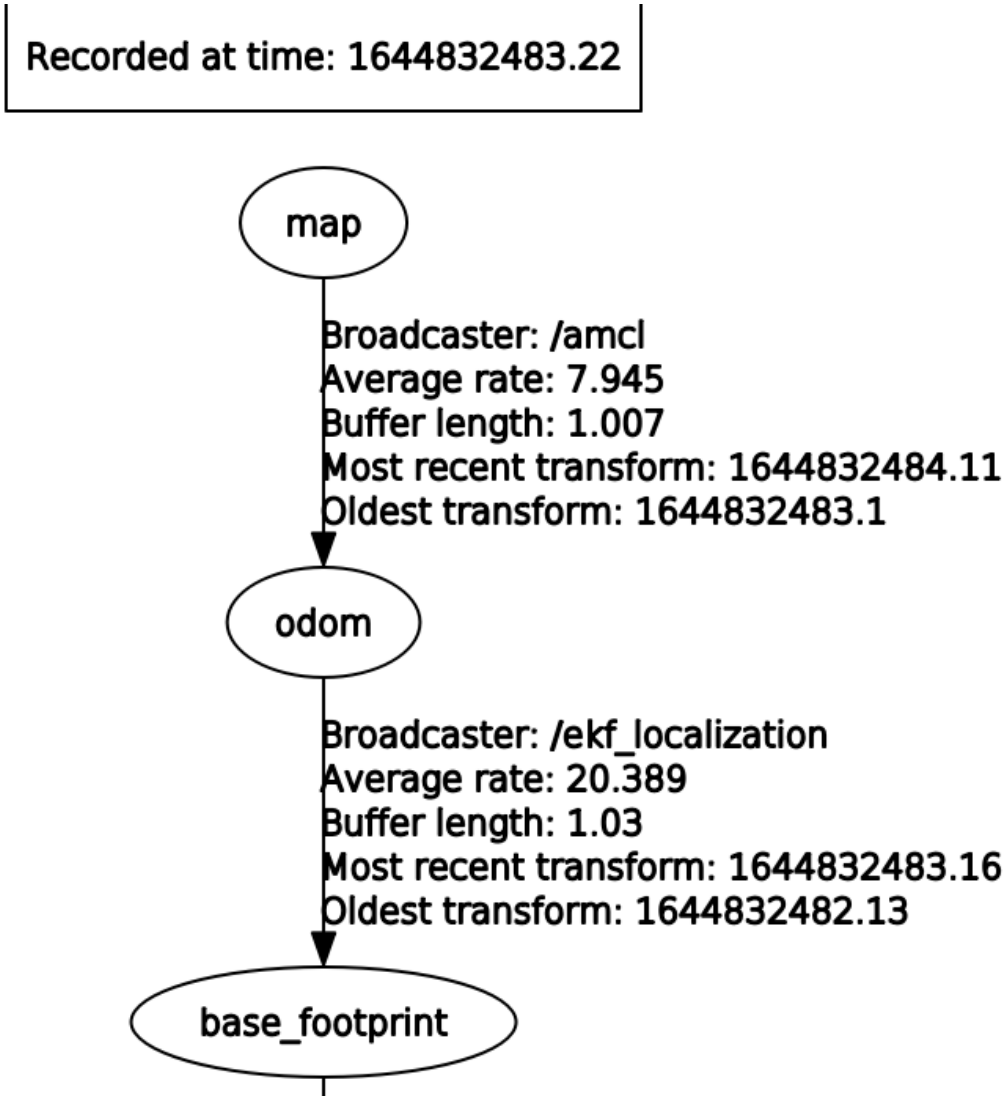
AMCL Map Localization: In amcl, the pose information of the base_frame corresponding to the map_frame has been obtained through particle filter positioning, but in order to ensure that the base_frame has only one parent node, the conversion will not be published directly, because the parent node of the base_frame is already odom_frame, then amcl can only publish the conversion of map_frame to odom_frame, which also has the advantage that we can get the cumulative error of odom.

We have been saying that the distance measurement information obtained by the wheel odometer will have a cumulative error, which is similar to the car slipping. If only the wheel odometer is used to calculate the moving distance, there will be an error:

For example: the robot walks straight ahead, and the result obtained by the wheel odometer should be 1 meter, then the distance from odom_frame should be 1 meter, but due to the slipping in place, in fact, the robot does not move at all through amcl positioning, then amcl needs to publish the conversion of map_frame to odom_frame to remove this 1-meter error, so as to maintain the normality of the entire tf tree.

The transformation relationship between coordinates.

```
rosrun rqt_tf_tree rqt_tf_tree
```



As can be seen from the above figure, the coordinate conversion from map->odom is completed by the amcl node.