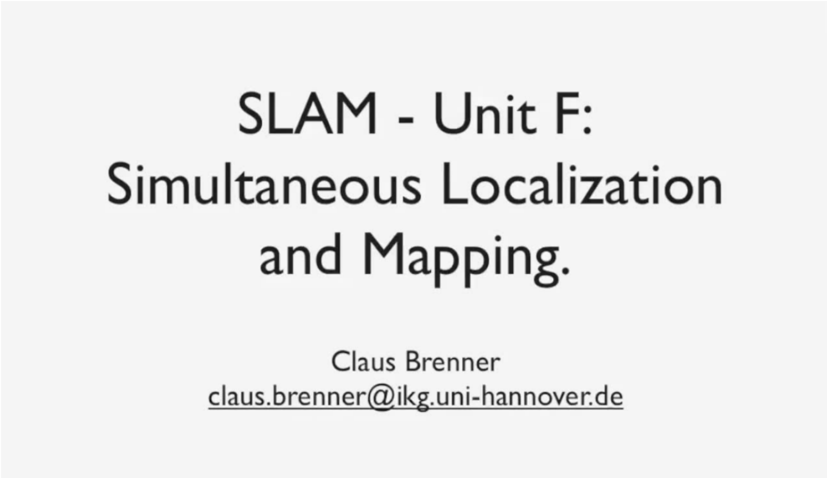
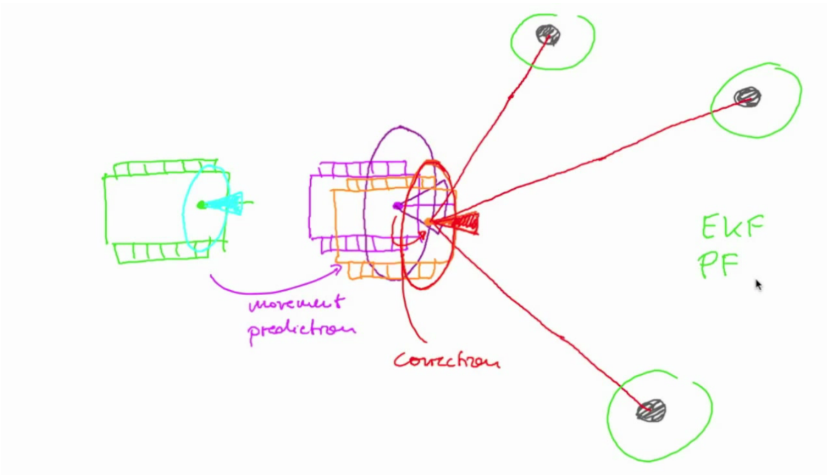
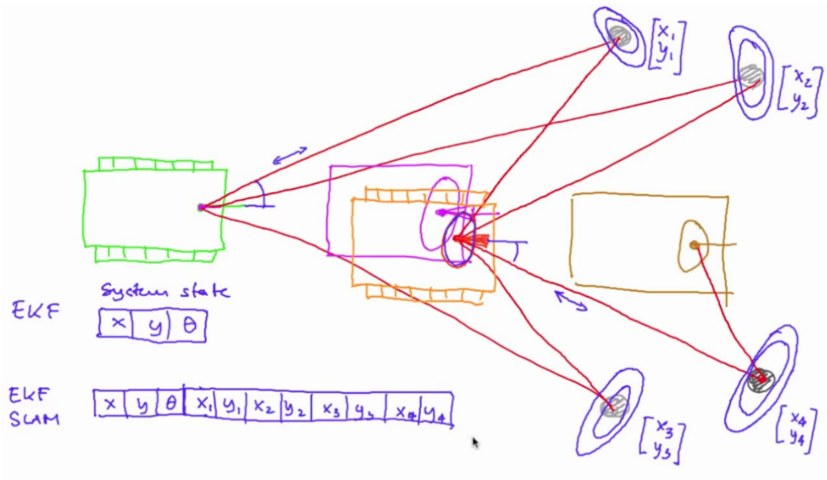


This lecture is about the simultaneous localization and mapping algorithm, which is the topic that gives name to this course.



Let's have a look at what we have done so far. Here's the robot at a given position having a certain orientation and we know that there is some uncertainty (error) associated to its position and orientation. The uncertainty in the robot's position, $(x_t,\, y_t)$, is expressed with an ellipse, Σ_t, while the uncertainty in the robot's orientation, θ_t, is expressed with a circular sector, $\pm\,\sigma_{\theta_t}$. Now, the robot moves and the inaccuracies in the movement induce an increase in the uncertainty of the robot's pose. After the robot's motion the EKF algorithm calculates the predicted pose for the robot, $\vec{\overline{\mu}}_t = \left(\overline{\mu}_{x_t}, \overline{\mu}_{y_t}, \overline{\mu}_{\theta_t}\right)$, aka, $\vec{\overline{x}}_t$. If the robot goes on moving and the algorithm only carries out the prediction step, the uncertainty associated to the position and orientation will increase continuously. But fortunately there are some landmarks in the scene with **known positions** and by measuring distances and bearings to those well-positioned landmarks the algorithm is able to correct the pose for the robot. This correction step also decrease the uncertainty associated to the position and orientation for the robot. Again, until this lecture, to perform the correction step it is essential that the landmarks' coordinates are known in advance, and with that data the EKF algorithm, or the PF algorithm, can resolve the localization problem.

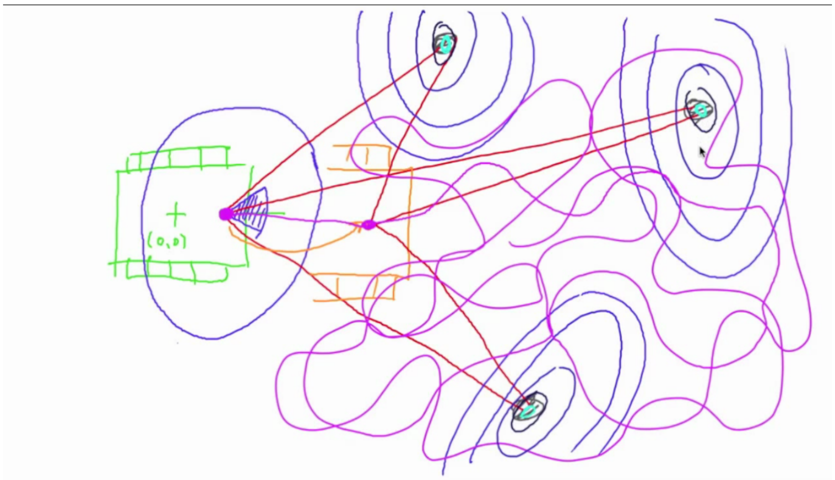


What happens if you don't know the positions of the landmarks in advance? This is actually the usual case, because it is very hard to get hold of cadastral maps or floor plans and even if you manage to do so you will often notice that they are not very useful for localization because the buildings have been built in a different way or they have been modified later on or there are so many additional items like chairs and tables, that are not part of the map, but modify a huge portion of what the robot sees.

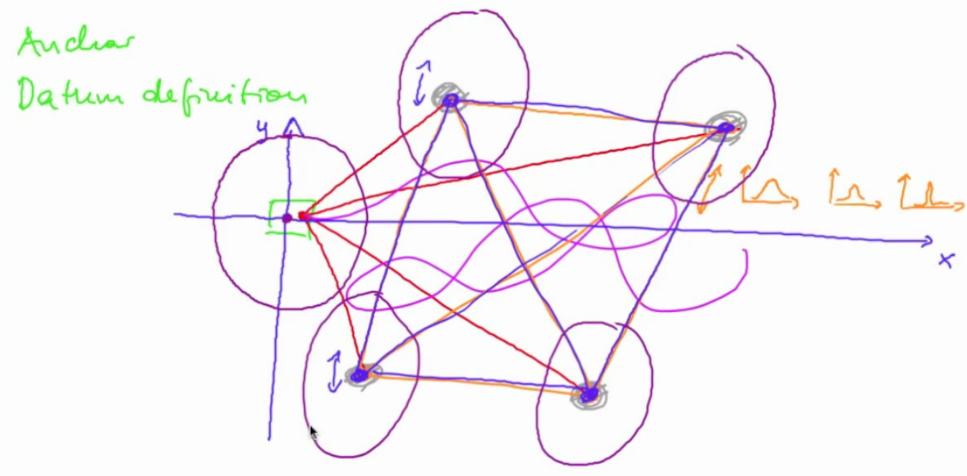
Let's think about the following. The robot is somewhere and since there isn't a map of landmarks the algorithm will have to produce that map on its own. Since the algorithm starts with an empty map it can define the robot's position in the map origin, (0, 0), and define the orientation along the x-axis, (0°). Besides, it can consider the uncertainty in position and heading angle as 0. From the pose occupied by the robot, the robot's laser scanner measures the distance and the bearing to each landmark within its range of view. The algorithm can use all those pair of measurements to define the landmarks' positions in the real world, i.e, in the world that has its origin in the starting position of the robot. It has to be noted that the defined landmarks are oriented along the heading angle of the robot at the starting position. Having defined those landmarks the algorithm will do the same as it did in the previous lectures. Therefore, the robot moves along, the algorithm carries out the prediction step, the uncertainty for the position and heading angle of the robot increases, then the laser scanner get some landmark observations (distance and bearing to each landmark within its range of view) and finally the algorithm uses those measurements to correct the position and orientation for the robot and get a smaller uncertainty ellipse for the position and a smaller circular sector for the heading angle. Instead of taking the landmarks from a map, which was obtained by some external means, the algorithm takes the following steps:

Whenever the algorithm recognizes a landmark for the first time it determines its position, relative to the map which it currently builds up, and after that this landmark can be used for the localization of the robot at all subsequent poses where that landmark is observed again by the laser scanner, i.e, whenever that landmark is within the range of view of the laser. Well, it is not exactly as easy as that because when the algorithm recognises a landmark for the first time the measurement of the distance and bearing to the landmark induces an uncertainty (error) in the landmark's position. What becomes clear is that the algorithm can't simply put a landmark into the map when it recognizes the landmark for the first time and then to assume that the landmark's position is correct. When the algorithm recognizes a landmark for the first time it puts that

new landmark into the map with a certain uncertainty in position. Then, every time the laser scanner takes a scan that contains a measurement for that landmark (distance and bearing) the algorithm updates the landmark's position and reduces its uncertainty in position. This is the same process that the algorithm carries out with the robot's pose.
In the previous EKF implementation, the system state was the robot's pose, i.e, its position and heading angle. Now, in the SLAM algorithm the system state comprises the robot's pose and the positions of the landmarks that the algorithm finds (coordinate x_{L_k} and coordinate y_{L_k} of each found landmark). What you see now, immediately, is that the state vector doesn't have a constant size anymore. For each landmark that the algorithm observes, and that it didn't observe before, the state vector grows by two elements.

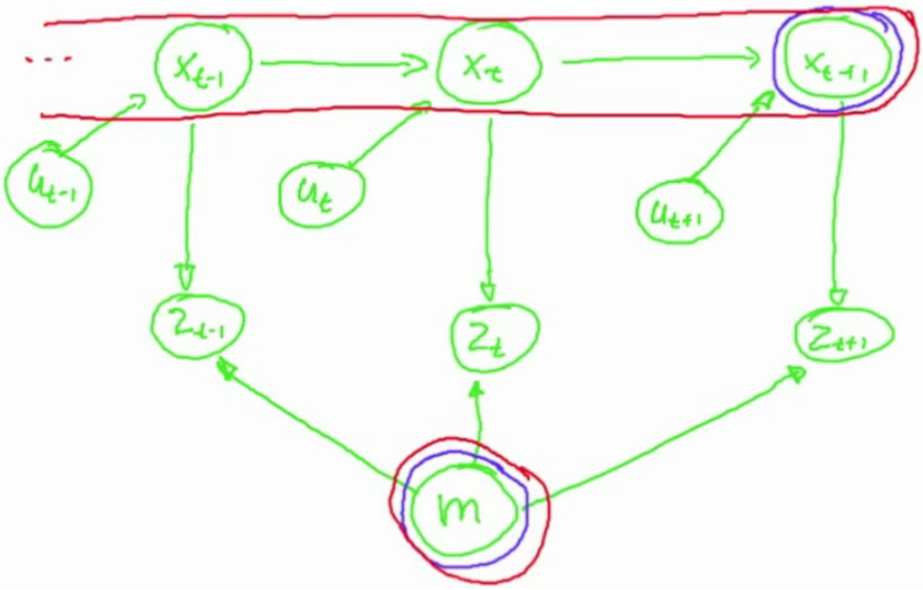


Let's consider that the robot starts in the pose (0, 0, 0°) with a large uncertainty in position and heading angle. Later on the robot observes some landmarks and since the uncertainty for its pose is large the uncertainty ellipses for those landmarks will be large too. The robot moves and observes those landmarks again, so all those uncertainty ellipses will get a bit smaller. Let's consider that the robot moves for a real long time in the environment, observing those landmarks over and over again. Therefore, my hope is that those uncertainty ellipses get smaller and smaller until they are really really small so that the landmarks are not uncertain anymore. So that this situation is equivalent to what we had earlier, in the EKF approach, where the landmarks were assumed to be error-free. What do you think? Will the uncertainty in the landmarks' positions go down to zero as the number of measurements goes to infinity?



Online SLAM : $p(x_t, m \mid z_{1:t}, u_{1:t})$

Full SLAM : $p(x_{1:t}, m \mid z_{1:t}, u_{1:t})$

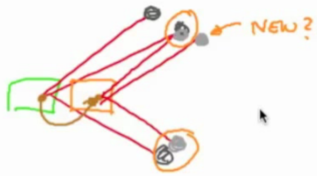


SLAM

- Continuous component

  $x, y, \theta, \quad x_1, y_1, x_2, y_2 \ldots, x_N, y_N$ (online SLAM)

- Discrete component



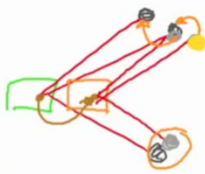
SLAM

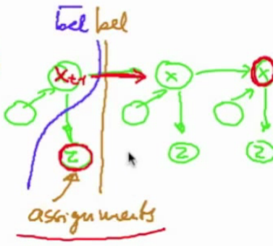
- Continuous component

  $x, y, \theta, \quad x_1, y_1, x_2, y_2 \ldots, x_N, y_N$ (online SLAM)

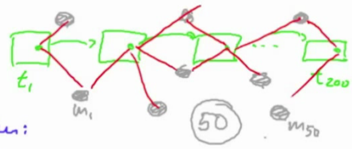
- Discrete component

  correspondence of objects to previously detected objects

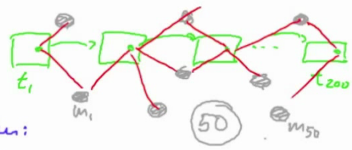




- Calculation of the full posterior usually infeasible
  - High dimensionality of parameter space
  - Large number of correspondences



For the online SLAM problem:
How many variables would be in our state?



For the ~~online~~ FULL SLAM problem:
How many variables would be in our state?