## Robotic SLAM

# 1 Introduction

## Terms

- State estimation find out the pose
- Localisation pose w.r.to landmark or map
- Mapping
- navigation and motion planning a star, wave front dijkstra

## 1.1 What is SLAM

Computing robot's poses and the map of the environment at the same time.

**Localisation**: estimating robots location

**Mapping**: building a MAP

#### Given

• Robots control inputs

$$u_{1:T} = \{u_1, u_2, u_3 .... u_T\}$$

Observations

$$z_{1:T} = \{z_1, z_2, z_3, ..., z_T\}$$

#### Wanted

• Map of the environment

m

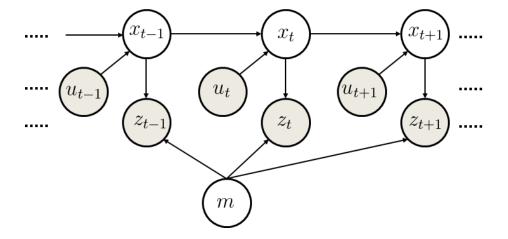
• path of the Robot

$$x_{0:T} = \{x_0, x_1, x_2, ..., x_T\}$$

Using the robots control inputs we can predict the position of the robot. From the observations  $z_{1:T}$ , we can calculate the position of the robot. Both the steps have some error associated with it. Lets call the first one the model noise and second one the sensor noise. So we have to associate a probability with both of them. The error accumulates over time(even if the error in individual measurements is really small)

So in the probalistic terms our problem minimises to

$$p(x_{0:T}, m|z_{1:T}, u_{1:T})$$



# 1.2 Full Slam vs online SLAM

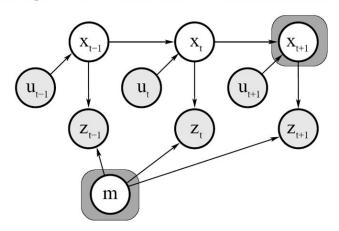
• Full SLAM estimates the entire path

$$p(x_{0:T}, m|z_{1:T}, u_{1:T})$$

• Online SLAM estimates only the most recent pose

$$p(x_t, m|z_{1:T}, u_{1:T})$$

# **Graphical Model of Online SLAM:**



$$p(x_{t}, m \mid z_{1:t}, u_{1:t}) = \iiint \dots \int p(x_{1:t}, m \mid z_{1:t}, u_{1:t}) \, dx_{1} dx_{2} \dots dx_{t-1}$$

# 1.3 Volumetric SALM vs Feature based SLAM

occupancy maps created from lidars, sonars etc. - volumetric SLAM feature based approach - store features and localise based on that volumetric SLAM maybe better for navigation applications . Topological representations vs geometric representations