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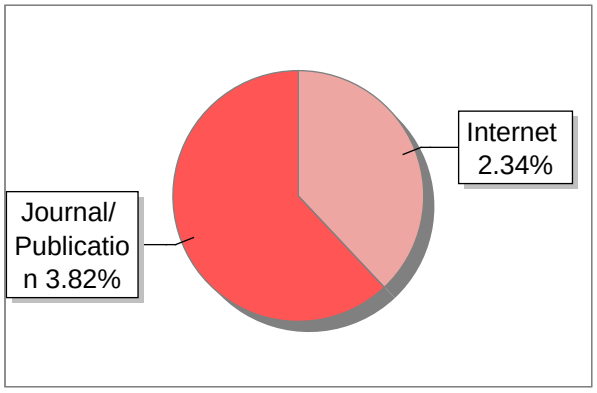

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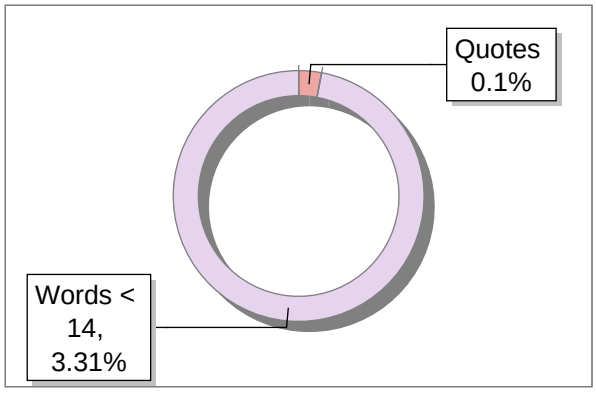

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Chapter 1: Introduction

1.1 Background

Artificial intelligence research is very technical and specialized, and it is divided into numerous subfields that frequently fail to communicate with one another. Some of the divide is due to social and cultural factors: subfields have developed around specific institutions and researchers' activity. Several technological difficulties also split AI research. Some subfields concentrate on solving specific challenges. Others concentrate on one of several alternative approaches, the use of a specific instrument, or the completion of specific tasks.

We will use numerous artificial intelligence approaches for localization in this project, including Kalman Filters, Histogram Filters, and the heuristic approach algorithm A* for dynamic path finding, to create a programme for Google's self-driving automobile.

The dynamic path finding feature is quite beneficial because it provides real-time path instructions based on the current location of the car. In comparison to Dijkstra and BFS, the A* algorithm, which is used to implement paths based on current and final locations, is extremely fast. We then use a PID controller to discover the smoothest path to the target, as A* only provides square paths.

Problem Statement

Create and optimise a software implementation for position detection (localization), dynamic path finding from a fixed source to a fixed destination in a real-time scenario, and the appropriate controller for efficient control of an autonomous or self-driving car.

Solution

We will be using several artificial intelligence techniques for localization such as Kalman Filters, Histogram Filters and the heuristic approach algorithm A* for dynamic path finding.

1.2 Motivation

Self-driving cars' very sophisticated technology allows the onboard computer to do hundreds of calculations per second. These include your distance from the objects, your current speed, the conduct of other drivers, and your geographic location. Because the only accidents so far have occurred while human drivers were in control, these ultra-accurate measurements have almost eliminated driving errors for test cars on the road.

Self-driving cars have a tremendous potential for reducing traffic congestion because they are rarely involved in accidents and also they can communicate with one another, traffic lights would be obsolete. Better traffic coordination might result in less congestion if people drove slower but made fewer stops.

1.3 Scope

Technological progress is accelerating at an uncontrollable rate. The more a country invests in emerging technology, the better off it will be in the long run. These incentives range from improved infrastructure to increased employment creation. Nowadays, technology's main goal is to reduce human interaction in everyday chores. The big players in this are Machine Learning, Artificial Intelligence, and Computer Vision. We've arrived at a point where we can automate routine chores like driving. Isn't that insane? Autonomous Cars is a frequent term for this type of computer vision. These autonomous vehicles can sense their environment and based on their surrounding these vehicles can navigate without the assistance of humans.

1.4 Objective

The project's goal is to use path finding algorithms to create a dynamic path for a car to reach its destination and then use a PID controller on the path obtained by the algorithm to find the smoothest path for the car to get there.

Chapter 2: Literature Review

2.1 Introduction

Machine intelligence is known as artificial intelligence (AI). An ideal "intelligent" machine in computer science is a flexible rational agent that senses its surroundings and makes such decisions which maximize its chances of achieving an arbitrary goal. When a computer uses cutting-edge technology to competently perform or replicate "cognitive" processes that we intuitively identify with human minds, such as "learning" and "problem solving," the phrase "artificial intelligence" is most probably to be used. Artificial intelligence has a negative connotation, especially among the general public, because it is associated with "cutting-edge" machines (or even "mysterious"). This subjective barrier between "artificial intelligence" and "human intellect" seems to blur with time; for example optical character recognition, is no longer seen as an exemplar of "artificial intelligence," but rather as a banal regular technology. Computers that can beat elite players at chess and go, as well as self-driving automobiles that traverse packed city streets, are modern instances of AI.

The research work for AI is very technical and specialized, and it is divided into numerous sub fields that use to fail frequently to communicate with one another. Some of the divide is due to social and cultural factors: sub-fields have developed around specific institutions and researchers' activity. Several technological difficulties also split AI research. Some sub-fields concentrate on solving specific challenges. Others concentrate on one of many alternative approaches, the use of a specific instrument, or the completion of specific tasks.

Reasoning, knowledge, planning, learning, NLP(communication), perception, and the ability to move and manipulate objects are all fundamental goals in AI research. General intelligence is one of the field's long-term objectives. Statistical methodologies,

computational intelligence, and conventional symbolic AI are all currently popular approaches. Artificial intelligence uses a variety of methods, such as search and mathematical optimization, logic, probability, and economics-based methodologies, and so on. Artificial intelligence is an interdisciplinary field that encompasses a wide range of sciences and professions, including computer science, mathematics, psychology, linguistics, philosophy, and neuroscience, as well as more specialised fields such as artificial psychology.

2.2 Goals

The difficulty of imitating (or creating) intelligence has been broken down into sub-problems. Researchers are looking for specific features or abilities in an intelligent system. The following features have received the most attention.

2.2.1 Problem solving, Reasoning and Deduction

Previous Artificial Intelligence research produced algorithms that mimicked humans' step-by-step reasoning while solving puzzles or making logical conclusions. AI research in the late 1980s and 1990s had created extremely successful methods for coping with uncertain or partial information based on probability and economics ideas.

Most of these systems involve a "combinatorial explosion" when the problem size surpasses a certain threshold, in which the memory usage used grows drastically. Researchers in Artificial Intelligence are focusing on developing more efficient problem-solving systems.

Humans solve the majority of issues by drawing rapid, instinctive conclusions rather than the laborious, sequential calculations that early AI research could imitate. Embodied agent methods highlight the role of sensorimotor skills in higher reasoning;

neural net research aims to recreate the brain mechanisms that lead to this ability; statistical AI techniques imitate the probabilistic character of human guesses.

2.2.2 Knowledge representation

An ontology is a set of ideas within a field and their interconnections that represents knowledge.

AI research revolves around knowledge representation and engineering. Many of the issues that robots are supposed to address will need a detailed comprehension of the world. Among the things AI must represent are objects, qualities, categories, and interactions between objects; situations, events, states, and time; causes and consequences; knowledge about knowledge; and many other, less well-studied areas. The collection of things, connections, theories, and other things that the machine is conscious of is represented by an ontology. The most broad ontologies try to offer a base for all other information.

2.2.3 Planning

A hierarchical control system is one that uses a hierarchy of devices and software to make decisions.

A hierarchical control system makes decisions using a combination of devices.

Intelligent agents must be able to set and achieve objectives. They require a method for considering the future and making actions that improve the efficiency of the alternatives accessible to them.

In traditional planning issues, the agent might assume that is the only object in the environment and that the outcomes of its actions are easy to predict.

2.2.4 Learning

Machine learning, or the study of self-improving computer systems, has always been at the centre of AI research.

The capacity to find patterns in a stream of data is known as unsupervised learning. Both classification and numerical regression are part of supervised learning. Classification is used to establish where something belongs after looking at multiple instances of items from various categories. The process of developing a model that describes the relation between inputs and outputs and estimates how the outcomes should vary as the inputs change is known as regression. The agent is rewarded for favourable replies and penalised for poor ones in reinforcement learning. The agent devises a strategy for working in its issue based on this collection of rewards and punishments.

2.2.5 Natural language processing (communication)

Natural language processing allows machines to comprehend and interpret human speech. Natural language user interfaces and direct knowledge acquisition from human-written sources such as newswire texts may be possible with a sufficiently capable natural language processing system. Feature extraction (or text mining), question answering, and translation are only a few of the applications of natural language processing.

Semantic indexing is the study of natural language and the extraction of meaning from it. Indexing vast numbers of representations of the user's input is becoming significantly more efficient as processor speeds have grown and data storage costs have decreased.

2.2.6 Perception

Machine perception is the ability to derive features of the world using sensor input (such as cameras, microphones, tactile sensors, sonar, and other more exotic devices). The capacity to analyse visual information is known as computer vision. Speech

recognition, facial recognition, and object recognition are a few examples of subproblems.

2.2.7 Motion and manipulation

Robotics and artificial intelligence are closely connected topics. For robots to perform tasks like object manipulation and navigation, intelligence is required, with sub-problems like localization (recognising where things are), mapping (learning what is around), and motion planning (calculating out what to do next) or path planning (shifting from one location in space to another, which may require complex moves).

2.2.9 Social Intelligence

Affective computing is the research and development of systems and devices that can recognise, understand, process, and reproduce human sentiments. This interdisciplinary field includes computer science, psychology, and cognitive science. While the field's origins can be traced back to early philosophical examinations of emotion, Rosalind Picard's 1995 paper on emotional computing helped to establish the current branch of computer science. One of the research's motivations is the ability to reproduce empathy. The system should be able to detect people's emotions and adjust its behaviour accordingly, providing appropriate responses.

The emotional and social abilities of an intelligent agent serve two functions. To begin, AI must understand people's motivations and emotional states in order to forecast their actions. (Game theory, decision theory, the ability to model human emotions, and perceptual skills for identifying emotions are all examples.) Furthermore, an intelligent machine may wish to be able to exhibit emotions—even if it does not experience them—in order to appear responsive to the emotional dynamics of human contact in order to enhance human-computer connection.

2.3 Tools used to implement AI

AI has generated a significant number of tools to handle the most difficult issues in computer science over the period of 50 years of research. A couple of the more common techniques are listed here.

2.3.1 Search and Optimization

Many AI issues can technically be resolved by considering a vast set of possibilities: A search could be used to express logic. For example, logical proof may be thought of as going down the path from arguments to results, each stage needing the application of an inference rule. To discover a path to a target goal, planning algorithms employ means-ends analysis to search across branches of objectives and sub goals. Local searches in coordinate space are used in robotics algorithms to move limbs and grab items. Many learning algorithms employ optimization-based search methodologies.

For most real-world issues, simple thorough searches are rarely sufficient: the search space (the number of places to seek) soon increases to astronomical proportions. As an outcome, the process either takes too long or never ends. "Heuristics" or "rules of thumb" are frequently employed to rule out choices that really are unlikely to produce to the desired outcome (called "pruning the search tree"). Heuristics provide the software with a "best guess" of the solution's location. The total sample of the solution search is reduced using heuristics.

In the 1990s, a new type of search emerged, one based on the mathematical theory of optimization. In many cases, you may start with an estimate and steadily refine it until there are no more refinements available. We start our search at a random location on the terrain and then move our guess uphill utilising leaps until we reach the peak,

equivalent to blind hill climbing. Simulated annealing, beam search, and random optimization are some of the other optimization techniques.

In evolutionary computation, optimization search is used. They may start with a population of organisms (guesses) and let them evolve and integrate over time, with only the fittest surviving each iteration. Evolutionary computation includes swarm intelligence approaches and evolutionary programming.

2.3.2 Logic

Logic is commonly used to describe and solve problems, but it may also be used to other difficulties. For example, the satplan algorithm employs logic to plan, whereas inductive logic programming is a training aid.

Several distinct forms of logic are employed in AI research. Propositional or sentential logic is the logic of statements that can be true or false. Quantifiers and predicates are also supported by first-order logic, allowing the declaration of facts about things, their attributes, and their connections. The truth of a proposition is assigned a value between 0 and 1, rather than merely True (1) or False (1), in fuzzy logic. For uncertain reasoning, fuzzy systems are frequently employed in today's industrial and consumer product control systems. Subjective logic expresses uncertainty in a different and more clear way than fuzzy logic: inside a Beta distribution, a given binomial opinion meets belief + disbelief + uncertainty = 1. This method differentiates ignorance from very confident probabilistic claims made by an agent.

Default logics, non-monotonic logics, and circumscription are examples of logics that aid with default reasoning and the qualifying problem. Description logics, situation calculus, event calculus, and fluent calculus (for capturing events and time), causal calculus, belief calculus, and modal logics are some of the extensions of logic that have been suggested to handle particular types of knowledge.

2.3.3 Probabilistic methods for uncertain reasoning

Many AI challenges need the agent's ability to deal with ambiguous or incomplete data. Using concepts from probability theory and economics, AI researchers have built a number of sophisticated tools to handle these problems.

Bayesian networks can assist in reasoning (using the Bayesian inference process), learning (using the expectation-maximization technique), planning, and perceiving. By filtering, forecasting, smoothing, and providing explanations for streams of data, probabilistic algorithms can assist perception systems in analysing processes that occur across time.

"Utility" is a term used in economics to describe how useful something is to a rational agent. Using decision theory, decision analysis, and information value theory, precise mathematical tools have been constructed to examine how an agent makes decisions and plans. Markov decision processes, dynamic decision networks, game theory, and mechanism design are some of the strategies that can be used.

2.3.4 Classifiers and statistical learning methods

The two most fundamental types of AI applications are classifiers and controllers. However, because controllers must first recognise situations before inferring actions, categorization is a critical component of many AI systems. Classifiers are functions that compare patterns to get the closest match. They are particularly intriguing for use in AI since they may be adjusted based on examples. The phrases used to describe these occurrences are observations or patterns. In supervised learning, each pattern belongs to a certain class. A class might be viewed as a decision that must be made. All of the observations and their class labels make form a data set. When a new observation is obtained, it is classified based on previous knowledge.

A classifier can learn using a number of methods, such as statistics and machine learning. The neural network, kernel techniques such as the support vector machine, k-nearest neighbour algorithm, Gaussian mixture model, naive Bayes classifier, and decision tree are the most commonly used classifiers. These classifiers' performance has been compared across a number of tasks. The qualities of the data to be classified

have a considerable influence on a classifier's performance. The "no free lunch" theorem states that no one classification technique is optimal in all situations. It seems more like an art than a science to pick the correct classifier for the job.

2.3.5 Neural networks

A neural network is a collection of nodes that resembles the human brain's massive network of neurons. Walter Pitts and Warren McCullough pioneered the concept of non-learning neural nets a decade before the field of AI research was established. The perceptron is similar to linear regression, was invented by Frank Rosenblatt.

The two most common forms of neural networks are acyclic or feedforward neural networks (in which the signal only flows one way) and recurrent neural networks. The most common feedforward networks are perceptrons, multi-layer perceptrons, and radial basis networks.

The backpropagation method, initially developed as the reverse mode of automated differentiation and later extended to neural networks, is now widely used to train neural networks.

Hierarchical temporal memory is a technique for replicating some of the structural and algorithmic properties of the neocortex.

2.3.6 Control Theory

Control theory is an engineering and mathematics interdisciplinary discipline that analyses the behaviour of dynamical systems with inputs and how feedback impacts their behaviour.

2.3.7 Languages

Several specialised languages for AI research have been developed, notably Lisp and Prolog.

Chapter 3: Design and Methodology

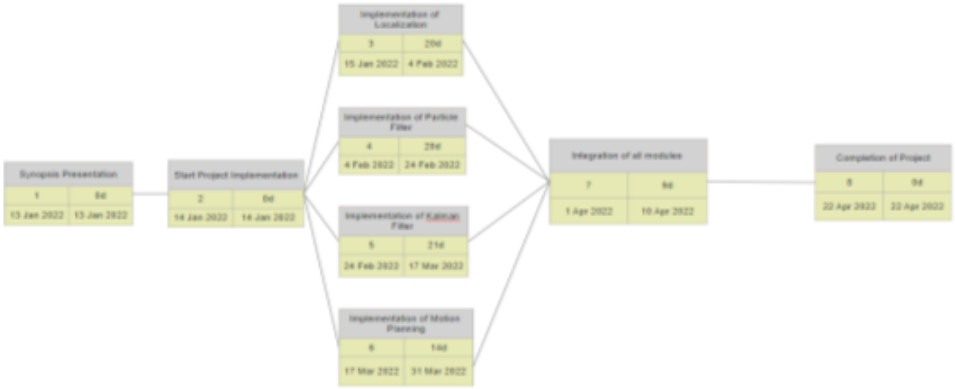


Figure 3.1 - Design

3.1 Localization

In order to drive the car must first we have to locate it. However it is not quite possible to measure a car location using an instrument. Even the GPS have margin of error of around 5 m. Now, think about this error on a standard driving lane whose width is 3.5 m. So, to solve this problem a method called Localization is used.

Localization is the ability for a machine to locate itself in space or we can also say which is a program that can measure location indirectly. Rather than install a GPS device in our robot, we are going to write a program to implement localization which will locate position of our car and also reduce the margin of error caused by GPS earlier and will make it between 2cm to 10cm. This high level of accuracy enables a self-driving car to understand its surroundings and establish a clear image of road and its lanes. With this a car can even detect diverging and merging of a lane, plan lane changes and determine lane paths even when markings aren't clear.

Imagine a car is lost in a 1D world where only forward and backward movements are possible and sideways motion is not possible. Since our car is unaware of its position, it believes that every point in this one dimensional world is equally likely to be its current position. It can be described mathematically by saying that car's probability function is uniform over the sample space which is 1D.

Currently, the majority of self-driving cars being developed by automakers and tech companies do not include probability in their AI systems. We recognize that this may

come out as a surprising statement. Given that human driving entails constantly assessing and modifying probability as well as coping with uncertainty, you'd think that self-driving car AI would do the same.

Then we will draw a graph of this probability function with probability on the y-axis and location on the x-axis, we would draw a straight, level line. This line describes a uniform probability function, and it represents the state of maximum confusion.

Now, assume there are three landmarks on the road which is 1D, and assume these landmarks as bumps on the road. Since the robot has just sensed that it is near a door, it assigns these locations greater probability (indicated by the bumps in the graph) whereas, all of the other locations have decreased belief. This function represents another probability distribution which is the best representation of car's current position relative to the bump on the road.

3.1.1 Robot Movement

Suppose car moves to the right a certain distance, then we can shift the location accordingly and all the bumps also shifts to the right as expected but not perfectly as some of the bumps are also flattened. This flattening occurs due to the uncertainty in car motion because the car doesn't know exactly how far it has moved, its knowledge became less accurate and so the bumps have become less sharp.

Here, we perform convolution by shifting and flattening these bumps. Convolution is a mathematical operation that takes two functions and measures their overlap or basically we can say which is the measure of overlap of two functions over one another. For example, if two functions have zero overlap, the value of their convolution will be equal to zero. If they overlap completely, their convolution will be equal to one. As we slide between these two extreme cases, the convolution will take on values between zero and one.

In our convolution, the first function represents the location function, and the distance moved is represented by the second function.

Now, again car reaches to another bump and senses itself right next to it so, again the measurement is same as before. Just like after our first measurement, the sensing of a

bump will increase our probability function by a certain factor everywhere where it found a bump. So, should we get the same location that we had after our first measurement? No! Because unlike with our first measurement, when we were in a state of maximum uncertainty, this time we have some idea of our location prior to sensing. This prior information, together with the second sensing of a bump, combine to give us a new probability distribution.

Localization, specifically the Monte Carlo localization method that we are using here, is nothing but the repetition of *sensing* and *moving*. There is an initial belief that is tossed into the loop. If you sense first it comes to the left side. Localization cycles through move and sense. Every time it moves it loses information and every time it senses it gains information. Measure of information in a distribution is called as Entropy.

3.1.2 Bayes' Rule

Suppose we are driving a car, and a situation came where we have to apply brakes. Do we considering the possibility that the car ahead of you will slam on their brakes next? Are we evaluating the chances that the automobile in front of we will be able to make a timely stop? Did the possibility of colliding with the automobile ahead of us and the car behind us cross our mind? Most folks aren't making those kinds of probability calculations in their heads. Instead, they've learnt to make probabilistic judgments over time. On other days, we may choose to disregard some of those possibilities and increase your risks. On other days, you become more aware of the chances and drive with extreme caution.

As we are used to the idea of probability, most self-driving cars now being developed by automakers and tech companies do not yet have probability embedded in their AI systems. We recognise that this may come out as a surprising statement. Given that human driving entails constantly assessing and modifying probability as well as coping with uncertainty, you'd think that self-driving car AI would do the same.

Uber has created a new programming language called Pyro as a result of their recent efforts. The Uber AI Labs is attempting to establish Pyro as the programming language of choice for anyone working with AI who also needs to deal with probability.

We have the frequentists, who look at the universe in a rather generic way based on long-term frequencies of recurring events, and the conditional probability camp, which believes that the nature of your probabilities is determined by the scenario. We'll look at best well-known parts of the conditional probability camp, the Bayesian view of probability, in a moment.

Bayes' Rule is a tool for updating a probability distribution after making a measurement.

- x = grid cell
- Z = measurement

The equation for Bayes' Rule looks like this:

$$P(x \vee Z) = \frac{P(Z \vee x)P(x)}{P(Z)}$$

The left hand side of this equation should be read as "The probability of X after observing Z." In probability, we often want to update our probability distribution after making a measurement. Sometimes, this isn't easy to do directly.

Bayes' Rule tells us that this probability (the left-hand side of the equation) is equal to another probability (the right-hand side of the equation), which is often easier to calculate. In those situations, we use Bayes' Rule to rephrase the problem in a solvable way.

To use Bayes' Rule, we first calculate the non-normalized probability distribution, which is given by $P(Z|X)P(X)$, and then divide that by the total probability of making measurement Z, P(Z), which is called the normalizer.

3.1.3 Theorem of total probability

Now let's look at motion, which will turn out to be something we will call total probability. Hopefully you remember caring about a grid cell "xi" and we asked what is the chance of being in xi after robot motion. Now, we will use a time index to indicate after and before motion:

Compute this by looking at all the grid cells the robot could have come from one time step earlier (at time t-1), and index those cells with the letter j, which in our example ranges from 1 to 5. For each of those cells, look at the prior probability $P(X_j^{t-1})$, and multiply it with the probability of moving from cell X_j to cell X_i, $P(X_i|X_j)$. This gives us the probability that we will be in cell X_i at time t:

- $P(X_i^t) = \Sigma_j P(X_j^{t-1}) P(X_i|X_j)$

You can see the correspondence of *A* as a place *i* of time *t* and all the different *Bs* as the possible prior locations. This is often called the Theorem of Total Probability.

3.1.4 Perception

Once a car knows where it is, its next job is to perceive and track objects it might collide with (for example other cars or pedastrians). This problem has many similarities to localization. The sensors of other objects are noisy and we want to predict where they are. Again, the underlying model is a modification of a hidden markov model to allow for continuous variables. The picture below shows a variable representation. At each time point there are two variables.

However, though a robot represents localizing itself and perceiving others with very similar underlying models, the two problems are solved using different algorithms. Instead of using a particle filter to estimate position, perceiving other objects is solved with kalman filters. Kalman filters make an additional assumption about the variables that they are tracking. The algorithm assumes that the location variables are gaussian. This assumption simplifies the problem into one where the solution to where the other cars are can be computed exactly (and thus much faster).

Localization can be represented as the following iteration of sense, move and initial belief.

"It first sets an initial belief senses with the measurements and then moves."

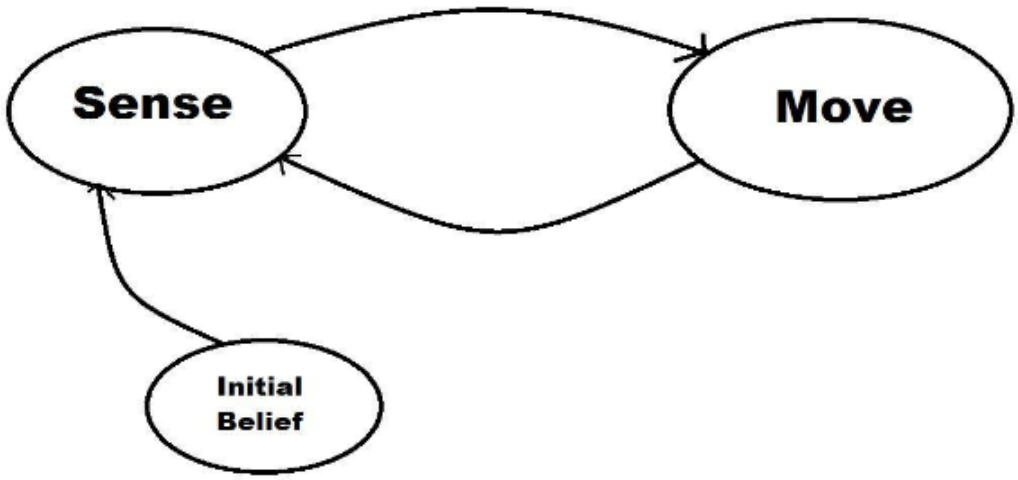


Fig 3.2 Localization Perception

3.2 Kalman Filter

Kalman filter is an estimator that infers parameters parameters of interest from indirect, inaccurate and uncertain observations. We can say a Kalman Filter is an optimal estimator. Kalman filter has a recursive nature so that new measurements can be processed as they arrive.

We need to represent unpredictable disturbances with a discrete time linear dynamic system described by a vector difference equation with additive white noise.

A deterministic dynamic system's state is the smallest vector that sums up the system's whole history. In the absence of noise, knowing the state allows for theoretical prediction of the deterministic system's future (and prior) dynamics and outputs.

Optimization- If all noise is Gaussian, the Kalman filter minimizes the mean square error of the estimated parameters.

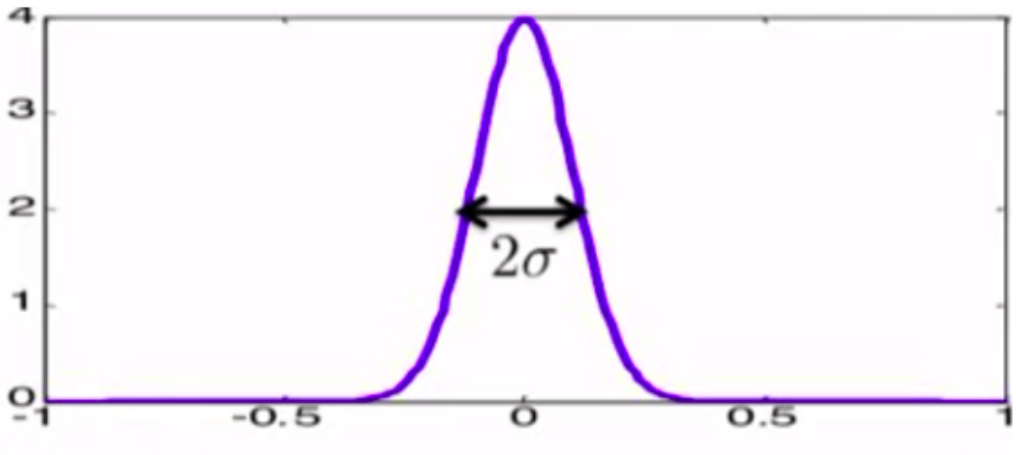


Figure 3.3 Variance

Junior, Stanford's most current self-driving car, is equipped with laser range finders that take distance scans ten times per second, resulting in approximately one million data points. The main purpose of gathering all of this information is to locate other vehicles. The Kalman filters use data from the range finders as input.

Our self-driving automobile will avoid colliding with other vehicles if we can figure out how to detect them. To avoid collisions, we need to know not only where other automobiles are - as in the case of localization - but also how fast they are traveling.

3.2.1 Why Kalman Filter is better?

- Due to optimality and structure, good results in practice.
- Convenient form for online real time processing.

- Gives a fundamental understanding, it is simple to formulate and implement.
- There is no need to invert the measurement equations

3.2.2 Why Filter?

The process of determining the "best estimate" from noisy data is referred to as "noise filtering."

A Kalman filter, on the other hand, not only cleans up the data measurements, but also projects them onto the state estimate.

3.2.3 Tracking

The Kalman Filter is a well-known method for estimating the state of a system as it produces a uni-modal distribution by estimating a continuous state.

Example- A car (the large rectangle) senses an object in space (*) at times *t=0, t=1, t=2, t=3*.Where would you assume the object would be at *t=4*?

The velocity is changing according to a vector. Assuming there is no drastic change in velocity, we can expect t=4 to be along the same vector line.

The Kalman filter is a piece of software that allows you to take points, even if they are unclear, and anticipate where future locations might be, like in this example. You'll also be able to determine the speed of the moving object. Based on laser and radar data, the Google self-driving car employs tactics like these to figure out where the traffic is.

3.2.4 Gaussian

A histogram is a visual representation of continuous space divided into discrete areas. It's a technique for simulating a continuous distribution.

The distribution is presented in a Gaussian, which is a continuous function over the space of locations, in Kalman filters. The total area beneath the Gaussian add upto one.

If we call the space (x-axis), x, then the Gaussian is characterized by two parameters - the mean (greek letter mu, μ), and the width of the Gaussian, called the variance (often written as a quadratic variable σ2.

Any Gaussian in a one-dimensional parameter space, is characterized by (μ,σ2). Our task when using Kalman filter is to maintain a μ and a σ2, that serves as our best estimate of the location of the objects we are trying to find.

The exact formula is an exponential of a quadratic function:

- $f(x) = \frac{1}{\sqrt{2\pi\sigma 2}} exp\left[\frac{-1}{2}\frac{(x-\mu)2}{\sigma 2}\right]$

The Kalman Filter represents all distributions of the Gaussians and iterates two things:

1. Measurement updates
2. Motion updates

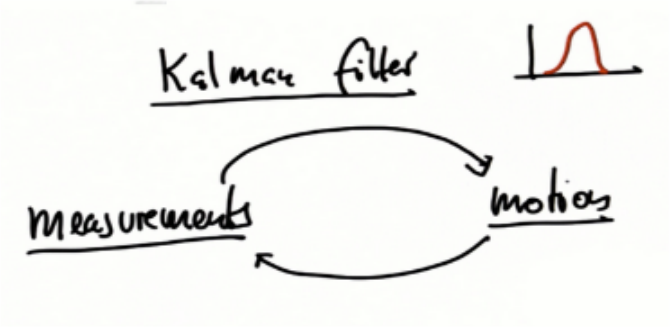


Figure 3.4 Distribution Visulization of Gaussian

The measurement cycle is commonly referred to as a measurement update when utilising Kalman filters, whereas the motion cycle is referred to as prediction. The Bayes Rule - a product, multiplication - will be used in the measurement update. Total probability will be used in the prediction update - a convolution and an addition.

Gaussians can be used to discuss these two cycles.

Assume you're trying to locate another vehicle and you have the following prior distribution with a mu mean:

Then, in blue, with a mean nu, we have a measurement that informs us something about the vehicle's localization.

Predicting the peak can be done by the resulting Gaussian that is more certain than the two component Gaussians. That is, the covariance is smaller than either of the two covariances in isolation. Intuitively speaking, this is the case because we can actually gain information from the two Gaussians.

This outcome may appear counter intuitive at first. It's helpful to imagine these two measures being taken at the same time (perhaps one is from a laser and the other from a radar sensor). Each of these sensors may make a mistake, but we MUST obtain greater assurance about our position by utilizing both sensors than we would if we only used one (otherwise, why would we use a second sensor?). As a result, the resulting peak will have to be higher.

3.2.5 Co-Variance

Co variance is determined as:

The covariance of two random variables x_1 and x_2 is

$$\begin{aligned} \mathrm{cov}(x_1, x_2) &\equiv E[(x_1 - \bar{x}_1)(x_2 - \bar{x}_2)] \\ &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(x_1 - \bar{x}_1)(x_2 - \bar{x}_2)p(x_1, x_1)dx_1 dx_2 \\ &\equiv \sigma^2_{x_1 x_2} \end{aligned}$$

where p is the joint probability density function of x_1 and x_2.

The ***correlation coefficient*** is the normalised quantity

$$\rho_{12} \equiv \frac{\sigma^2_{x_1 x_2}}{\sigma_{x_1}\sigma_{x_2}}, \quad -1 \le \rho_{12} \le +1$$

The covariance of a *column vector* $\mathbf{x}=[x_1 .. x_n]'$ is defined as

$$\begin{aligned} \mathrm{cov}(\mathbf{x}) &\equiv E[(\mathbf{x} - \bar{\mathbf{x}})(\mathbf{x} - \bar{\mathbf{x}})'] \\ &= \int_{-\infty}^{\infty}\cdots\int_{-\infty}^{\infty}(\mathbf{x} - \bar{\mathbf{x}})(\mathbf{x} - \bar{\mathbf{x}})'\, p(\mathbf{x})\; dx_1 .. dx_n \\ &\equiv \mathbf{P_{xx}} \end{aligned}$$

and is a *symmetric* n by n matrix and is *positive definite* unless there is a linear dependence among the components of $\mathbf{x}$.

The $(i,j)^{th}$ element of $\mathbf{P_{xx}}$ is $\sigma^2_{x_i x_j}$

Interpreting a covariance matrix:

diagonal elements are the variances, off-diagonal encode correlations.

3.2.6 Diagonalising a Covariance Matrix

cov(x) is symmetric => can be diagonalised using a basis that is orthonormal We achieve separation of error contributions by shifting coordinates (pure rotation) to these unity orthogonal vectors. The eigenvectors create the axes of error ellipses, and the basis vectors are the eigenvectors. The axes' lengths correspond to the standard deviations of the independent noise contribution in the direction of the eigenvalues and are the square root of the eigenvalues.

3.2.7 Equal Variance

Suppose we have two Gaussians, as in Baye's Rule, a prior μ and a probability σ^2, and the measurement has a mean of ν (nu) and a covariance of r^2, so that the new mean, μ' is the weighted sum of the old means, where μ is weighted by r^2, ν is weighted by σ^2 and normalized by the sum of the weighting factors.

The new variance term after the update is given by the following equation:

$$\frac{1}{\sigma^{2'}}=\frac{1}{\sigma^2}+\frac{1}{r^2}$$

We can determine the location of the new mean on the graph because we know that:

1. The prior Gaussian has a much higher uncertainty, a longer, lower slope, therefore σ2 is larger
2. This means the ν is weighted much larger than the μ

3. So the mean will be closer to the ν than the μ

3.2.8 Multivariate Gaussian

We've just talked about one-dimensional motion so far, and while this covers all of the elements of a Kalman filter, we should at least touch on what happens when we go from one to higher dimensions.

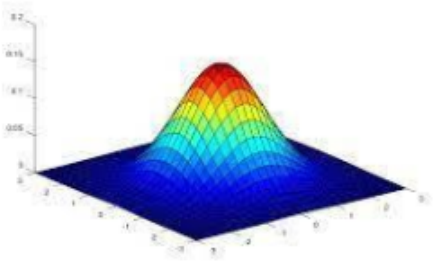


Figure 3.5 Multivariate Gaussian

1. Instead of being a number, the mean becomes a vector with one element for each of the dimensions.

2. The variance is replaced by the covariance, which is a matrix with d rows and d columns when the space has d dimensions.

3. This gives us a complicated formula, but it is not something you need to remember.

Create a two-dimensional estimate with the x-axis representing location and the y-axis representing velocity, which we'll refer to as v, but Sebastian uses an x with a dot over it. (The first derivative of x (position) with respect to t (time), which is another way to indicate velocity, is represented by an x with a single dot above it.)

Here is an illustration of multivariate Gaussians. In this image the mean is indicated by x_0 and y_0 and the covariance is the contour lines:

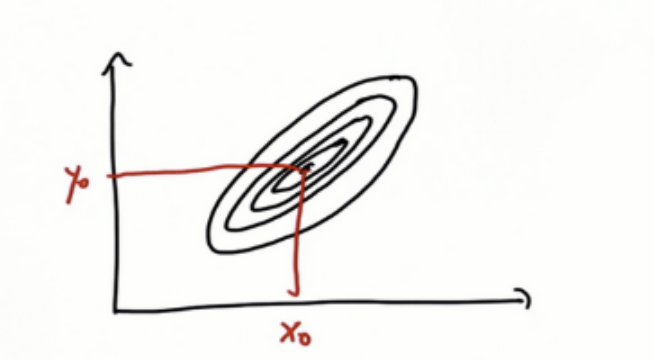


Figure 3.6 Covariance

Gaussians with a smaller amount of uncertainty would have smaller contour lines:

Figure 3.7 Gaussian with smaller uncertanity

It is also possible to have a small uncertainty in one dimension and a huge uncertainty in another:

Figure 3.8 1-D view

When the Gaussian is tilted it means the x and y are correlated:

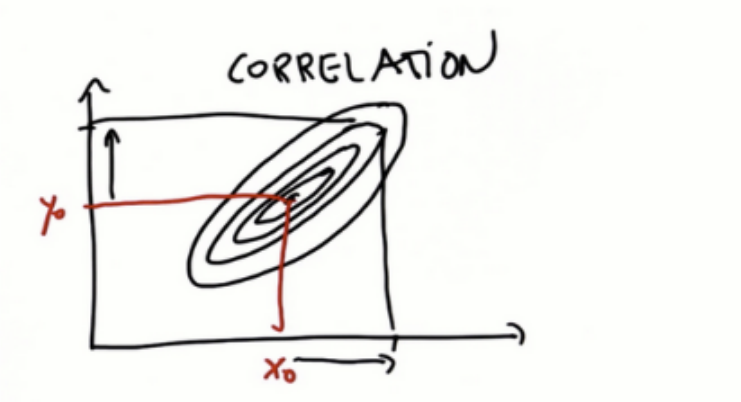


Figure 3.9 Gaussian tilted correlation

If you know where you are but not how fast you are going, you can express it with an extended Gaussian about the proper position but quite broad in the velocity space.

We can't forecast the location you'll assume in the prediction step because we don't know the velocity. There are, nevertheless, some intriguing connections.

If the velocity is 0 and the prediction is correct, where would the posterior be after the prediction?

If you know you start at position 1, a velocity of zero will put you exactly where you started (1, 0).

3.2.9 Motion Update

Let's say we move to the right, which has its own set of uncertainties. The motion instruction is then added to the mean, resulting in a prediction with a higher uncertainty than the initial uncertainty.

This makes sense intuitively; as you walk to the right, your uncertainty grows as you lose information about your location (as manifested by the uncertainty).

The math: New mean is the old mean plus the motion, u. The new $\sigma^2$is the old σ^2plus the variance of the motion Gaussian,r^2. This is *very* similar to Unit One, where motion decreased our knowledge and updates increased our knowledge. This is a fundamental aspect of localization.

3.2.9 Kalman Filter Designing

A state transition function and a measurement function, both of which are represented as matrices, are required when creating a Kalman Filter. The state transition matrix F and the measurement matrix H are referred, respectively.

The update step and the prediction step are separated in our Kalman filter. The names of the matrices and variables, as well as the equations for these steps, are listed below.

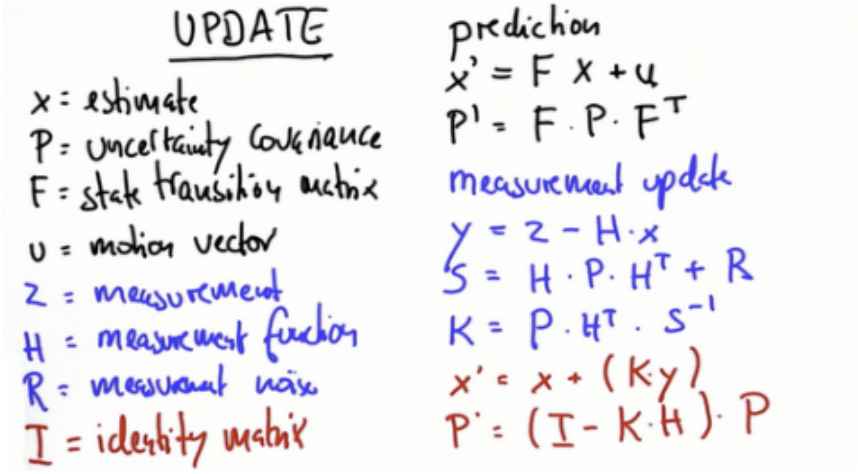


Figure 3.10 Variable Table

This is essentially a more complex version of the one-dimensional situation we've been discussing.

When you use the given measurements to run the filter, you can estimate the velocity and make better forecasts.

When you run the filter, you want the measurement update to come back first, followed by the motion update.

```
measurements=[1,2,3]
x=matrix([[0.],[0.]])
p=matrix([[1000.,0.],[0.,1000.]])
u=matrix([[0.],[0.]])
F=matrix([[1.,1],[0,1.]])
H=matrix([[1.,0]])
R=matrix([[1.]])
I=matrix([[1.,0.],[0.,1.]])
filter(x, P)
```

Once you fill it in you get an output. This output iteratively displays *x* and *P* as they update. Notice that at the first output of *x,* we know nothing about the velocity. This is because we need multiple location measurements to estimate velocity. As we continue making measurements and motions, our estimate converges to the correct position and velocity.

This is the model that Google's self-driving car uses to create predictions about where other cars are and how fast they're moving. The car has radar on the front bumper that measures distance from other vehicles and provides a noisy estimate of speed. Additionally, the automobile utilises its roof-mounted lasers to measure the distance between other cars and calculates a noisy estimate of velocity.

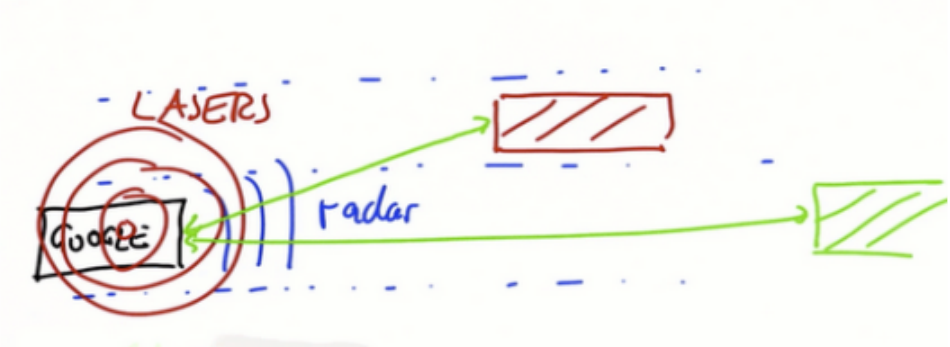


Figure 3.11 LIDAR

So, when the Google car is on the road it uses radars and lasers to estimate the distance and the velocity of other vehicles on the road using a Kalman filter, where it feeds in range data from the laser and uses state spaces of the relative distance, x and y, and the relative velocity of x and y.

3.3 Particle Filter

Particle filters have recently been used to overcome a number of difficult perceptual challenges in robotics. Particle filters' early accomplishments were limited to low-dimensional estimation problems, such as robot localisation in known-map situations.

When it comes to efficiency, the decision is still out. In some cases, particle filters scale exponentially, thus representing particle filters in more than four dimensions would be a mistake. However, they scale far better when it comes to tracking domains.

Range sensors are represented by the blue stripes on the robot, which is positioned in the upper right hand corner of the environment. The sensors gauge the distance of nearby barriers using sonar sensors, which are sound sensors. These sensors aid the robot in calculating an appropriate posterior distribution for its location. What the robot doesn't realise is that it's starting in the middle of a corridor and has no idea where it's going.

The goal of particle filters is to have the particles guess where the robot is moving while still allowing them to live, akin to "survival of the fittest," with particles that are more consistent with the measurements having a better chance of surviving. As a result, high-probability locations will accumulate more particles, making them more indicative of the robot's posterior beliefs. The robot's approximate belief as it localises itself is made up of the particles.

The versatility of particle filter technology is due to its supremacy in nonlinear and non-Gaussian systems. Furthermore, the particle filter's multi-modal processing capabilities is one of the reasons for its widespread use. Particle filtering has been used in a variety of fields around the world.

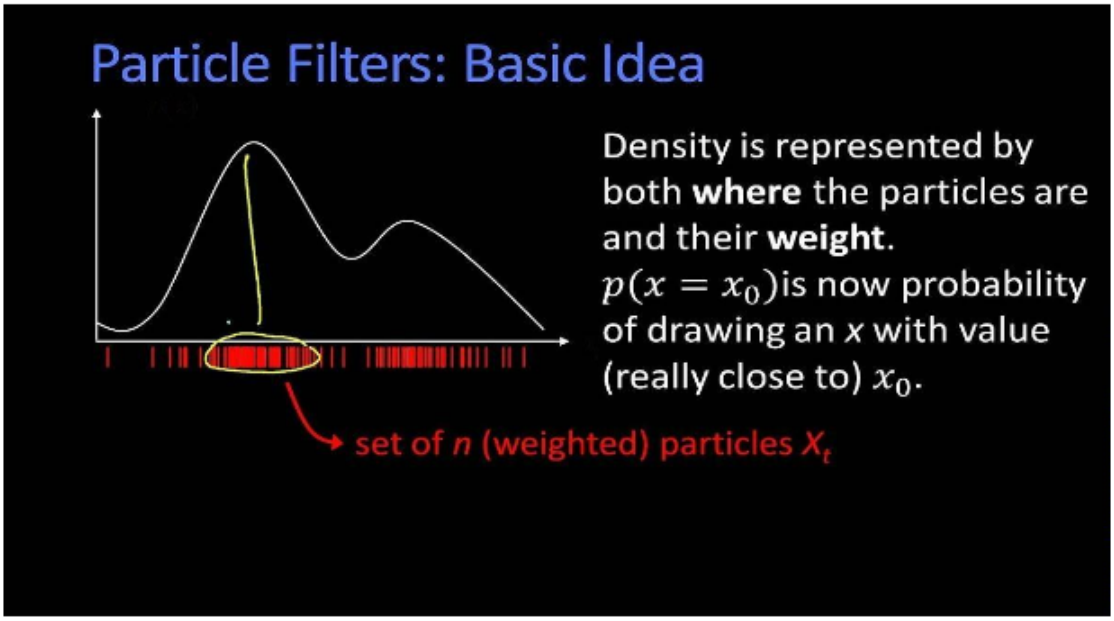


Figure 3.12 Particle Filter Basic Idea

Particle filters are currently commonly used in the estimate of financial market models, especially stochastic volatility models.

When the model is nonlinear and the noises are not Gaussian, particle filters methods are recursive Bayesian filters that give a practical and appealing solution to approximate the posterior distributions.

These methods provide broad solutions to a wide range of issues where linearisation and Gaussian approximations are either intractable or produce unacceptable results. Non-Gaussian noise assumptions and the integration of state variable limitations can also be done naturally. Furthermore, particle filter methods are extremely adaptable, simple to construct, parallelizable, and useful in a wide range of situations.

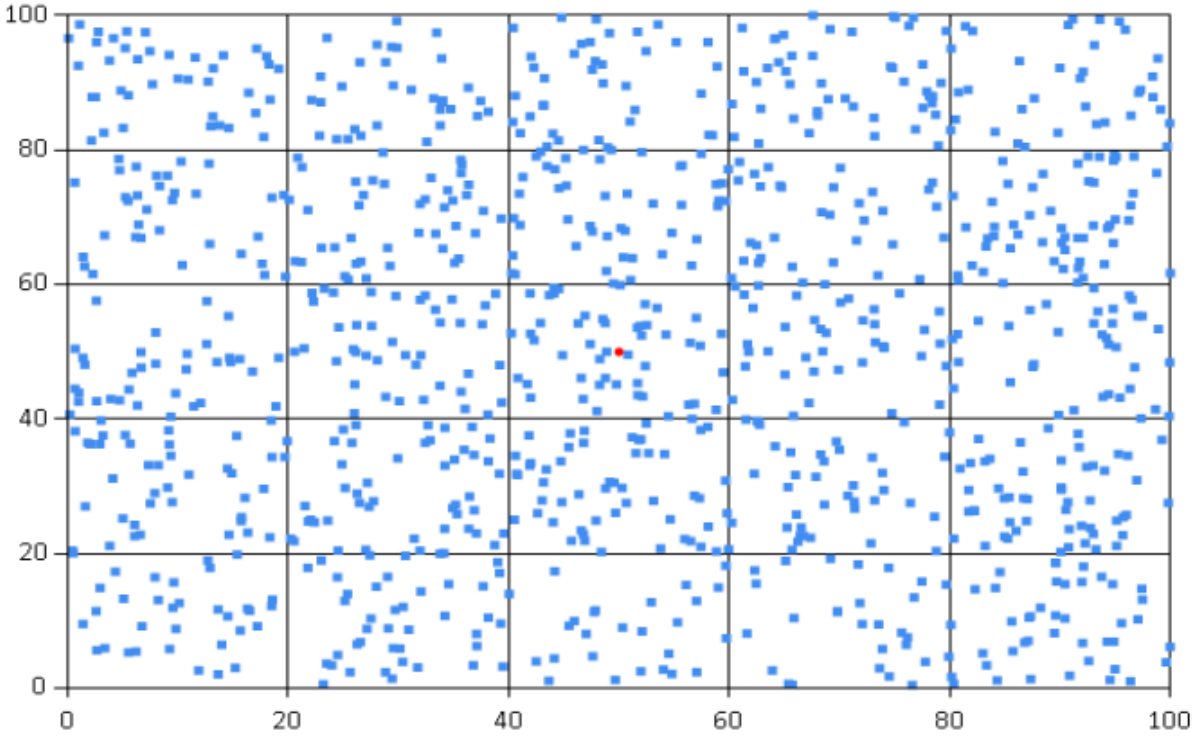


Figure 3.13 Particle Filter Working

Researchers have lately begun to take advantage of structural features of robotic domains, resulting in practical particle filter applications in areas with up to 100,000 dimensions. Because no model, no matter how comprehensive, can capture the complete complexity of even the most basic robotic settings, specific methods and procedures are required for particle filter performance in robotic domains. This section discusses some of these recent developments and gives links to more detailed publications on particle filters in robotics.

The more broader case of (almost) unrestrained Markov chains is addressed by particle filters. The primary concept is to approximate the posterior of a set of sample states x that correspond to Xi, or particles. Each of these is a concrete state sample of index I where i's range represents the particle filter's size.

The most basic version of particle filters is given by the following algorithm.

- Initialization: At time t=0, draw M particles according to p(x0).

Call this set of particles X0

- Recursion: At time t>0 , generate a new particle for each already existing particle by drawing from the actuation model . Call the resulting set XT

Subsequently, draw M particles from Xi , so that each particle in X is drawn (with replacement) with a probability proportional to p(zi | xi) .

Call the resulting set of particles Xt.

Particle filters appeal to robots for a variety of reasons. To begin with, they may be used to simulate practically any probabilistic robot model that can be expressed as a Markov chain. Furthermore, particle filters can be used at any time and do not require a predetermined computing period; instead, their accuracy rises as computational resources become available. This makes them appealing to robotics, which frequently deals with stringent real-time limitations that must be met with difficult-to-control computer technology.

Finally, they are relatively simple to put into practise. The implementer does not need to linearize non-linear models or care about closed-form solutions of conditional statements of multiple forms, as in Kalman filters. The fundamental objection levelled by particle filters is that, in general, populating a d-dimensional space necessitates an increasingly large number of particles in d.

As a result, the majority of effective applications have been limited to low-dimensional state spaces. Structure (for example, conditional independences), which is used in many robotics challenges, has only lately led to applications in higher dimensional environments.

3.3.1 Working of Particle Filter Visualization

Our car only drives in one direction for the purposes of debate. The GPS is used to locate the car's original location. We sample 10 locations (particles) based on the measurement noise parameter provided by the GPS manufacturer because GPS is not reliable. The amount of particles utilised is adjustable, and we chose a low number only to make things easier to see. In practise, we can start with hundreds to thousands of particles and experiment to find the right amount that strikes a reasonable balance between precision and processing cost.

Figure 3.14 Phase 1

Now suppose that there is no GPS then we can distribute the particle uniformly along the track. This is the same as we did in Localization i.e we don’t know the position of the car

Figure 3.15 Phase 2

For each particle, we apply a dynamic model (like x’ = x + v δt) to calculate the next position at time t + δt.

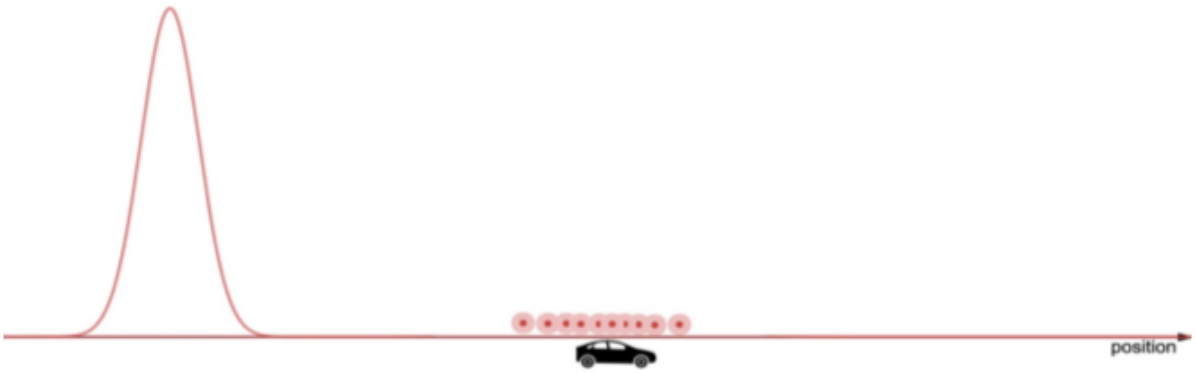


Figure 3.16 Phase 3

We add separate random noise to each particle's location to represent process noise produced by factors such as weather and road conditions. Experimental data or an analytical model are used to determine the level of the noise. Because of the uncertainty effects, the particles should spread wider apart.

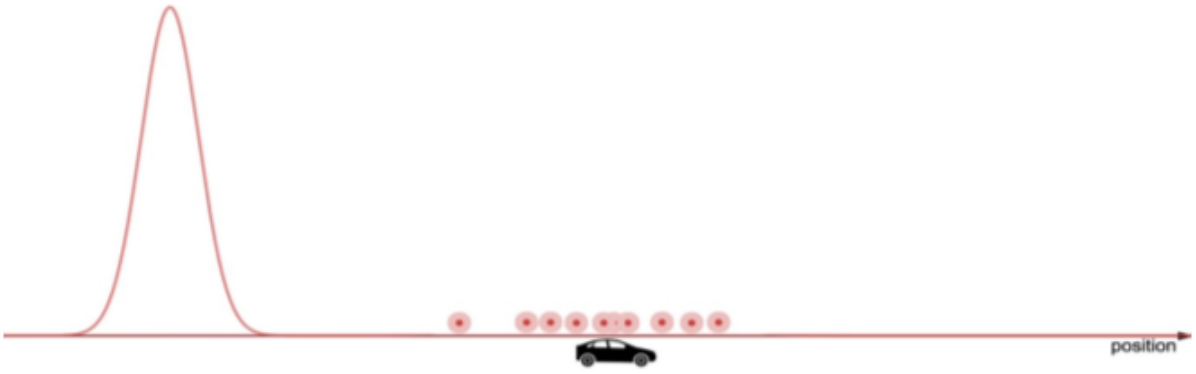


Figure 3.17 Phase 4

Now we will find all of the surrounding landmarks using the per-defined map

Figure 3.18 Phase 5

Now, we remove the landmarks that are out of sight (left most land mark in this case)

Figure 3.19 Phase 6

Each particle indicates the car's possible location. We want to compute the probability utilising data from our sensors. A distance and an orientation from a landmark are included in each reading. However, as previously stated, the measurement does not

identify the landmark. Instead, we use the distance and orientation information to use a map to find the nearest landmark. In P2, for example, we use our first sensor reading to select the right-most stop sign.

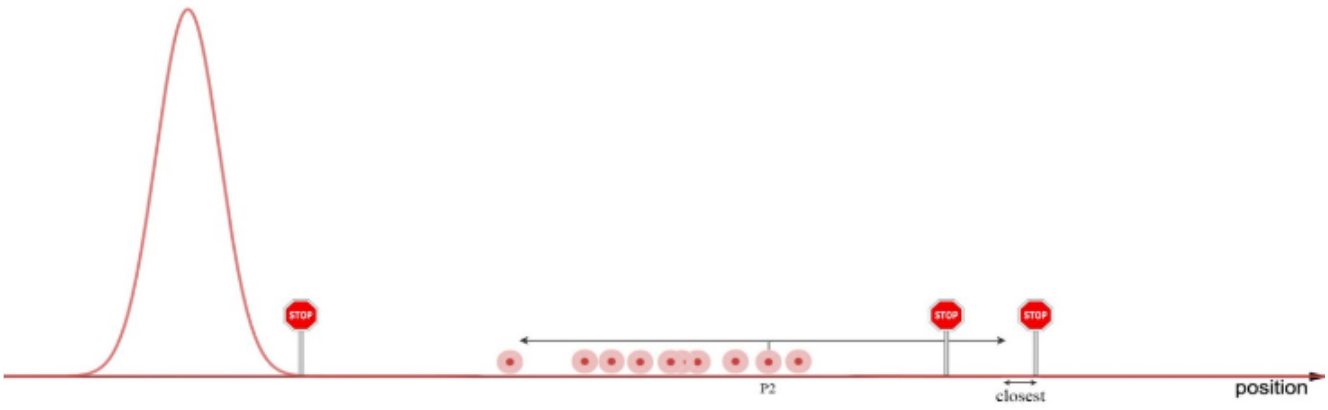


Figure 3.19 Phase 7

Now, we assume that the measurement noise is Gaussian Distributed, so we find out the probability of P2 representing our current location

$$PDF = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2}$$

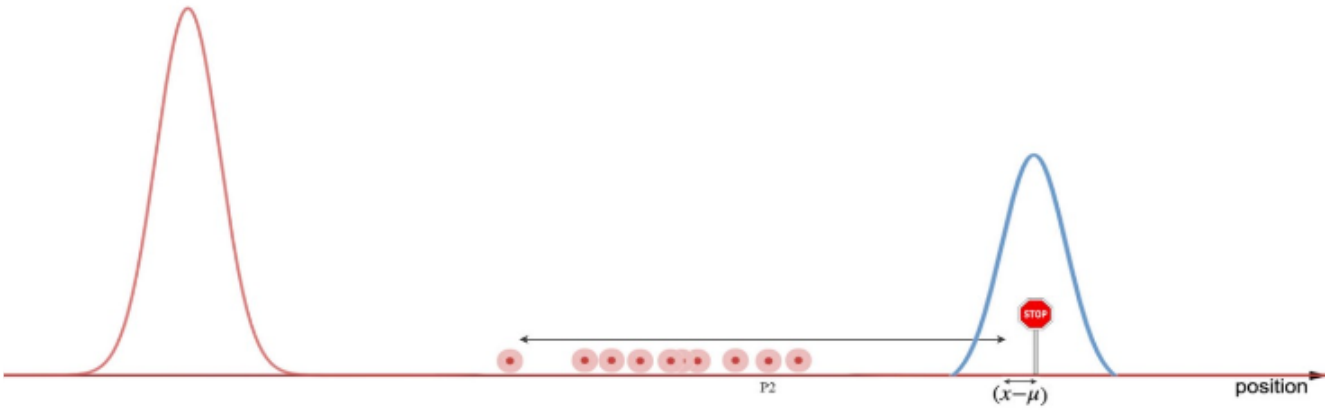


Figure 3.20 Phase 8

Now, we have to repeat the calculations for every received measurement. Then by multiplication of all the PDFs we get the final most probable position of the particle/car .

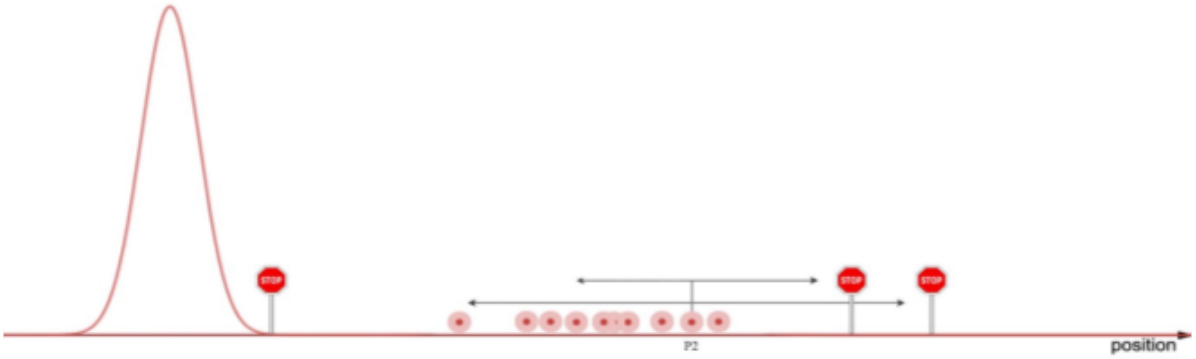


Figure 3.21 Phase 9

For each particle, we repeat the procedure. After that, we normalise their probabilities till the entire probability equals one. Our particles' weight is determined by this. Our automobile is estimated to be in the particle with the highest weight.

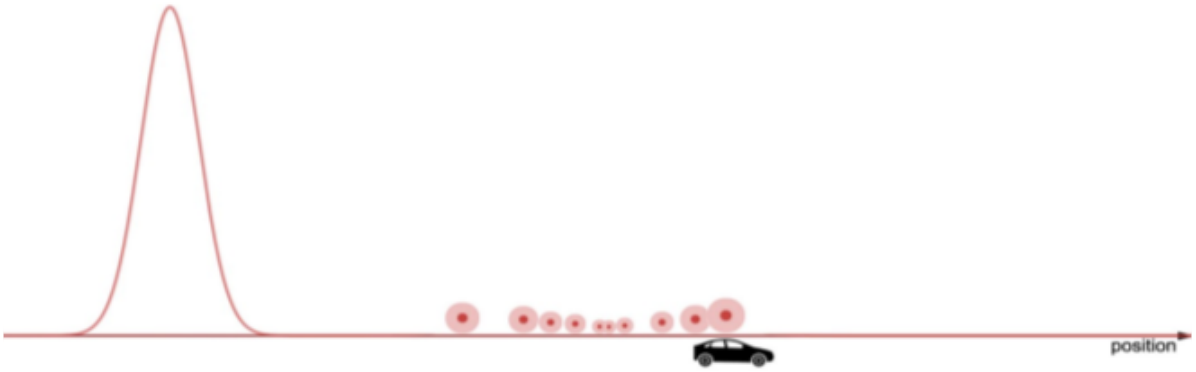


Figure 3.22 Phase 10

Based on the weights, we resample another 10 particles. If P2 has double the weight of P1, it will have twice the chance of being chosen. We have two clusters of places in our situation. This means that our measurements indicate that our car might be parked in two different places. This kind of ambiguity can be reduced by increasing the number of landmarks in the map or reduce the time (δt) between predictions.

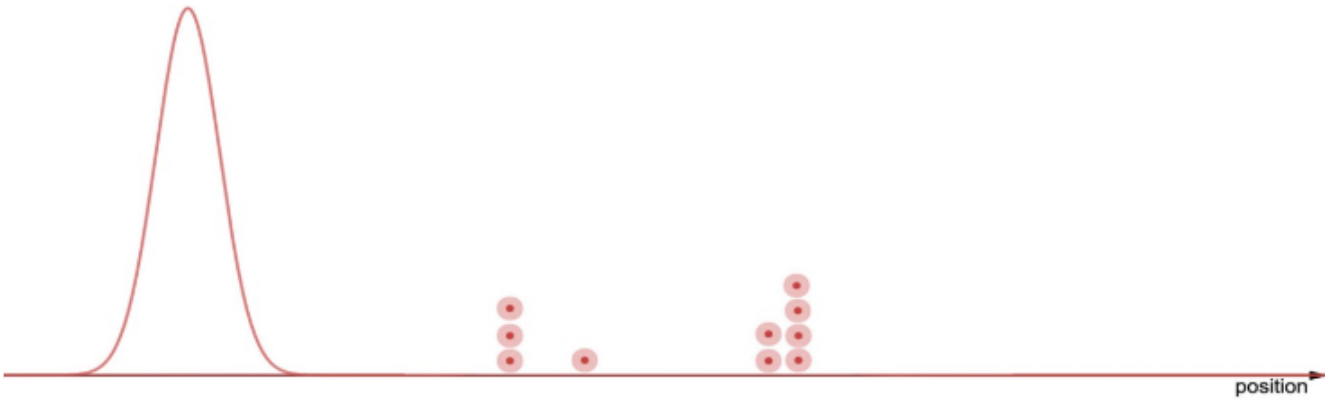


Figure 3.23 Phase 11

Now, for each particle we have to apply our car's dynamic model again for getting the next position and then we have to add random process noise.

Figure 3.24 Phase 12

The process is then repeated with a new set of measurements. Our sensor readings are less unclear this time. The particles from the original cluster have been removed, and the fresh ten particles have formed a tight cluster.

Figure 3.25 Phase 13

3.3.2 Particle Filter in low dimension space

The 'classical' successful application of particle filters in robotics is mobile robot localization. The problem of estimating a mobile robot's pose relative to a given map using sensor measurements and commands is addressed by mobile robot localization. To define the pose a two-dimensional Cartesian coordinate and the robot's rotational heading direction are used generally.

If the inaccuracy can be assured to be modest at all times, the problem is known as position tracking. The global localization problem, which is the difficulty of locating a robot in the face of global uncertainty, is more usual. The kidnapped robot problem, in which a well-localized robot is teleported to another place without being told, is the most challenging variant of the localization problem. This issue was raised, for example, during the Robocup soccer competition, in which judges randomly selected up robots and placed them somewhere else. Multiple robots that can observe each other are used in various localization difficulties.

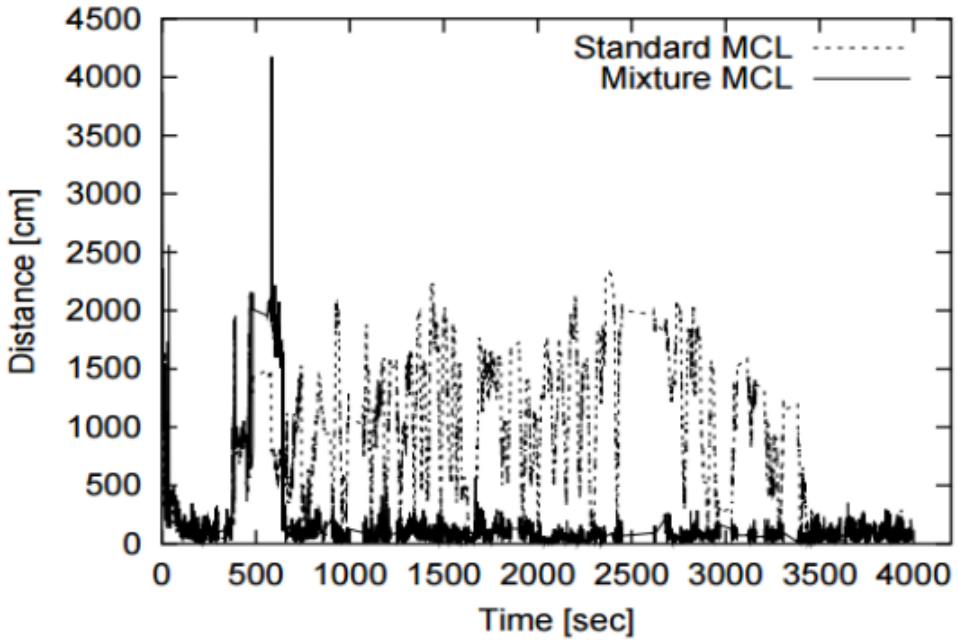


Figure 3.26

Figure illustrates particle filters in the context of global localization of a robot in a known environment. At various stages of robot activity, a number of particles approximate the posterior (1), as seen in a development of three instances. Each particle is a representation of a three-dimensional pose variable that includes the robot's Cartesian coordinates as well as its orientation in relation to the map. The pictures in Figure 1 show how the particle filter approximation has evolved over time, from worldwide uncertainty to a well-localized robot.

Particle filters are also known as Monte Carlo localization in the context of localization (MCL). MCL was inspired by the condensation method, a particle filter that was widely used in computer vision applications at the time. Particle filters routinely outperform alternative strategies in most variations of the mobile localization issue, including parametric probabilistic techniques like the Kalman filter and more classical techniques.

3.3.3 Particle Filter in High Dimensional Spaces

The poor performance of plain particle filters in higher dimensional spaces is an often cited drawback. This is due to the fact that the number of particles required to populate a state space rises exponentially with its dimension, similar to the scaling constraints of traditional HMMs. Many robotics challenges, on another side, have structure that can be used to design more efficient particle filters. The simultaneous localization and mapping problem is an eg of such a problem. The difficulty of creating a map of the environment using a moving robot is addressed by SLAM. The SLAM problem is difficult to solve because faults in the robot's localization produce systematic problems in the map's environmental feature localization. The lack of an initial map in the SLAM problem makes employing techniques like MCL to locate the robot during mapping difficult. Furthermore, the robot must determine if two environment features detected at separate times relate to the same physical feature in the environment, which is a difficult data association problem. To make problems worse, a map's space can have hundreds of thousands of dimensions. Because the size of the state space is frequently unknown at the start of mapping, SLAM methods must also estimate the problem's dimensionality. Furthermore, most SLAM applications necessitate real-time processing.

3.3.4 Creating a particle

The particle filter you are going to program maintains a set of 1,000 ($N = 1000$) random guesses as to where the robot might be, represented by a dot. Each dot is a vector that contains an x-coordinate (38.2), a y-coordinate (12.4), and heading direction (0.18). The heading direction is the angle (in radians) the robot points relative to the x-axis; so as this robot moves forward it will move slightly upwards.

In your code, every time you call the function robot() and assign it to a particle p[i], the elements p[i].x, p[i].y, p[i].orientation (which is the same as heading) are initialized at random.

In order to make a particle set of 1,000 particles, you have to program a separate piece of code that assigns 1,000 of those to a list.

```
N = 1000

p = []

for i in range(N):

        x = robot()

        p.append(x)

print len(p)
```

3.3.5 Second half of Particle Filter

The second half of particle filters works like this: imagine a robot that sits between four locations and can measure their exact distances. The figure on the right displays the location of the robot and the distances it measures, as well as "measurement noise," which is modelled as a Gaussian with a mean of zero. This means that there's a chance the measurement will be too short or too long, and that likelihood is determined by a Gaussian distribution.

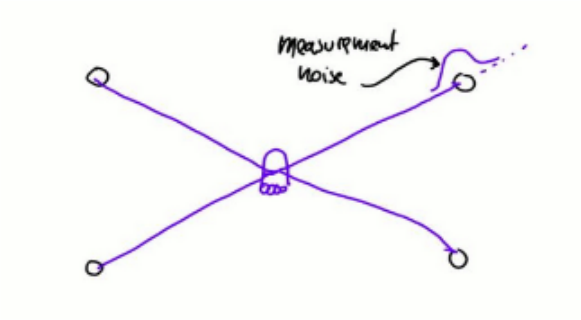


Figure 3.27 Measurement Vector Phase 1

We now have a measurement vector made up of the four values of the four distances between L1 and L4. The situation described below occurs when a particle hypothesises that its coordinates are somewhere other than where the robot actually is (the red robot represents the particle hypothesis).

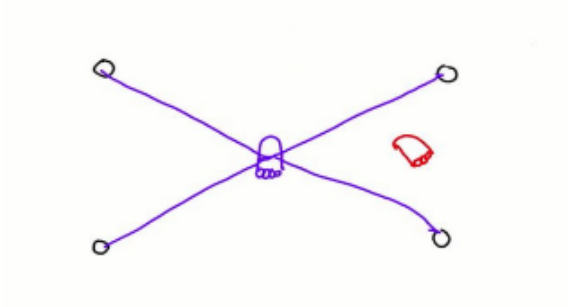


Figure 3.28 Measurement Vector Phase 2

A different going direction is also hypothesised by the particle. You can use our robot's measurement vector and apply it to the particle.

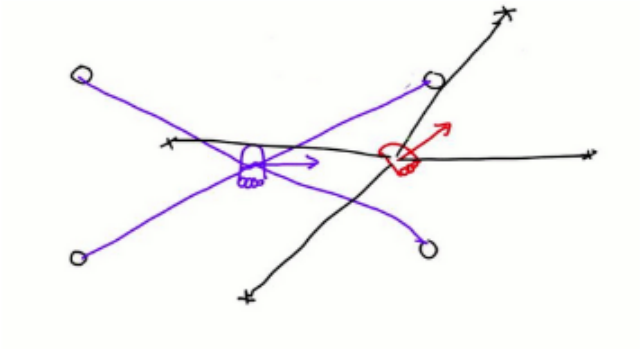


Figure 3.29 Measurement Vector Phase 3

However, this ends up being a very poor particle measuring vector. If the red particle was a good match for the robot's real location, the green represents the measurement vector we would have anticipated.

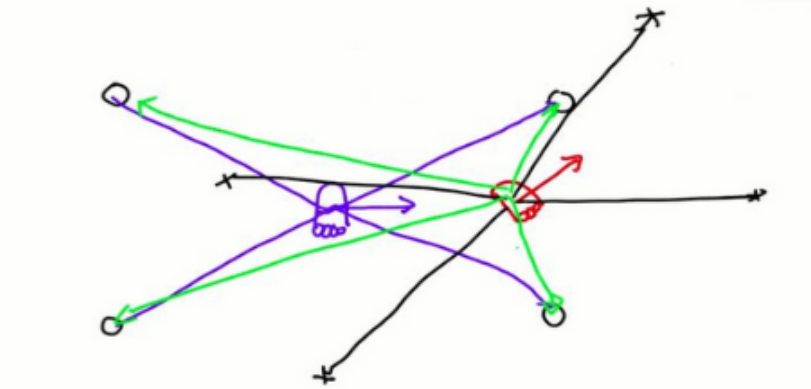


Figure 3.30 Measurement Vector Phase 4

The more likely the set of measurements given that position will be, the closer your particle is to the correct place. The trick to particle filters is that the difference between the actual and projected measurements results in an importance weight, which informs

you how essential that individual particle is. The more significant the weight, the more significant it is.

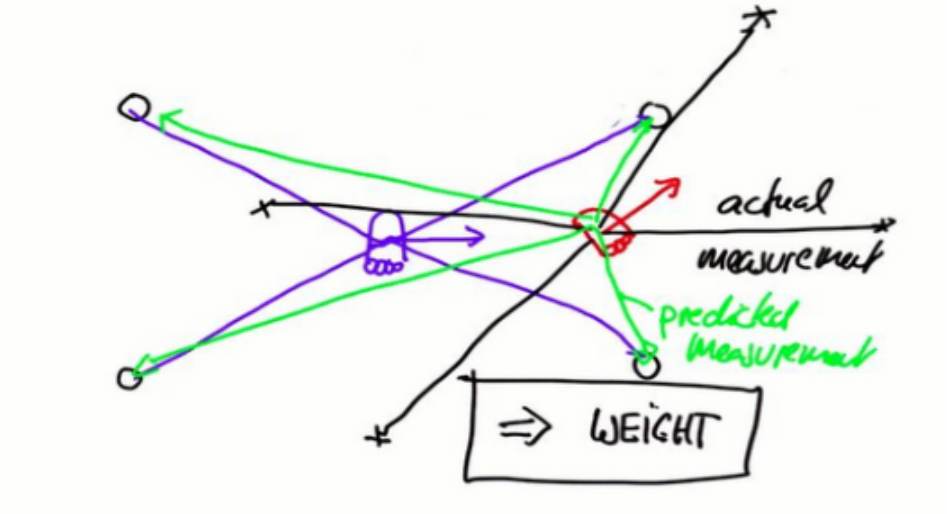


Figure 3.31 Measurement Vector Phase 5

When you have a group of particles, each one has its own weight; some appear to be highly believable, while others appear to be quite implausible, as indicated by the particle's size.

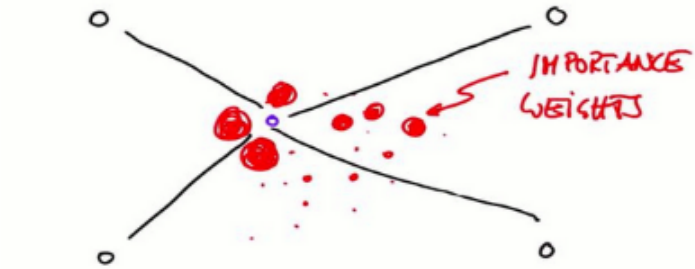


Figure 3.32 Measurement Vector Phase 6

The particles will then be allowed to survive at random, but their chances of surviving will be proportional to their weights. That is, a particle with a higher mass will survive in greater numbers than a particle with a lower mass. This means that after re-sampling, which involves drawing new particles at random from old ones and replacing them in proportion to their importance weight, the particles with a greater importance weight will survive while the smaller ones would perish. This selection method's "with replacement" feature is critical because it allows us to choose the high probability particles several times. As a result, the particles tend to congregate in areas with a high posterior probability.

From here, you'll want to develop a mechanism for calculating importance weights based on the likelihood of a measurement, as well as a resampling approach that collects particles in proportion to those weights.

3.4 Motion Planning

Once we have located the car or the robot and its surrounding environment for various obstacle using the concepts such as localization and Kalman filter. Next step is to find the path so that the robot or can perform motion on that path.

The fundamental problem in motion planning is that a robot might live in a world that looks like the one pictured below and will want to find a goal like $. The robot has to have a plan to get to its goal, as indicated by the red line route.

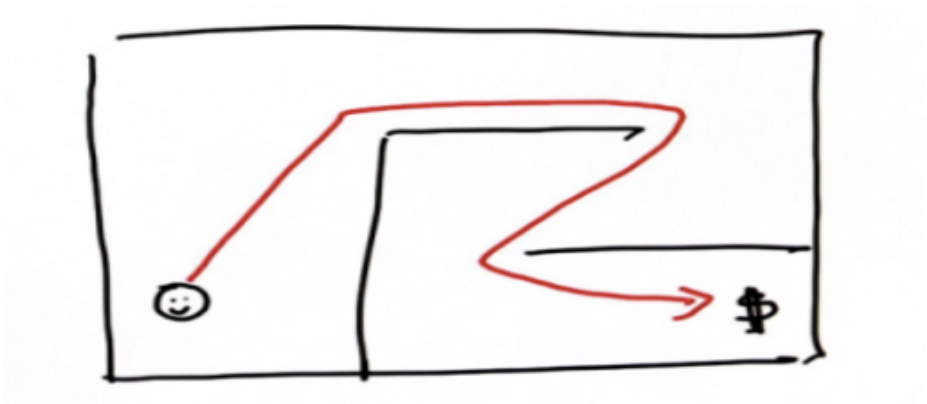


Figure 3.33 Robot Path

Given:

- Map Starting Location
- Goal Location Cost (time it takes to drive a certain route)
- **Goal**: Find the minimum cost path.

Computing Cost (Compute Cost):

Suppose you live in a discrete world that is split up into grid cells and your initial location is facing forward, while your goal location is facing to the left.

Assume that for each time step you can make one of two action -- either move forward or turn the vehicle. Each move costs exactly one unit.

This same problem occurs for a self-driving car that lives in a city and has to find its way to its target location by navigating through a network of streets and along the highway.

We are concerned with 2 topics path planning and motion planning. There is a very small difference between these 2 terms. Suppose that there two positions on a binary occupancy grid or in simple words environment, starting position (X pos) and Goal position (Y pos). Finding the path between starting position and goal position is known as **Path Planning**. In **Motion Planning** also we find the path between starting and goal positions but here we are also concerned with the derivatives of path such as velocity, acceleration, rotation etc. With motion planning we are trying to dictate precisely how the robot moves through the environment. With path planning we are just concerned with the path it takes and not have fast the robot accelerates or moves through it.
There are many methods to implement motion planning such as-

- Search based methods
- Sampling based methods
- Grid based search
- Graph based methods
- Interval-based search
- Geometric based algorithms etc.

But in this project, we have considered two methos namely Search based and Sampling based.

Figure 3.34 Start and Goal Pose

Consider a simple environmental map (fig 6.2), there are staring and goal positions on the map. To find minimum distance between start pose and goal pose we can try a straight line between these two positions. If the robot moves this path, it will reach the goal position in the shortest time. But as we know that in real life the environment is filled with many obstacles, therefore we cannot find solution for many problems in this way.

3.4.1 Graph based methods

Graph based algorithms work by discretizing the environment that is breaking it up into discrete points or nodes and then finding the shortest distance to the goal. Let's approach this problem (figure 3.34) in a Radom way. We have to find the shortest path between start pose and goal pose.

The first node in our graph is start pose and it has a cost of 0 since we are already there, so we will put a 0 inside the node and then we move in a random direction and place a node in the graph at new location. The edge between the nodes is how far we have travelled and cost of getting to this node is the length of that one edge. Now we take another step in a completely random direction, place another edge and the cost of this node is the total of three units and we can continue to this process until we reach the goal as shown in figure 3.35 .

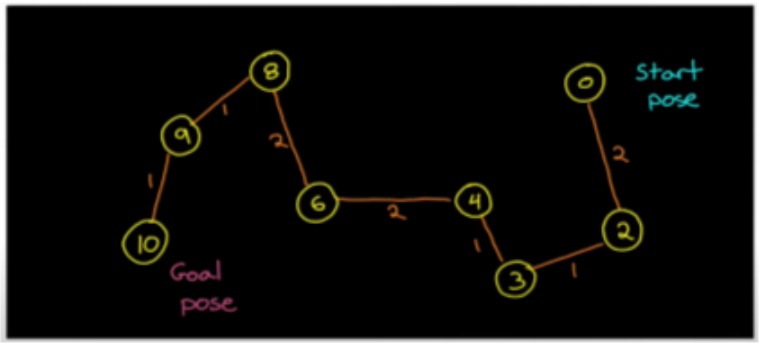


Figure 3.35 Random path

The cost of this random path is 10 units (2+1+1+2+2+1+1). We have found out a path, but we are not sure if this is the shortest path. So, we have start again and adding a node and connecting it with an edge and recording its cost and if we happen to reach a node that we visited before we can compare the cost between the two different paths that we took to reach it and keep the smallest one. We don't need to build a fully interconnected graph. We can build a tree which is subset of a graph, in a tree each node only has a single parent. In a tree we can get to anode two different ways, it doesn't make sense to keep the path that is longer if we are finding the shortest path so we can remove the edge for the longer path keeping a tree structure. In this way a tree would start at the location of the robot and the branches would venture out to other states but never recombine. Now to find shorter distance to the goal we can just keep randomly wandering the environment Updating the tree until we find a branch that gets the goal with a cost that is low. This process doesn't guarantee a optimal path but it will continue to approach optimal as number of nodes go to infinity.

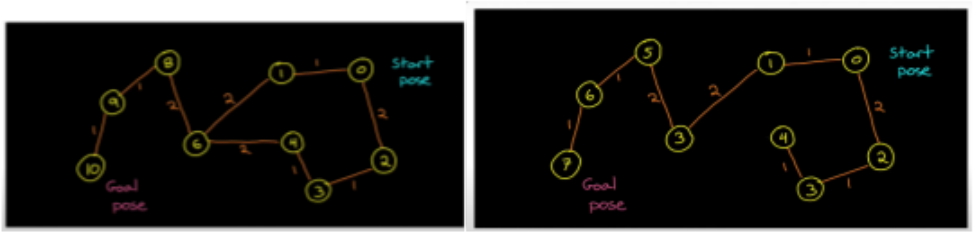


Figure 3.36 Path Options

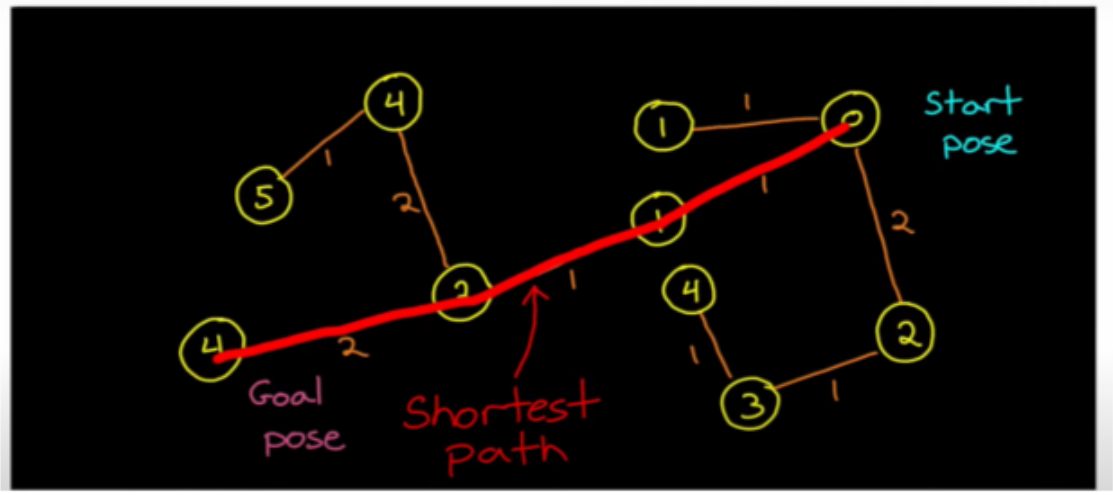


Figure 3.37 Random Wandering Robot

Random wandering is not the best solution, this is where path planning algorithms comes. These provide more efficient ways to build this tree.

3.4.2 Search based methods

Search based method is one of the motion planning methods. In this method we use graph search methods to find paths over a discrete representation of the problem.
In search-based method we build up the tree by adding nodes in an ordered pattern. One way to do this task is that we start with grid-based map like the occupancy grid. We have to go cell by cell and determine the cost or the distance the robot would have to go in order to reach that cell.

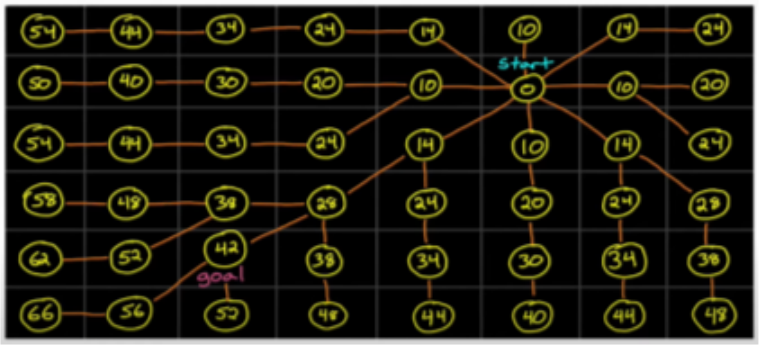


Figure 3.38 Search based Method

As we can see in fig 6.6 the entire space is divided into cells. Here we have assumed that adjacent moves cost 10 unit whereas diagonal moves cost 14 units. This method is similar to the random approach that we did in graph based method except we are methodically working our way through each cell and calculating the cost to reach it and if it's the shortest path to that node then we update the cost and the tree to reflect it. Once we have covered every single cell in the grid the optimal path is simply the sequence of cells that produce the minimum cost at the goal.

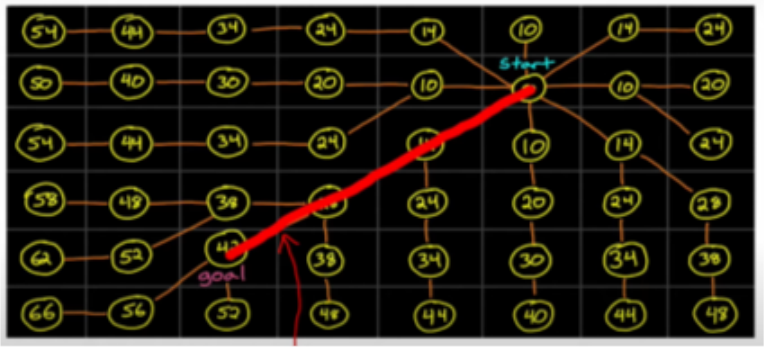


Figure 3.39 optimal using in search based method

Search based methods provide optimal path but these are also computationally expensive since it is kind of brute force method.

Some common search base algorithms are-

- A* algorithm
- Breadth first search
- Dijkstra algorithm

The advantage of search-based methods is that these gives us optimal path and but its computationally expensive.

To solve the problem of search based algorithms the researchers came up with A* (A star) algorithm. This was done in 1968 to give shakey the robot the ability to determine where to go on its own. This was done first time for a general-purpose mobile robot.

3.4.3 Pros and cons

Both methods, search based and graph based have their pros which can debated for hours. The main differences between graph-based method and search-based method are speed and optimization.

Search based methods gives us optimal path and but its computationally expensive.

3.4.4 A* search algorithm (A Star):

The A* (A-star) algorithm can be used for our path finding problem. It is a variant of the search algorithm that we implemented, that is more efficient because you don't need to expand every node. The A* algorithm was first described by Peter Hart, Nils Nilsson and Bertram Raphael in 1968. If you understand the mechanism for searching by gradually expanding the nodes in the open list, A* is almost the same thing, but not quite.

A* uses a heuristic function, which is a function that has to be set up. If it's all zeroes, A* resorts back to the search algorithm already implemented. If we call the heuristic function h, then each cell results in a value.

A* algorithm is a search based method. It still adds nodes in a ordered way but it does so by prioritizing the nodes that are more likely to produce the optimal path and searching them first. It does this by keeping a track of heuristic value like the straight line distance from a node to the goal in addition to the cost of the node and the sum of these numbers is the absolute minimum cost of the path. Let's take an example given the figure below. In the figure there is a straight line shot to the goal then imagine the total path length for this node would be 48. We have already gone 10 units and now we have a minimum of 38 units left to reach the goal. In this case other node is prioritized even though its current cost is 14 since there is the potential of only having 28 more units to go for a total of 42.

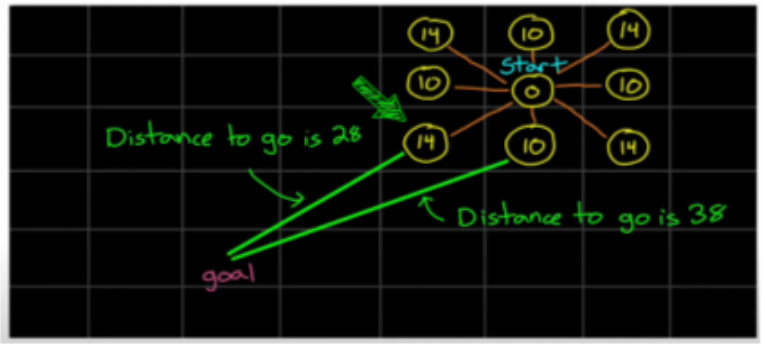


Figure 3.40 A algorithm*

It makes sense to keep trying this path so in this way A* allows us to search through the nodes in a way that will get us to the goal node without necessarily having to add every node into our tree.

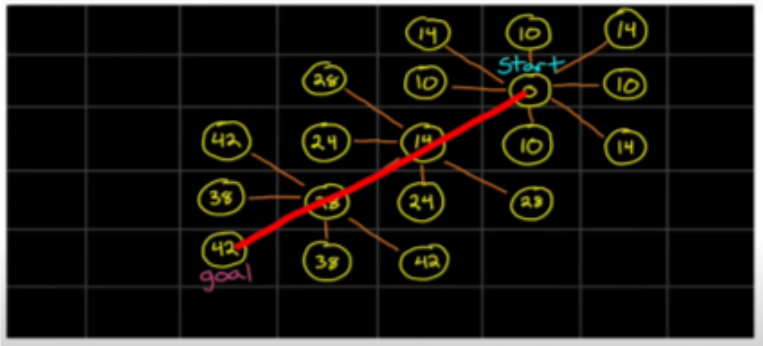
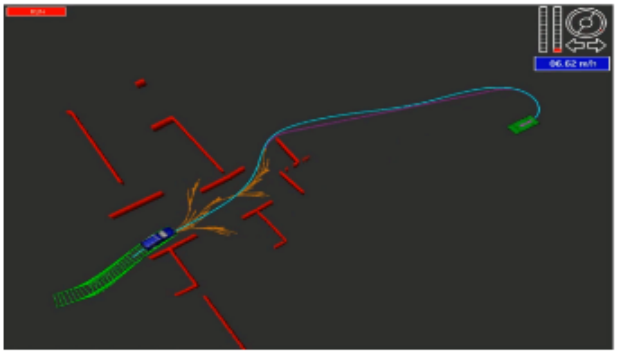


Figure 3.41 A algo output*

Using A star algorithm, once we reach to the goal node, we know that we took the optimal path since every other path would have a cost plus distance to go that is greater than the path we found.

3.4.5 Examples of A* in the real world:



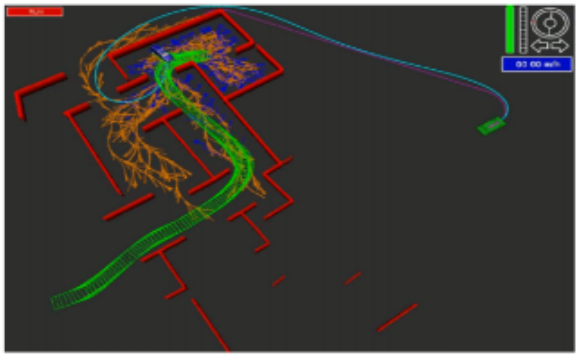


Figure 3.42 A algo in real environment*

3.4.6 Writing a Search Program (First Search Program)

Now, the question is, can you write a program that computes the shortest path from the start to the goal? The first step towards writing this program is to name the grid cells. Across the top, name the columns zero to five, and along the side you can name the rows zero to four. Think about each grid cell as a data point, called a node and the goal point is called the goal node.

1. From here you will make a list of nodes that you will be investigating further -- that you will be expanding. Call this list open. The initial state of this list is [0,0]. You may want to check off the nodes that you have already picked.
2. Now, you can test whether this node is your final goal node -- which, just by looking at the grid you can tell that it obviously is not. So, what you want to do next is to expand this node by taking it off the open list and looking at its successors
3. Then, you can check those cells off on your grid. Most importantly, remember to note how many expansions it takes to get to the goal -- this is called the g-value. By the end of your planning, the g-value will be the length of the path
4. The process of expanding the cells, starting with the one with the lowest g-value, should yield the same result you found as the number of moves it takes to get from the start to the goal.

3.4.7 A* algorithm implantation

Make an open list containing the first place
When it arrives at its destination:
Make a blank closed list
If it does not reach the destination, consider the area with the lowest f-effect on the open list.
We're done

Else:
List the current node and check its neighbors

To each neighbor of the current node:
If a neighbor has a lower value of g than the current node and is on a closed list:
Replace the neighbor with this new node as the neighbor's parent

Else If (current g is low and neighbor is on open list):
Replace the neighbor with the minimum value of g and change the neighbor's parent to the current node.

Else If the neighbor is not on both lists:
Add to the open list and set g

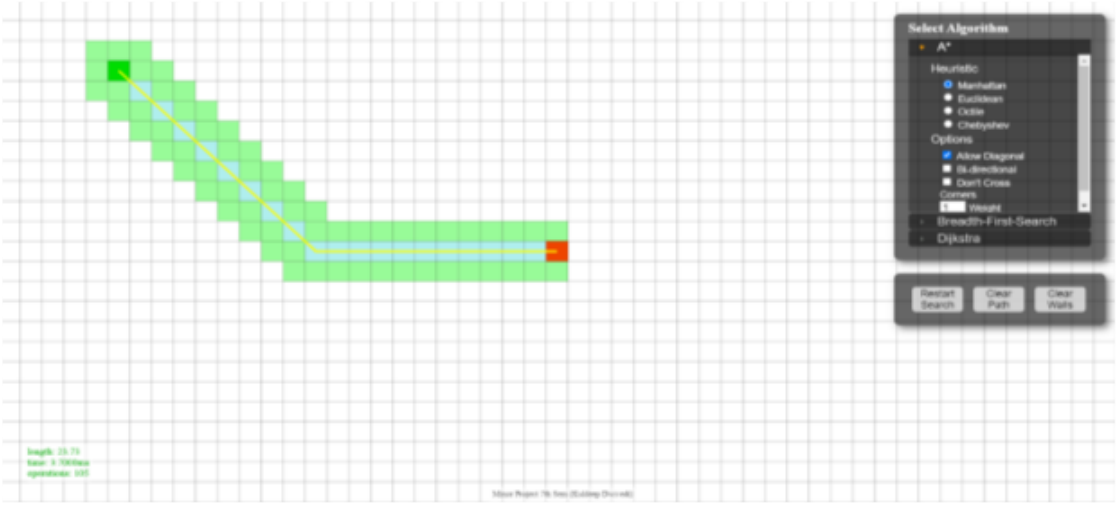


Figure 3.43 path finding using A algorithm*

3.4.8 Disadvantage of A* star algorithm

One problem with search based algorithms such as A* is that they become very computationally expensive as the size and dimensions of the state space increases. We can imagine how the number of grids points grow exponentially as the number of dimension increase which can slow everything down. Therefore these algorithms are not to be used for high dimensional state space for eg things like determining the path for multi-joined robot manipulators or for really large dimensional state space ones that might have millions or more grid cells. For such problems Sampling based algorithms are useful.

Other issue with A* algorithm is that it tends to gives straight paths. Straight path creates issue for a robot when it is trying to take turn.

Considering the disadvantages of A* algorithm we have use two more search algorithms which are Breadth First search (BFS) and Dijkstra Algorithms so that we don't have to depend on only one algorithm. If one fails to give path other will give us the path.

3.4.9 Breadth First Search

The breadth first search (BFS) is a fundamental search algorithm used to explore nodes and edges of a graph. It runs with a time complexity of O(V+E) and is often used as a building block in other algorithms.

The BFS algorithm is particularly useful for one thing: finding the shortest path on unweighted graph.

A BFS starts at some arbitrary node of a graph and explores the neighbor node first, before moving to the next level neighbors.

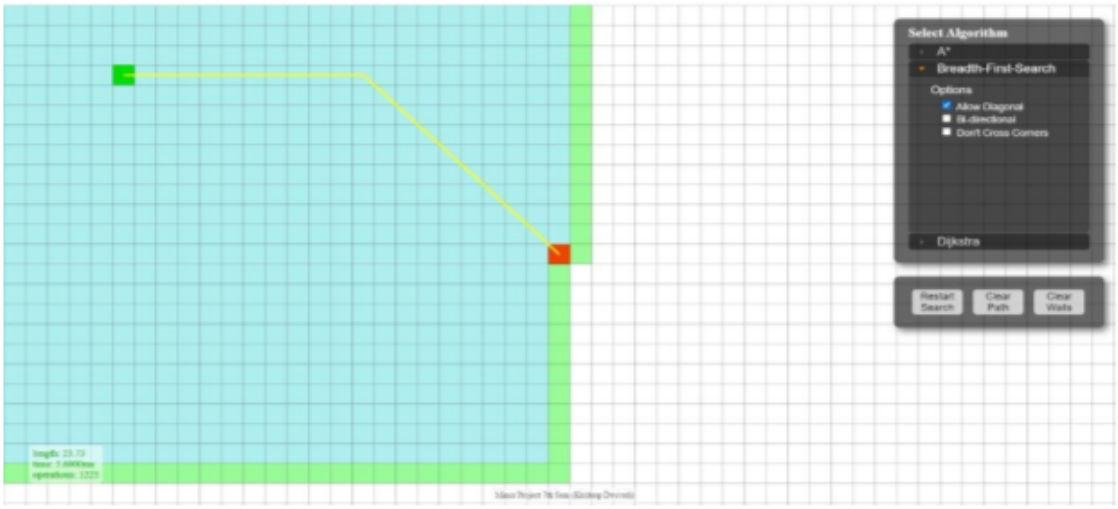


Figure 3.44 path finding using bfs.

3.4.10 Dijkstra algorithm

Dijkstra's algorithm is a single source shortest path algorithm which is used for graphs with non-negative edge weights.

Depending on how the algorithm is implemented and what data structures are used the time complexity is typically o(E*Log(V)) which is competitive against other shortest path algorithms.

One constraint for Dijkstra's algorithm is that the graph must only contain non-negative edge weights. This property is especially important because it enables Dijkstra's algorithm to act in a greedy manner by always selecting the next most promising node.

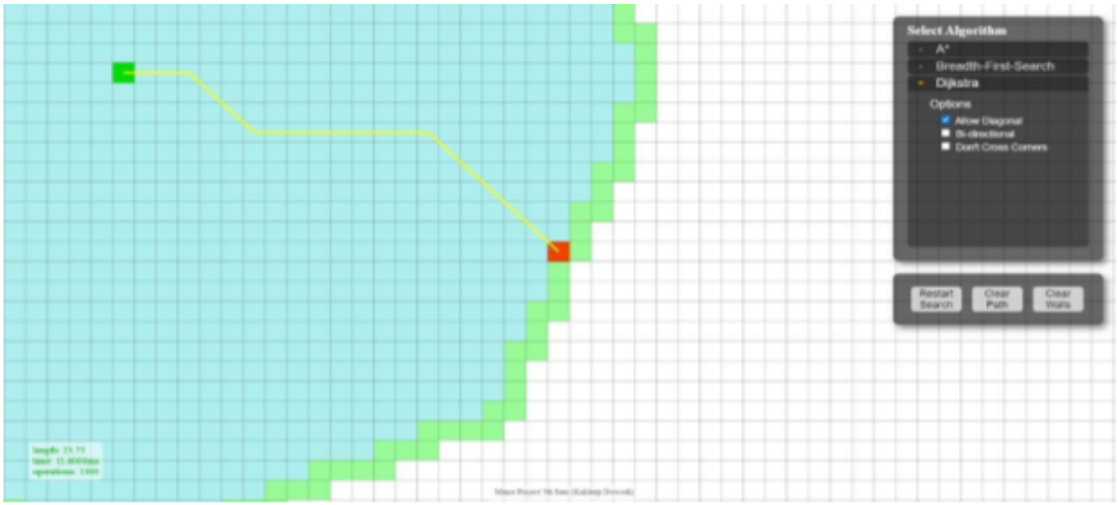


Figure 3.45 path finding using Dijkstra's algorithm

3.4.11 Future work and improvements

For motion planning we can use **sampling-based methods** such as RRT (Rapidly-exploring random trees) and RRT* algorithms. These algorithms will not necessarily give us optimal path every time but these algorithms are faster than A*, BFS and Dijkstra.

Modern day self driving cars such as tesla uses Neural Network along with dozens of sensors to perform motion planning.

3.5 PID Controller

Robots and self-driving cars, in general, do not manoeuvre with flawless precision. Their trajectory can be influenced by their surroundings (such as non-flat surfaces) as well as minor mechanical misalignments (such as mis-aligned wheels wheels).
A human driving a car with erroneously aligned tyres may constantly self-correct to ensure that they are on the straight and narrow. How can a self-driving automobile be taught to do the same?

Assuming we have a desired path for the automobile to follow, we can use the PID Control method to assure that it will re-align itself to the target.

To describe what PID controllers are and why we use them. Let us first see what a controller is. One way to write an open-loop system is like this where inputs act on a plant or the system to be controlled and then some output signal is generated. The performance of these open-loop systems is frequently insufficient to meet the requirements.

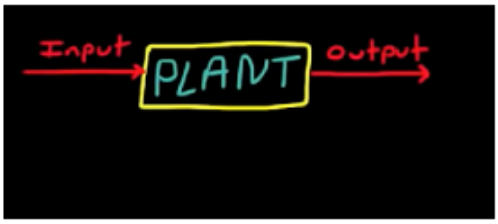


Figure 3.46 Basic Idea

Lets take a example suppose we are a task to build a robot that needs to move from one spot to the red spot as shown in figure 3.47. we could figure out how fast the robot moves and then from that we can determine how long the robot needs to drive for before it gets to the red X. This type of system is called open loop system because the amount of time the robot drives is not adjusted based on the actual position of the robot. Open loop commanding is perfectly fine for systems that don't change much or where accuracy isn't important.

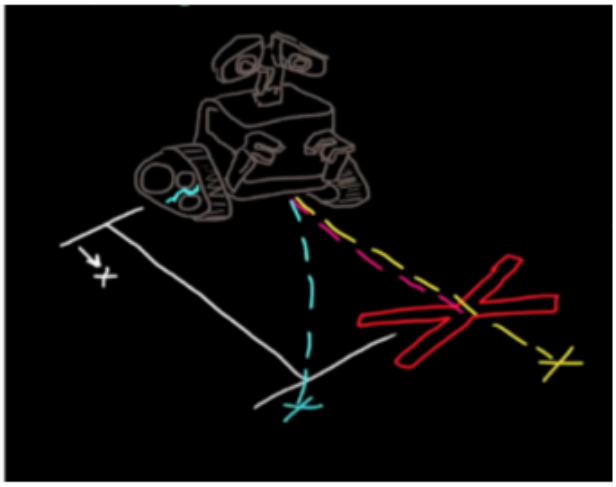


Figure 3.47 Basic Idea for path

However in some case if there's some dirt in one of the wheels and robot veers off to the side or if the robot moves slightly faster than you had predicted in both of these cases the robot wont stop on the red X because it has no way of compensating for these errors and making adjustment on its own. The solution for this is **feedback control** which essentially means you're sensing the output of the plant and feeding it back to the system so that system can make adjustments appropriately. In a feedback system there is a Reference signal and this is the desired value or the ultimate goal, we can compare the desired value to the measured value and now what we are left with is the error or the delta between when the robot is and where we want the robot to be. In this case error would be the difference from the reference position which is shown as the distance from the start to the red X (in meters) and the current position of the robot which is measured by the robot (in meters).

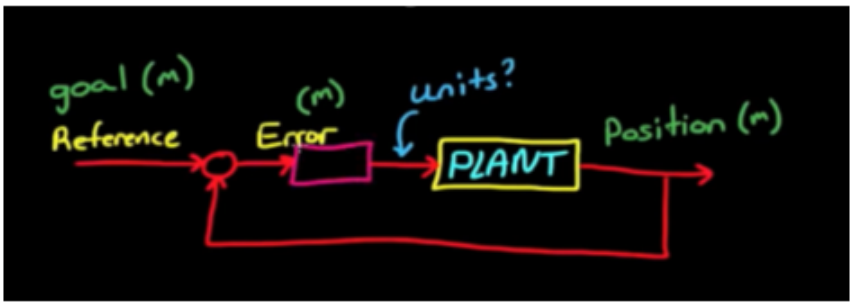


Figure 3.48 Feedback Control

Now at this point we have to find out how we can convert an error signal which as same units as the output of the plant into an input signal that has units that may or may not be same as the output. Apart from changing the units, the error needs to be adjusted in such a way that the input into the robot causes it to eventually reach the Red X. This is exactly what a controller does. A controller takes the error signal and convert it into a command that is then sent into that plant. One of a control engineer's goals is to construct this controller so that the error, or the difference between the current location and the goal, decreases with time. The measured location is exactly where we want it to be, indicating that the system satisfies all of its requirements.

There are many different types of controllers, with PID being one of the most common. In our project, we constructed a PID controller. PID is extensively employed because it is efficient and effective in a wide range of applications; in fact, it accounts for the vast majority of controller types and industrial applications.

3.5.1 PID

PID is an acronym and it stand for proportional internal derivative and each of these terms describe how the error term is treated before being summed and sent into the plant.
A PID controller analyses an error value, which is defined as the difference between a target point and a measured process variable, on a continuous basis. By varying a control variable, the controller attempts to minimise the error over time, for e.g. by changing the position of a control valve, a damper, or the power given to a heating element, to a new value determined by a weighted sum:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt}$$

Here K_p, K_i, and K_d, are all non-negative constants and these denote the coefficients for the proportional, integral, and derivative terms, respectively (sometimes denoted *P, I,* and *D*).

In this model-

• P accounts for the error's current values. If the error is high and positive, for example, the control output will be large and positive as well.

• I account for previous incorrect values. If the current output isn't strong enough, for example, errors will build up over time, and the controller will respond by taking a stronger action.

• D takes into consideration the error's potential future values depending on its current rate of change.

Because they rely purely on the measured process variable and not on knowledge of the underlying process, PID controllers are frequently used. The three parameters of a PID controller can be tuned to deal with individual process requirements. The degree to which the system overshoots a setpoint and the degree of any system oscillation can all be characterised in terms of the controller's response. The use of the PID algorithm does not guarantee that the system will be well regulated or stable.

To offer the proper system control, some applications may only require the use of one or two words. The other parameters are set to 0 to achieve this. In the absence of the appropriate control actions, a PID controller is referred to as a PI, PD, P, or I controller. Because derivative action is susceptible to measurement noise, and the absence of an integral term may prevent the system from attaining its target value, PI controllers are rather prevalent.

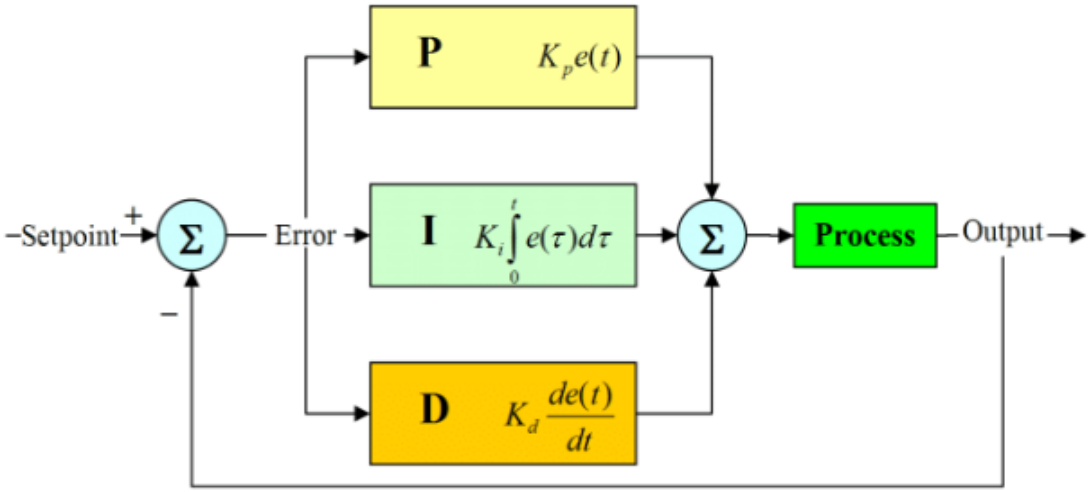


Figure 3.49 PID controller block diagram

In one of its block diagrams forms a PID controller is written like this as shown in Figure 3.49. In the proportional path the error term in multiplied by a constant Kp, in the integral path the error term is multiplied by a constant Ki and then integrate it. In the derivative path its multiplied by Kd and then differentiate it. Then these three terms are summed together to produce the controller output. The three K terms are called gains, and these can be adjusted or tuned to a particular plant with a defined set of requirements. By changing these we are adjusting how sensitive the system is to each of these different paths.

Let's understand this concept with few plots (figure 3.50)

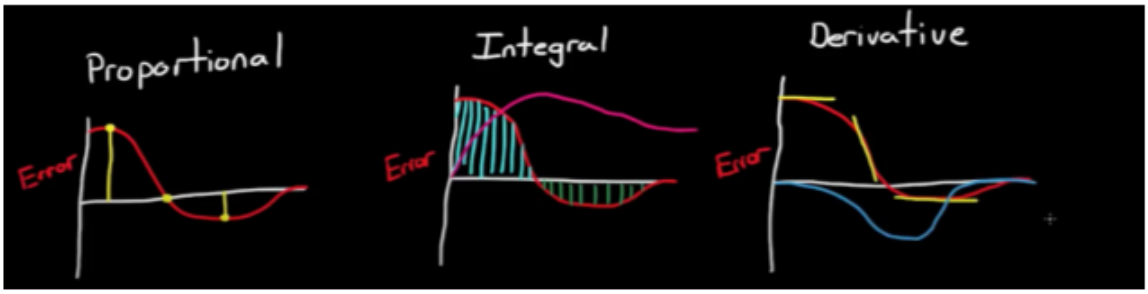


Fig 3.50 P, I And D vs error plots

The red line shows how the system error changes over time. The output of a proportional path is the error scaled by a constant Kp. As we can see, the proportional approach produces a huge output when the mistake is large. When the error is zero, the path's output is zero; when it is negative, the path's output is negative.

As the mistake travels over time in the integral path, the integral will add it up and multiply it by a constant Ki. The integral route is the area under the curve in the plot, where blue represents positive area and green represents negative area. The integral path is used to remove constant faults in a control system since the aggregate of those errors, no matter how little, will eventually be substantial enough to modify the controller output.

The rate of change of the error contributes to the output signal in the derivative path. When the change in error moves slowly, as it does at the start, the derivative route is modest, and as the error changes faster, the derivative path becomes larger.

To get the output of PID controller we can sum these three paths. However we don't always need all paths so we can remove a path completely by setting its associated gains to zero. When we do this we generally refer to that controller with the letters of the path that are left for example we can have a proportional integral controller PI if we set Kd to zero and just a P controller if Both Kd and Ki are set to zero. We do this because this will controller simple , a simple controller is easy to implement, easy to tune and easy to troubleshoot.

Chapter 4: Result Discussion

4.1 Localization

Figure 4.1 Localization

8.2 Kalman Filter

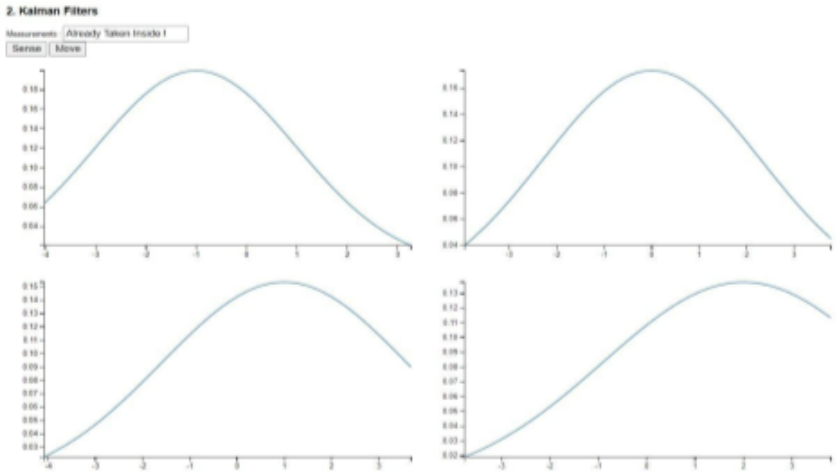


Figure 4.2 Kalman Filter

8.3 Motion Planning

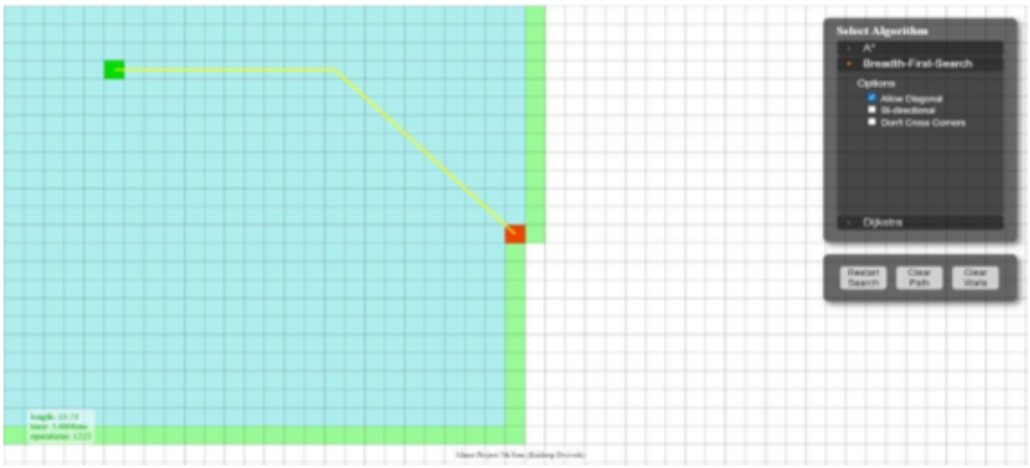


Figure 4.3 Motion Planning 1

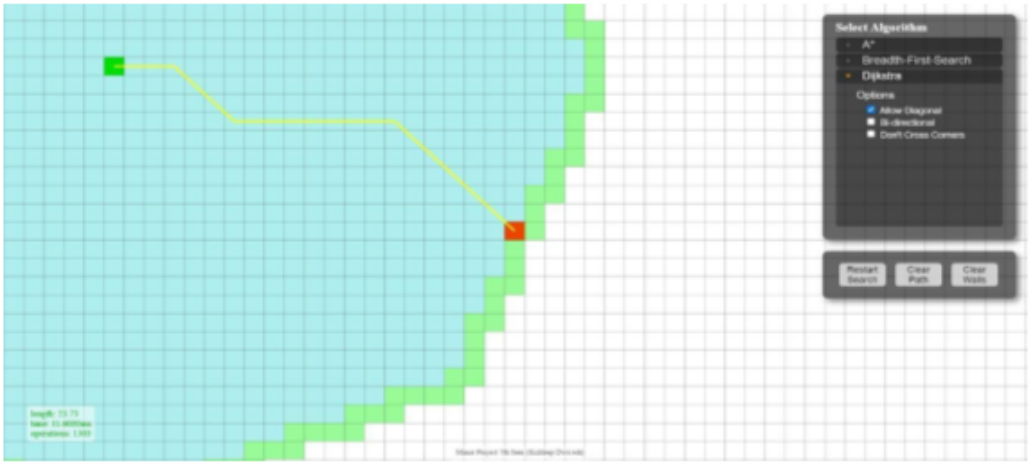


Figure 4.4 Motion Planning 2

8.4 Particle Filter

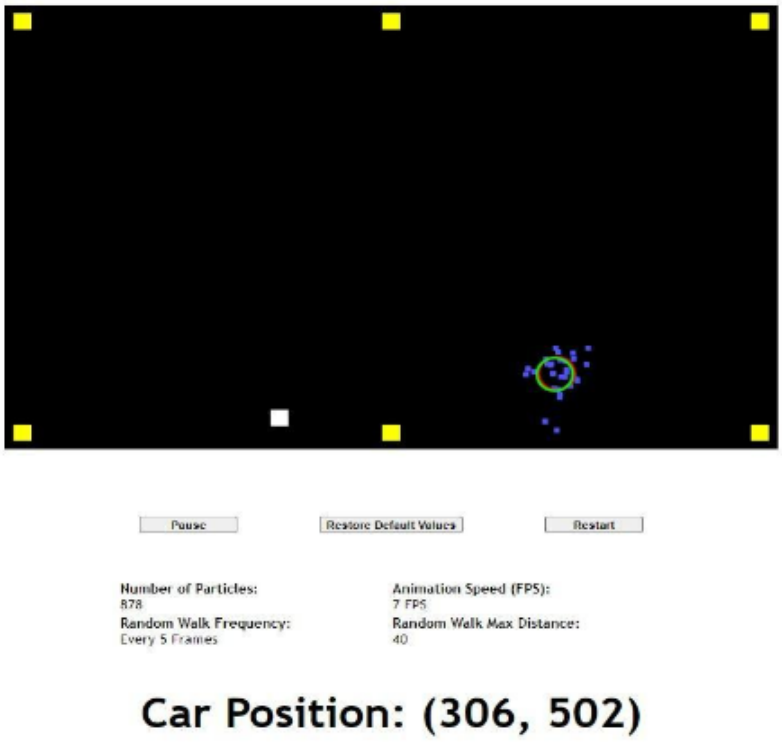


Figure 4.5 Particle Filter

Chapter 5: Conclusion and Future Wok

The software implemented will be a key part in designing the self-driving car. The techniques used for particle tracking , motion planning and smoothing minimizes error rates to maximum extent and helps in designing a reliable Working self – driving car . Except for the software implementation, a lot goes into implementing the actual car itself .

Efforts can be made to further optimize the error rates in future so that such cars can be used in future in general traffic.

In the last decade, automobile manufacturers have made great progress toward making self-driving cars a reality; nevertheless, there are still a number of technological hurdles to surmount before self-driving vehicles are safe enough for road use. GPS can be unreliable, computer vision systems have limits when it comes to recognising road scenes, and changing weather conditions can impair on-board processors' capacity to accurately detect and track moving objects. Self-driving cars have yet to show that they can recognise and navigate unstructured surroundings like construction zones and accident zones in the same way that human drivers can.

These obstacles, however, are not insurmountable. The amount of road and traffic data available to these cars is growing, newer range sensors are recording more data, and road scene analysis algorithms are improving. The move from human-driven vehicles to completely autonomous vehicles will be gradual, with vehicles doing just a subset of driving functions automatically at first, such as parking and driving in stop-and-go traffic. More driving activities can be reliably outsourced to the car as technology develops.

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