

MCL Algorithm:

Pseudocode:

Algorithm MCL (X_{t-1} , U_t , Z_t)

Previous belief

Sensor measurement

↑
Action Command

Initialize from sensor ip.

$\leftarrow X_t = X_t = \phi$ (later we update this estimate)

Generate 'M' particles

\leftarrow for $m=1$ to M :

hypothesis state

$\leftarrow X_t^{[m]} = \text{motion-update}(U_t, X_{t-1}^{[m]})$

weight

$\leftarrow w_t^{[m]} = \text{sensor-update}(Z_t, X_t^{[m]})$

$\bar{X}_t = \bar{X}_t + \langle X_t^{[m]}, w_t^{[m]} \rangle$

prev state (belief)

motion & sensor measurement

end for.

Resampling

particles with high probability survive & are redrawn

for $m=1$ to M :

draw $X_t^{[m]}$ from \bar{X}_t with probability $\propto w_t^{[m]}$

$X_t = X_t + X_t^{[m]}$

In next iteration,

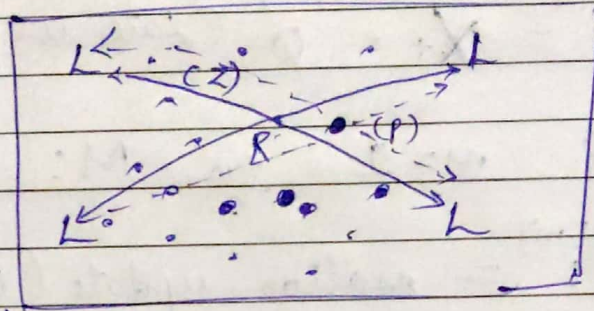
while other particles die

end for.

return X_t

→ op of new belief

- ① Generate the particles. (eg: $N=1000$)
- ② Randomly & uniformly spread the particles throughout the map.
- ③ Importance weight = $Z-P$



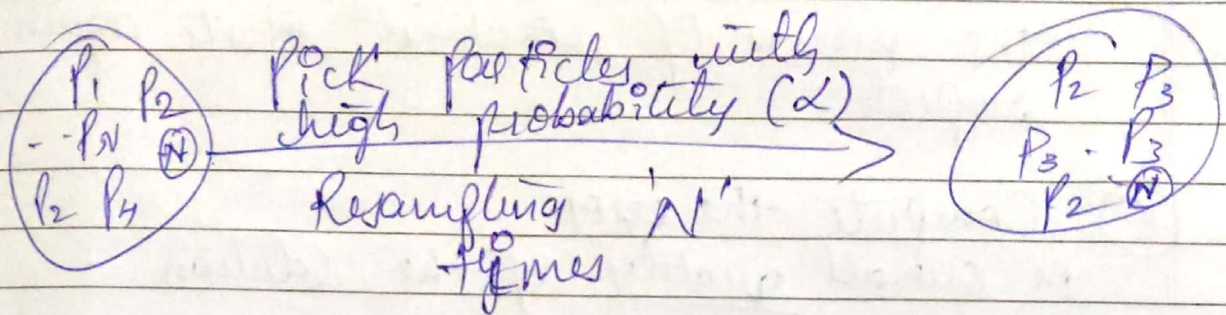
$Z = \overset{\text{(sensor)}}{\text{actual measurement}}$ (Robot to landmark)
 $P = \text{Predicted}$ " (particle to landmark)

→ Higher the weight, more important the particle is & more likely to represent the position of robot.

④ Resampling

	particles	Poses	weights	Normalised weights
N (1000)	P_1	(x_1, y_1, θ_1)	w_1	$\alpha_1 = w_1 / W$
	P_2	(x_2, y_2, θ_2)	w_2	$\alpha_2 = w_2 / W$
	⋮	⋮	⋮	⋮
	⋮	⋮	⋮	⋮
	P_N	(x_N, y_N, θ_N)	w_N	$\alpha_N = w_N / W$
			$W = \sum_i w_i$	$\sum_i \alpha_i = 1$

→ Randomly draw new particles from old one with replacement (i.e. particles with high probability are drawn multiple number of times, so that @ any given point there would be $N=1000$ particles) in proportion to importance weight.



Ex: Suppose we have $N=6$ particles $p_1, p_2, p_3, p_4, p_5, p_6$ and p_3 & p_6 have high weights than others, we will run resampling $N(6)$ times.

I Iteration = p_6 was chosen, again p_6 chosen, next p_3, p_3, p_5, p_1

So our particle list at I Iteration look like $p_6, p_6, p_3, p_3, p_5, p_1$

after N Iteration = the list may look like $p_6, p_6, p_6, p_6, p_6, p_6$

and we see all particles approximately at the last location \therefore can say that our p_6 is localized.

✓ This was just for one frame of instant,
In the next instant the car knows see
all the particles,

These particles are once from the previous
step of resampling.

The process of localization starts again &
repeats.

⑤ Compute the error
is overall quality of the solution

computing the avg. distance betⁿ the
particle & the robot.

ie difference between the x,y posⁿ of
robot with x & y posⁿ of ~~robot~~ particle
also normalizing the values.

next, Compute the Euclidean distance of
the difference.

$$\begin{aligned} \text{ie } dx &= \text{part}.x - \text{rob}.x \\ dy &= \text{part}.y - \text{rob}.y \\ \text{error} &= \sqrt{dx^2 + dy^2} \\ \text{sum} &+ = \text{error} \end{aligned}$$

return sum / N.