



Project DIEGO via Particle Filter

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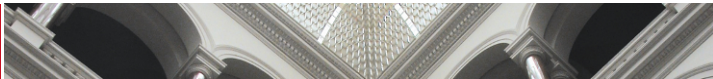


Project statement: What is DIEGO ?

The DIEGO is a robotic-assisted device that removes the effects of gravity on one or both arms. The system is designed so you can replicate the 3D movements used in daily activities. It has an independently adjustable weight support system around the elbow and wrist. This extends the range of movement but also improves coordination and reduces evasive movements.



Abbildung: From <https://www.motionrehab.co.uk>



Project Task

A method should be designed so that human upper-limb motion can be tracked during robotic rehabilitation therapy. More specifically, orientations and positions of the upper arm and forearm should be estimated. I divided the project process into 3 steps:

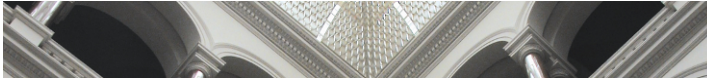
1. learn how to implement particle filter algorithm. Actually, I found a nice tutorial about particle filter and its programming. Here is the website: [tutorial of particle filter](#)
2. implement the algorithm by given data and improve it by comparing estimation and ground truth.
3. If possible, plot the results. Interpret the results and draw a conclusion.

Given Data:

- inertial-sensor data from the upper arm and forearm (gyro, magnet and acceleration)
- robotic forearm cuff position measurements

GROUND TRUTH:

- camera-based two-dimensional marker positions over time



Particle Filter

Algorithm:

1. Initialization:

Generate sample set $\{\mathbf{x}_0^i\}_{i=1}^N$ from the initial distribution $p(\mathbf{x}_0)$, set $k = 1$.

2. Prediction:

Draw predicted sample $\mathbf{x}_k^i \sim p(\mathbf{x}_k | \mathbf{x}_{k-1}^i)$, $i = 1, \dots, N$

3. Update:

Once the observation data \mathbf{z}_k is measured, evaluate weight of sample $\tilde{w}_k^i = w_{k-1}^i p(\mathbf{z}_k | \mathbf{x}_k^i)$, and normalize $w_k^i = \tilde{w}_k^i / \sum_{q=1}^N \tilde{w}_k^q$, $i = 1, \dots, N$.

4. Resampling:

Generate new sample set $\{\mathbf{x}_k^i\}_{i=1}^N$ by resampling (with replacement) N times from $\{\mathbf{x}_k^i\}_{i=1}^N$, where $\Pr(\mathbf{x}_k^j = \mathbf{x}_k^i) = w_k^i$, and set weight $w_k^j = 1/N$.

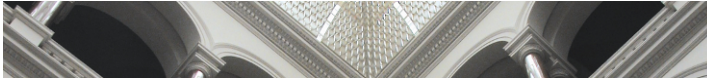
- Set $k = k + 1$ and go back to step 2.

Particle Filter is a nonparametric filter

Samples (particles) are drawn from the original distribution.

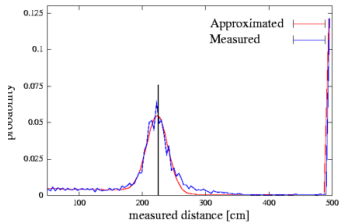
Each particle is weighted with an importance factor that incorporates the knowledge of the measurement.

These important factors are used to choose a new set of particles that appropriately represents the a posteriori probability density function (resampling).

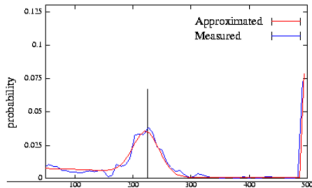


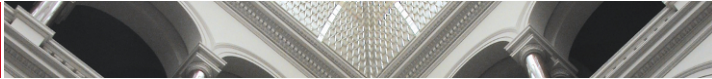
Possible Results

Results:



1. Comparison of Positions and orientations between estimation and ground truth
2. The accuracy of different numbers of particles.
3. The motion model of robot arm may have influence.
4. If possible, different filter types can be compared, such as Kalman Filter.





Interpretation and Conclusion

- Particle filters are an implementation of recursive Bayesian filtering
- Particle filters are relatively easy to implement
- It has high computational complexity
- It is difficult to determine optimal number of particles
- Number of particles increases with increasing model dimension
- The approach described so far is able to track the pose of a robot arm.



Reference

Thrun S. Probabilistic robotics[M].MIT Press,2006

