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Performance comparisons of particle-based and similarity measure-based kidnapping detectors in Monte Carlo localization

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This paper investigates new alternative approaches to detect the kidnapped robot problem event in Monte Carlo Localization. The approach is designed such that it can provide accurate detection in wide range kidnapping points and does not depend on the accuracy of localization. The underlying idea is based on the similarity measures of the environment seen by the robot at two consecutive time instances. Six different similarity measures are investigated and tested against particles weight-based detectors to see how good each detector's ability to distinguish normal condition from kidnapping event, i.e. Discrimination Performance, under two different kidnapping scenarios. These simulations show that Two-Dimensional Dynamic Time Warping promises better general accuracy across all kidnapping points compared to particles-based detectors and other detectors based on shape similarity measure. The Consistency Performance also shows that it can maintain the accuracy even when the localization process is heavily disturbed.

[**Keywords**: Monte Carlo Localization, Kidnapping Detection, Similarity Measures, Measurement Entropy, Maximum Current Weight]

Introduction

In mobile robotics localization, the kidnapped robot problem is defined as a condition when the robot is instantly moved to other position without being told during the operation of the robot[1]. Kidnapped robot problem (KRP) is one of the most difficult problem in Monte-Carlo Localization (MCL) [1]. This is due to the nature of particle filter used in MCL itself, where the convergence process of hypotheses (particles) causes an absence of particles in some areas. This absence leads to a failure in localization if the robot is kidnapped to that area.

One of the most important motivation on KRP study is the concern on robot's safety. An undetected and/or unsolved KRP leads to incorrect map and incorrect pose estimate, thus may render the robot from performing its task. A more dangerous problem is when the robot wanders around undefined/incomplete map while believing that it is still performing localization well. This condition is dangerous when there is a potential hazard in the undefined/incomplete map. The KRP event may happen at any time during robot's exploration. Therefore, an accurate online kidnapping detector is preferable in this case, such that there is an immediate and reliable information that the robot is kidnapped at any points in time. This type of detector will allow precautionary action to be taken right after kidnapping, and determine whether a global localization process is required. For decades, there have been several approaches in solving kidnapped robot problem. In Augmented MCL[2], random particles are injected in each iteration such that the possibility of particles' absence in kidnapping destination area is reduced. These random particles are drawn from either uniform distribution over pose space, or the posterior of the measurement. MCL with mixture proposal distribution[3] combines regular MCL sampling with its dual.

Despite its flexibility, the former two methods do not clearly draw a line between detection and recovery of kidnapping. This creates a problem when the concern is not only in the re-localization, but also the needs to know when the kidnapping really happens, such that preventive action might be implemented to protect the robot from potential hazard in incomplete map. Therefore, an accurate detection of kidnapping event becomes an integral part to solve in KRP.

Other solutions, which clearly separates detection from recovery in MCL can be found in previous literatures[4,5]. Zhang et al.[4] uses maximum weight of current particle set as the parameter (MW) to detect the kidnapping event. Yi, C. and B.-U. Choi[5] uses similar parameter, but instead of purely using current weight, they use the entropy of the information can be extracted from the weight.

Particle-based detectors such as Maximum Weight (MW) and Measurement Entropy (ME) are usually inaccurate across all possible kidnapping time instances and prone to false alarm due to its dependence on localization accuracy[6].

Materials and Methods

This paper investigates a new point of view in kidnapping detection to increase the accuracy of detection across all time instances of robot's operation. The underlying idea is that given a small natural movement at each time instance, a notable change in environment can be an indication that it is being moved unnaturally, such as slipping or being taken and 'woken up' somewhere else. Based on this idea, the problem is thus reduced to shape similarity between the environment scans at two consecutive time instances. A high similarity score indicates the natural movement, and vice versa. Several similarity measures are investigated and compared to the particle-based detection in terms on their ability to distinguish kidnapping event from normal condition.

This simulation-based study is based on the investigation of kidnapping detectors accuracy from the two aforementioned detectors and six shape similarity measures commonly used in shape recognition, namely Euclidean distance[7], Procrustes distance[8], Haussdorff distance[7], Discrete Frechet distance[7,9], 1-D Dynamic Time Warping (1D-DTW)[10-16], and Multidimensional Dynamic Time Warping (MD_DTW)[17]. The simulations are run with a mobile robot modelled as a two-wheeled robot with base wheel of one meter with a single laser range-finder sensor attached to it to observe the environment with MCL as the localization framework.

A. Maximum Weight

The detector is proposed by Zhang et al.[4] The detector works under the Monte Carlo Localization (MCL) which uses samples of possible poses to approximate a robot's pose belief. These samples (called particles in MCL terminology) are weighted based on how close the environment reading given by each sample to the reading of the robot, i.e. the higher the weight the better the sample in representing robot's true pose.

At each time step, maximum weight of current set of particles is calculated. A kidnapping event is determined by comparing this value against a threshold. Mathematically, it can be written as

$$Kidnapped_t = \begin{cases} 1 & \omega_t^{max} < \gamma \\ 0 & Otherwise \end{cases} \qquad (1)$$

B. Measurement Entropy

Choi et al.[5] also defines a kidnapping detector under Monte Carlo Localization in topological map with recognizable objects/landmarks at each node. In their work, a metric called measurement entropy, defined as follows

$$H_t(p) = -\sum_{x_t^{[y]}} p\left(s_t, o_t, z_t \middle| x_t^{[y]}, m\right) \log p\left(s_t, o_t, z_t \middle| x_t^{[y]}, m\right) \qquad (2)$$

where s_t, o_t, z_t are the distance context to objects at time *t*, objects seen by the robot at time *t*, and the features extracted from the objects at time *t*, respectively. $x_t^{[y]}$ is the state of particle *y* at time *t* and *m* defines the map. It can be seen that the term inside the summand in equation 2 is in fact the weight of particle *y* and thus the equation can be described as the sum of particle's weight entropy, that is

$$H_t(p) = -\sum_{x_t^{[y]}} \omega_t^{[y]} \log \omega_t^{[y]} \quad (3)$$

Kidnapping detection is based on the rise of this measurement entropy which can be written as

$$Kidnapped_t = \begin{cases} 1 & H_t(p) \geq \pi \\ 0 & Otherwise \end{cases} \quad (4)$$

C. Euclidean Distance

Let $\mathcal{P}$ and $\mathcal{Q}$ each be 2D point clouds obtained from the environment scan. The Euclidean distance between two shapes defined by these point clouds is

$$dist_{Euc} = \frac{1}{n}\sqrt{\sum_{i=1}^{n}\left(\left(\mathcal{P}_x^i - \mathcal{Q}_x^i\right)^2 + \left(\mathcal{P}_y^i - \mathcal{Q}_y^i\right)^2\right)} \quad (5)$$

D. Procrustes Distance

Procrustes distance is a distance calculated between two shapes, characterized by their boundary points set, $\mathcal{P}$ and $\mathcal{Q}$. Let $\mathcal{P}$ be the ‘reference set’, the distance between the two point clouds is determined after superimposing $\mathcal{Q}$ onto $\mathcal{P}$, i.e. applying an optimal affine transformation $\mathcal{A}$ which consists of translation, scaling, and rotation. The Procrustes distance is then commonly defined as

$$dist_{Proc} = \sqrt{\sum_{i=1}^{n}\left(\left(\mathcal{P}_x^i - \mathcal{Q'}_x^i\right)^2 + \left(\mathcal{P}_y^i - \mathcal{Q'}_y^i\right)^2\right)} \quad (6)$$

where $\mathcal{Q}'$ is the set of points by applying $\mathcal{A}$ on $\mathcal{Q}$.

E. Haussdorff Distance

Hausdorff distance is the maximum distance of a set to the nearest point on the other set. Let $d(p,q)$ be the Euclidean distance between two 2-D points p and q. The Haussdorff distance is formally expressed as

$$dist_H = max\left\{\left(\sup_{p\in\mathcal{P}}\left(\inf_{q\in\mathcal{Q}} d(p,q)\right), \sup_{q\in\mathcal{Q}}\left(\inf_{p\in\mathcal{P}} d(p,q)\right),\right)\right\} \quad (7)$$

F. Discrete Frechet Distance

Frechet distance is also commonly known as dog walking distance. Loosely speaking, this distance is defined as the minimum leash required between a man and a dog who travel along their own trajectory (curve) without restriction on their relative position given that no retracing step is allowed. In this paper, we implemented the variant of Frechet distance called Discrete Frechet Distance (DFD) which has similar definition except that the positions of the agents (dog and man) are restricted to the vertices of their respective trajectory. For two polygonal curves $\mathcal{P} : [0,\mu] \to \mathbb{R}^k$ and $\mathcal{Q} : [0,\nu] \to \mathbb{R}^k$, this distance is formally defined as

$$dist_{dFD} = \min_{\vartheta:[1:\mu+\nu]\to[0,M],\beta[1:\mu+\nu]\to[0,\nu]} \max_{s\in[1:\mu+\nu]} \left\{d\left(\mathcal{P}(\delta(s)), \mathcal{Q}(\beta(s))\right)\right\} \quad (8)$$

where δ and ϑ define all reparametrization of discrete non-decreasing surjection and $d(A,B)$ represents the distance function between A and B.

G. 1-D DTW

One key ability of DTW which distinguished it from other alignment method lies in its ability to non-linearly align two sequences, such that two similar signal will have small distance even though one of the signal is distorted or ‘warped’ in time, for example by shifting it a few steps ahead.

Given $\mathcal{P}$ and $\mathcal{Q}$, two one dimensional point clouds with length $\mathcal{L}_\mathcal{P}$ and $\mathcal{L}_\mathcal{Q}$ obtained by range sensor reading at two different time instances, that is $\mathcal{P} = (p_1, p_2, \dots, p_{\mathcal{L}_\mathcal{P}})$ and $\mathcal{Q} = (q_1, q_2, \dots, q_{\mathcal{L}_\mathcal{Q}})$. Let $\mathcal{D}(\mathcal{P},\mathcal{Q}) \in \mathcal{R}^{\mathcal{L}_\mathcal{P}\times\mathcal{L}_\mathcal{Q}}$ the pairwise distance matrix between $\mathcal{P}$ and $\mathcal{Q}$, such that $\mathcal{D}(\mathcal{P},\mathcal{Q})_{ij} = |p_i - q_j|$. The alignment problem is to find to sequences of indices $\mathcal{I}_\mathcal{P}$ and $\mathcal{I}_\mathcal{Q}$ of the same length $\ell(\ell \geq \max(\mathcal{L}_\mathcal{P}, \mathcal{L}_\mathcal{Q}))$ which match index $\mathcal{I}_\mathcal{P}(i)$ in $\mathcal{P}$ and $\mathcal{I}_\mathcal{Q}(i)$ in $\mathcal{Q}$ that minimizes the cost $\mathcal{C} = \sum_{i=1}^{l} \mathcal{D}(\mathcal{P},\mathcal{Q})_{\mathcal{I}_\mathcal{P}(i),\mathcal{I}_\mathcal{Q}(i)}$.

H. MD-DTW (2D variant)

Holt et al. introduced a variant of Dynamic Time Warping to work with multidimensional time series[17]. Let $\mathcal{P}$ and $\mathcal{Q}$ two real-valued sequences of time series with dimension K ($K = 2$ in this study) and length $\mathcal{L}_\mathcal{P}$ and $\mathcal{L}_\mathcal{Q}$, respectively. The algorithm of MD-DTW is summarized in Table 1.

Table 1 Multi-Dimensional Dynamic Time Warping (MD-DTW) Algorithm

1. **MD-DTW Algorithm**
2. Normalize each dimension of $\mathcal{P}$ and $\mathcal{Q}$ separately to zero mean and unit variance
3. Construct distance matrix $\mathcal{D}(\mathcal{P},\mathcal{Q}) \in \mathcal{R}^{\mathcal{L}_\mathcal{P}\times\mathcal{L}_\mathcal{Q}}$ according to

$$\mathcal{D}(\mathcal{P},\mathcal{Q})_{i,j} = \sum_{k=1}^{K} |p_{i,k} - q_{j,k}|$$

4. Find the minimum cost path using the regular DTW on this distance matrix

To test all aforementioned detectors, this study uses a feature-less planar corridor map, where the only information extractable at any time instances using range sensor is the distance to the wall. The robot also never knows which walls it measures the distance to, merely the distance. Using this map, there are two scenarios of kidnapping to test the detectors, namely Large Scale Kidnapping (LSK) and Small Scale Kidnapping (SSK) as depicted in Figure 1 with the parameters as presented in Table 2. Please be noted that in normal condition, the robot explores the map by moving clockwise along the corridors in Figure 1.

In LSK, the kidnapping destination is specified such that whenever the robot is kidnapped, the two environment scans before and after the event is significantly different. In SSK, kidnapping destination is varying. For any kidnapping event, the robot is moved two meters from its current position, such that the environment change is far less significant than in LSK.

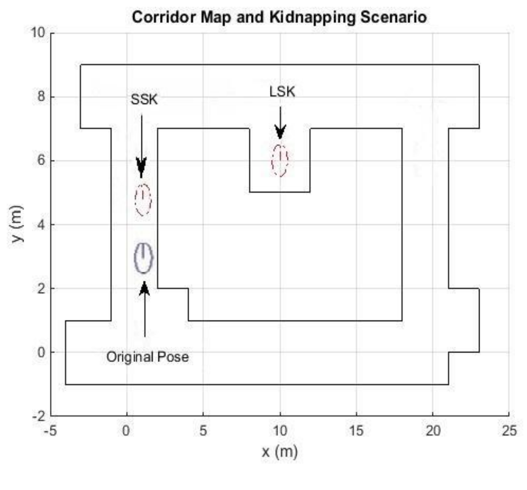

Figure 1 Feature-less planar corridor map and kidnapping scenarios

Table 2 Simulation setup for performance tests

Number of Particles	Maximum Range	Number of Sensor Beams	Distribution of Sensor Beams	Sensor Noise
1000 (Accurate Localization) and 200 (Inaccurate Localization)	7 m (LSK) and 2 m (SSK)	60	Uniformly at [-60, 60] degrees	Gaussian white noise with zero mean and 0.2 variance

For each simulation, the accuracy of each detector is evaluated based on two performance measures. The first is called a Discrimination Performance (DP), which describes how good a detector is in differentiating kidnapping event from normal event. Let tk be a time instance when the robot is actually kidnapped and $\mathcal{F}_{tk}$ defines the discrimination performance of the detector to detect kidnapping event happened at $t = tk$, then this performance measure is described by

$$\mathcal{F}_{tk} = \begin{cases} 1 - \left(\max_{\{\forall t | t\neq tk\}}(\mathcal{M})/\mathcal{M}_{tk}\right) & \mathcal{M}_t \text{ is } HPTF \\ 1 - \left(\mathcal{M}_{tk}/\min_{\{\forall t | t\neq tk\}}(\mathcal{M})\right) & \mathcal{M}_t \text{ is } LPTF \end{cases} \quad (9)$$

by which a detector is considered accurate when $\mathcal{F}_{tk} \sim 1$ for all possible tk. LPTF is a short of Low Pass Threshold Function, which we define as a threshold function which holds true when the function reaches value below a specified threshold, while HPTF (High Pass Threshold Function) as a threshold, which holds true when the function reaches value higher than a specified threshold.

In DP graph, each pixel describes $\mathcal{F}_{tk}$, the performance of detector for a kidnapping event happened at the time instance indicated by the x-axis value for the trial number indicated by its y-axis value. The second performance measure is called Consistency Performance (CP), which measures the effect of inaccurate localization on reducing the accuracy of detectors due to the added false alarms.

The effect is shown by comparing the DP of each detector under MCL with 1000 particles to reflect an accurate localization and the DP under MCL with 200 particles to simulate an inaccurate localization. Each detector is CP-evaluated by comparing the percentage of the number of failed detections, indicated by $\mathcal{F}_{tk} < 0$. Let $|\Delta|$ be the difference between the two cases in terms of the percentage of failed detection. A good detector in terms of this performance is specified by $|\Delta| \sim 0$, which means that the inaccurate localization process will not be mistakenly detected as kidnapping event.

Results and Discussion

A. Discrimination Performance under Large Scale Kidnapping

The DP of each detector under LSK scenario and accurate localization is shown in Figure 2. As seen in the figure, the two particle-based detectors (MW and ME) have some perfect detection when the robot is kidnapped at certain time instances, as indicated by the white pixels. However, from the overall performance point of view, these detectors failed to detect kidnapping event at many time instances.

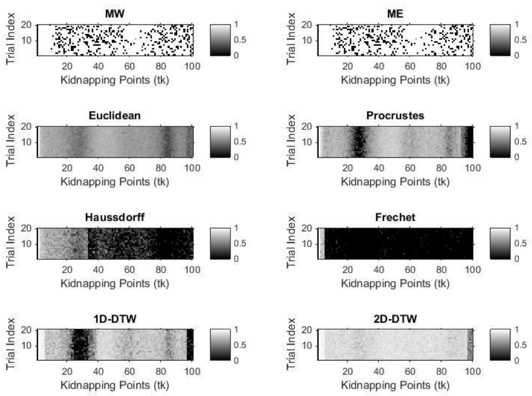

Figure 2 Particles vs similarity measures under LSK with accurate localization

Among the six similarity measures, Euclidean distance and 2D-DTW stand out as better detectors, as there are no failed detections. Upon closer inspection, however, 2D-DTW clearly shows better ability to distinguish kidnapping event and normal event, judging by the shades of the overall pixels.

B. Classification Performance under Large Scale Kidnapping

The DP of each detector under LSK with inaccurate localization can be seen in Figure 3. It is clear from the figure that the particle-based detectors are heavily disturbed by the inaccurate localization, since the DP results are very different from the DP under accurate localization. This difference is also evident from the number of failed localizations before and after reduced localization accuracy, as depicted in Table 3. The table also shows that the non-particle-based detectors are all more consistent in maintaining the result no matter how inaccurate the localization is.

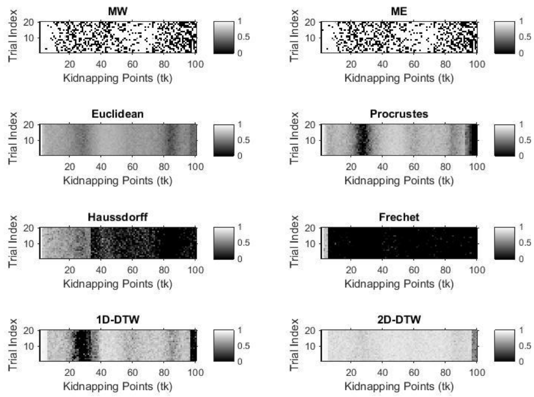

Figure 3 Particles vs similarity measures under LSK with inaccurate localization

Table 3 Consistency performance under LSK scenario

$\mathcal{M}$	Percentage of ($\mathcal{F} < 0$)		$\lvert\Delta\rvert$
	1000 Particles	200 Particles	
MW	18.28	31.72	13.44
ME	16.67	30.15	13.48
Euclidean	0	0	0
Procrustes	59.02	57.04	1.98
Haussdorff	28.34	29.85	1.51
Frechet	88.05	87.85	0.2
1D-DTW	7.95	9.10	1.15
2D-DTW	0	0	0

The DP and CP results based on LSK scenario in general show that

a) MW and ME performed poorly at many time instances of kidnapping event, even though the two environment scans before and after the event are significantly different.

b) MW and ME also have very high dependence on localization accuracy. When the localization is disturbed, many false detection occurred which reduced the accuracy of detectors.

c) Euclidean distance and 2D-DTW both successfully detect kidnapping event which happened at any time instances. However, from the DP point of view, 2D-DTW outperforms Euclidean distance.

d) Unlike particle-based detectors, similarity-based detectors perform better from the CP point of view. This is understandable because similarity-based detectors do not depend on the pose obtained from localization process, i.e. it acts separately from the localization.

C. Discrimination Performance under Small Scale Kidnapping

The DP under SSK with 1000 particles is shown in Figure 4. As expected, this figure shows that SSK scenario is much harder than LSK for all detectors. Because the scenario dictates that the robot is moved just slightly away from its position, the environment scans do not change much, thus making it difficult to differentiate the event from normal movement of the robot.

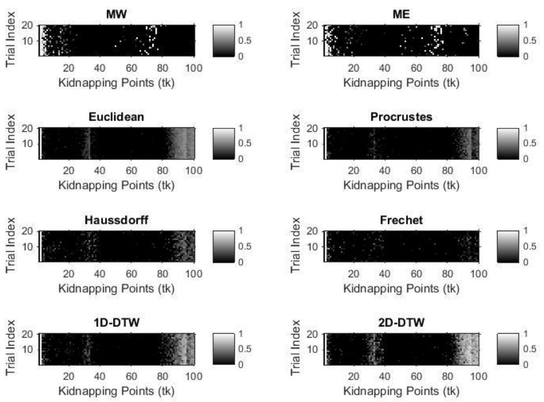

Figure 4 Particles vs similarity measures under SSK with accurate localization

However, as seen in Table 4, 2D-DTW performs better than the others, as indicated by less number of failed detection.

Table 3 Consistency performance under SSK scenario

$\mathcal{M}$	Percentage of ($\mathcal{F} < 0$)		$\lvert\Delta\rvert$
	1000 Particles	200 Particles	
MW	90.46	92.12	1.66
ME	81.21	83.79	2.58
Euclidean	69.35	69.37	0.02
Procrustes	77.15	77.14	0.01
Haussdorff	78.21	77.15	1.06
Frechet	86.63	86.61	0.02
1D-DTW	69.44	69.51	0.07
2D-DTW	68.33	68.31	0.02

D. Classification Performance under Small Scale Kidnapping

The effect of reducing the number of particles under SSK scenario is not as apparent as in LSK scenario. As seen in Figure 5, none of the detectors seem to be affected by the decrease in localization accuracy as much as in LSK. Upon closer inspection in Table 4, the particle-based detectors are not affected that much by the reduced localization accuracy. It is however still more apparent than other detectors.

These results under SSK scenario show that

a) SSK is proven to be very difficult to be detected by either particle-based detectors or the similarity-based detectors due to how small the change in robot's position and environment before and after kidnapping event. However, 2-D DTW still performs better than the others.

b) Similar to LSK scenario, particle-based detectors under SSK still have more difficulty in maintaining the detection accuracy under disturbed localization, than other detectors.

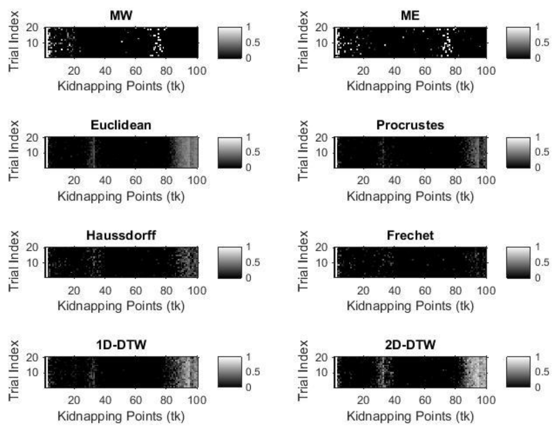

Figure 5 Particles vs similarity measures under LSK with inaccurate localization

Conclusion

A new idea of kidnapping detection in Monte Carlo Localization is investigated in this paper. The idea is based on the similarity measures of environment seen by the robot at two consecutive time instance. This idea departs from the use of particles as kidnapping detector in attempt to reach a good overall accuracy across all kidnapping points and removing dependence towards localization accuracy. Six similarity measures are investigated with 2-D DTW showing the most promising result both from DP and CP point of view, under two different kidnapping scenarios.

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