Application of Tabu Search Optimization in Real-time Video Tracking

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In this paper, a unique particle filter is proposed based on a population-based probabilistic tabu search algorithm. The memory oriented feature of the tabu search algorithm improves both accuracy and performance of the proposed filter. Quantitative results indicate that the proposed tabu search particle filter outperforms the generic particle filter in real-time human tracking applications.

tabu search; particle filter; real time vision tracking; accuracy

I. Introduction

Research of object and human tracking algorithms in computer vision have received a great deal of attention in recent years. Academic outcomes of the past research in this area can be found in some widely referenced survey papers, for example [1-5].

Among these researches, one important milestone was the introduction of particle filter into the computer vision based object tracking by Isard and Blake [6] in late 1990s. In contrast to other well established tracking algorithms, for example the Kalman filter [7] and its extensions [8-11], the particle filter eliminates some unrealistic assumptions of the target dynamic behaviours, for example being linear and Gaussian.

In this paper, a unique particle filter based on tabu search optimization algorithm is proposed. As illustrated quantitatively in section IV, the proposed tabu search particle (TSP) filter outperforms the most commonly used real time tracking algorithms, such as generic particle (GP) filter.

The paper is organized as follows. Firstly, a brief review of the GP filter and the tabu search (TS) algorithm is discussed in section II. Secondly, the proposed TSP filter is introduced in detail in section III followed by quantitative evaluations illustrated in section IV. Finally, this paper is concluded in section V.

II. Relevant Work

A. Particle Filter

Particle filter presents the belief distribution of a state vector in a nonparametric method with a set of Monte Carlo [6] samples (particles). Comparing with parametric presentation, for example the Kalman filter, a much larger range of distributions, rather than merely Gaussian, can be presented by the particles. Furthermore, the particle filter performs state transition through a set of Monte Carlo samples and therefore eliminates the requirement of linearization.

The Monte Carlo samples used in a particle filter are denoted as $\mathcal{X}_t := x_t^{[1]}, x_t^{[2]}, \dots, x_t^{[M]}$ where each particle $x_t^{[m]}, 1 \leq m \leq M$ is a concrete instantiation of the state vector. Each particle is associated with a weight $\omega_t^{[m]}$ to indicate the importance of a particular Monte Carlo sample in a belief distribution.

In the estimation step, particles are drawn from the posterior belief distribution $\mathcal{X}_{t-1} := x_{t-1}^{[1]}, x_{t-1}^{[2]}, \dots, x_{t-1}^{[M]}$ with regarding to the state transition probability $p(x_t|x_{t-1})$ of the estimation step. The weights of these particles are uniformly distributed because the current observation is not being incorporated yet. The (unweighted) distribution of these particles presents the prior belief distribution of the state vector in the system, i.e. $\overline{bel(x_t)} \sim \overline{\mathcal{X}_t} := \overline{x_t}^{[1]}, \overline{x_t}^{[2]}, \dots, \overline{x_t}^{[M]}$.

In the measurement process each particle distributed follows the prior distribution $\overline{bel(x_t)}$ which is weighted by incorporating the current observation vector. The posterior belief distribution of the state vector $bel(x_t)$ is presented by the weighted distribution of these particles.

The resampling process is unique to the particle filter. It draws M new particles from the current particle set and the probability of drawing each particle is given by its weight. The purpose of this process is to transfer the unweighted particle distribution from approximating the prior belief $\overline{bel(x_t)}$ to approximating the posterior belief $bel(x_t)$. A branch of resampling algorithms are proposed in the literature, which are catering for different application specific features.

B. Tabu Search Optimization

The TS optimization is a meta-heuristic optimization process [16-26]. In contrast to other algorithms of its category, the most distinctive feature [17] of TS is the emphatic use of memory during the optimization process. The main reason for the TS algorithm being selected in this research from a wide range of well established optimization algorithms, such as simulated annealing and iterative local search, is that the use of memory in TS offers significant performance benefit where a set of many Monte Carlo samples drawn from a Gaussian process being optimized.

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The TS algorithm maintains a list of recently visited solutions and uses the information being kept in this list to prevent cycling especially when the search moves away from local optima through non-improving moves. The tabu list is an example of short term memory being used in the TS algorithm and the life span of a visited solution being banned through the tabu list is controlled by a predefined parameter: the tabu tenure. However, some forbidden moves regarding to the tabu list and tabu tenure may be exempted if these moves satisfy some predefined aspiration criteria, which may improve the performance of the TS algorithm in some applications. For example, an otherwise disallowed move will be accepted if it yields a solution better than the best one obtained so far.

Furthermore, the TS algorithm also applies two advanced searching strategies, namely the intensification strategy and the diversification strategy, to improve its performance in an optimization task. The intensification process is to encourage the optimization process to explore more thoroughly in the regions where good solutions have been discovered. The diversification process is to discourage the optimization process waste too much time in restricted regions of the state space where optimal solutions are unlikely to be found. For example, the optimal solution is unlikely to be discovered in the regions of the state space where bad solutions are always being found.

III. THE PROPOSED TABU SEARCH PARTICLE FILTER

A. Overview

The proposed TSP filter is a hybridization of the particle filter and the TS algorithm. It significantly improves the quality of the posterior belief distribution in a tracking system while the performance cost is negligible.

The top level logic flow of the proposed TSP filter is illustrated in figure 1. As shown, the TSP filter consists of three main steps, namely the estimation process, the measurement process and the optimization process.

The prior belief distribution of a state vector is calculated in the estimation step based on its posterior belief distribution in the previous time step and a motion model selected based on the current state of the target.

The particles' weights are updated in the measurement step by evaluating the estimated particles with the latest observation. The weighted particles present the posterior belief distribution of the target's state vector at the current time step.

The initial posterior belief distribution calculated through the previous measurement step is optimized in the optimization step to find the best solution based on some predefined criteria.

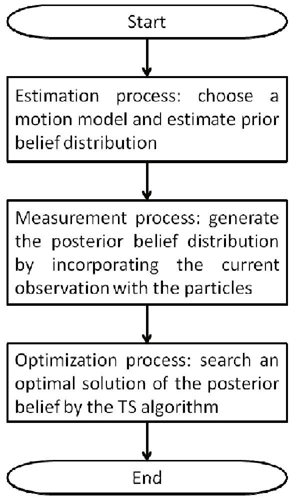

Figure 1: A brief logic flow of the proposed TSP filter.

B. Estimation

The processing logic of the estimation step in the proposed TSP filter is illustrated in figure 2.

Firstly one motion model is selected at a time among multiple motion models implemented in the proposed TSP filter to operate based on the target's state. For example, if the target is just created and there is no path history to reference, a blind motion model will be selected and the prior probability will be estimated as an omnidirectional Gaussian around the target. Alternatively, if the target has been tracked in previous time steps and the velocity of the target can be retrieved from its path history, then a first order inertia model will be selected so that the prior belief can be estimated specifically.

Secondly, some model specific auxiliary information is retrieved from the corresponding sources. For example, if the first order inertia model is selected, then the speed and direction of the target can be retrieved by analyzing the path history of this target. On the other hand, if the state transition is requested by the optimization process, then the pruned regions of interest can be found.

Finally, the actual state estimation process is performed and the predicted state vector is verified with some predefined constrains, for example within the image boundary, and then the corresponding particle is updated with the new estimated and verified state vector.

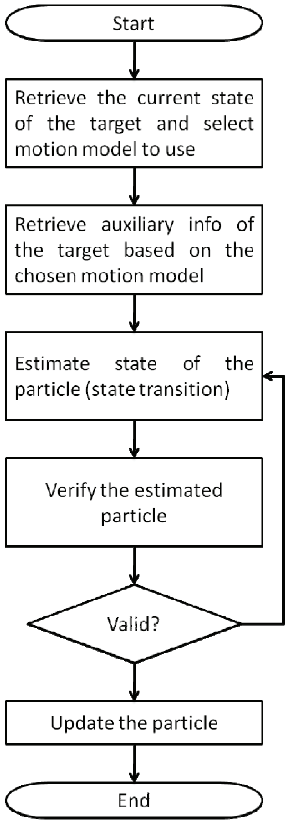

Figure 2: The logic flow of the estimation process in TSP filter.

C. Observation

The processing logic of the observation step in the proposed TSP filter is illustrated in figure 3. As shown, the particle passed into the observation process is hashed and checked in a cache table firstly. If the evaluation result of this particle is available, this value will be assigned to the current particle as its new weight. Otherwise, the particle will be evaluated through the measurement process.

The hashed cache table is designed as a partial implementation of the tabu list of the TS algorithm used in the optimization step. The measurement model used in this process is selected depends on the priori knowledge of the problem domain. For example, in most human tracking research, the colour histogram model is chosen to be the measurement model.

D. Optimization

The optimization step in the proposed TSP filter is implemented based on the TS meta-heuristic algorithm introduced previously.

A population based TS algorithm is implemented in TSP filter. The initial solution is defined as the whole set of weighted particles calculated by the measurement step. The expected result of the optimization step is a set of optimal particles presenting a better posterior belief of the target than the initial solution.

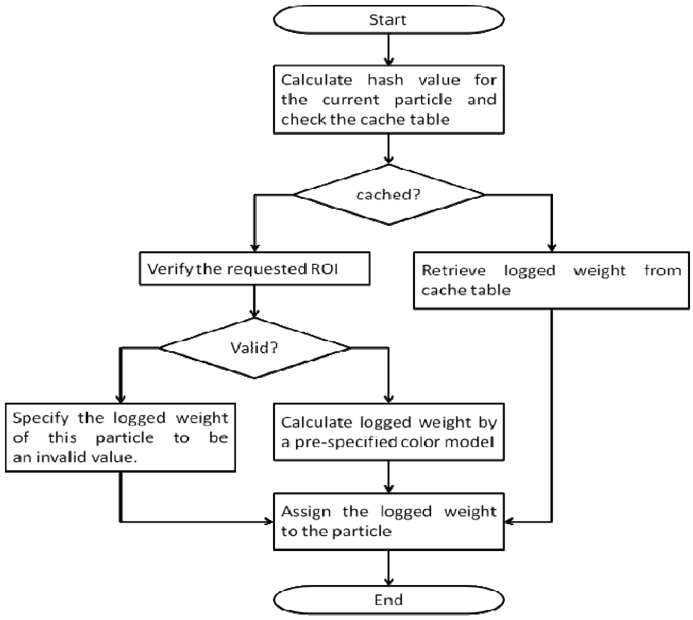

Figure 3: The logic flow of the measurement process in TSP filter.

In the proposed algorithm, the move operation is defined as a stochastic process that diffuses some particles regarding to a Gaussian distribution. The parameters of the Gaussian distribution are adjusted based on the situation of each particle. For example, the particles with high weight values are redeployed regarding to a Gaussian distribution with a small variance so that the region around an elite solution can be explored more thoroughly. On the other hand, the particles with low weight values are deployed regarding to a Gaussian distribution with a large variation so that the search in such regions are discouraged.

A hashed cache is designed as partial implementation of the tabu strategies in TSP filter. If a particle made a tabued move during the search process, it will be stopped and redeployed to the neighbourhood of elite particles.

Two aspiration criteria are defined in the proposed TSP filter to improve its performance. Firstly, the particles belonging to the elite group or poor group (discussed later) are exempted from the tabu rule. Secondly, a tabued move is allowed if this operation causes the particle to become more important, i.e. the weight of the particle is increased after the move.

In the proposed TSP filter, all particles in the system are classified into three categories during the optimization process. These categories are: the elite group, the average group and the poor group. The classification is performed based on the normalized weights of all particles. The thresholds of this classification process are predefined parameters of the TSP filter.

The search intensification and diversification are implemented as the following strategies. Firstly, a small variance is used to diffuse particles belonging to the elite group so that the region around an elite particle can be explored more thoroughly. Secondly, the particles belong to the poor group are redeployed to the neighbourhood regions of good particles so that the extended neighbourhood areas around good particles can be explored and in the mean time, exploration in the regions around low weight particles are discouraged.

The termination criteria of the optimization step in the proposed TSP filter is defined based on "minimum non-improvement iteration". Namely, the optimization process stops when the best particle discovered in the system remains at no change for a predefined minimum number of times.

IV. Quantitative Experiments

The accuracy and performance of the proposed TSP filter are evaluated quantitatively using the test footage downloaded from the PETS 2006 dataset (http://www.cvg.rdg.ac.uk/PETS2006/data.html). The video footage used in this experiment was taken in an indoor public space, i.e. a train station, with multiple pedestrians in sight. In this experiment, a human in the mentioned video footage is selected as the tracking target. The experiments are carried out with different particle numbers, i.e. ten particles, twenty particles … up to a hundred particles in ten particle steps.

The ground truth is defined as the tracking results of a generic particle filter tracking system with 100,000 particles (illustrated in figure 4).

The quantitative experiment results are listed in figure 5 and illustrated in figure 6 from an accuracy perspective and figure 7 from a performance perspective.

As shown in the bar graph illustrated in figure 6, the mean errors (in terms of Euclidean distance between measured position and the ground truth) of the proposed TSP filter are consistently and significantly smaller than the ones estimated by the generic particle filter. The largest improvement (illustrated in this figure) happens when a hundred particles are used in the system, where the tracking errors of the proposed TSP filter are reduced to 10.23% of the errors estimated by generic particle filter. The minimum improvement is observed when the system has only twenty particles. In this case, tracking errors reduced by about one third using the proposed algorithm.

As illustrated in figure 7, the processing speed of the proposed TSP filter is (1.97 times at 9.07ms) longer than the one of the generic particle filter when the number of particles is as small as twenty. However, the margins of difference in processing speed between the two algorithms are reduced consistently while the number of particles is increased. When particle numbers are increased to as much as ninety particles and beyond, the proposed TSP filter outperforms the generic particle filter in performance. This is because the caching strategies designed in the proposed TSP filter as a part of the tabu list implementation reduce the time used for measuring duplicated particles.

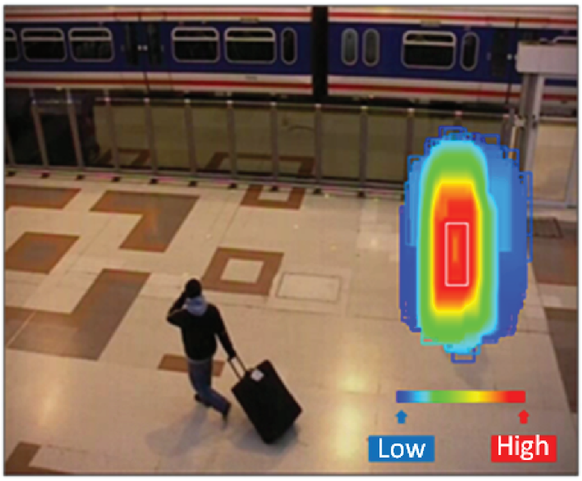

Figure 4: An image shows that the 'ground truth' is calculating in process with 100,000 particles. The target is fully coved by particles and the weights of particles are colour coded. The cold coloured (e.g. blue) particles have low weights and the warm coloured (e.g. red) particles have high weights.

Figure 8 illustrates another view of the original experimental results listed in figure 5. Some interesting findings are demonstrated clearly in this figure. As shown in the first line (ID = 1) of this figure, the mean tracking error achieved by the generic particle filter with a hundred particles is about 1.94 pixels and the time consumed to process one frame of image under this condition is 46.31ms. However, as shown clearly in the right side of this row, the proposed TSP filter achieves a better accuracy (mean error equals to 1.82 pixels) in much less average processing time (merely 11.47ms compare with 46.31ms) and much less particles (merely ten particles).

Furthermore, through row two to row nine of the figure 8, it shows that with similar processing time (the table listed in figure 8 is organized carefully to make sure that the processing time used by generic particle filter is almost aligned with the proposed TSP filter), the tracking accuracy achieved by the proposed TSP filter is much better than the one achieved by the generic particle filter and the number of particles used by the proposed filter is less than the one used by the generic one.

	GPF		TSPF	
Particle No.	**error**	**time**	**error**	**time**
10	112.8017	4.6588	1.8200	11.4706
20	3.7600	9.3511	1.1165	18.4217
30	3.7244	13.9486	0.8849	22.9096
40	3.0315	18.5878	0.5859	27.2925
50	2.6031	23.2478	0.5302	30.4166
60	2.2948	27.8231	0.4611	34.4156
70	2.2624	32.5150	0.4219	36.2563
80	1.9818	37.1811	0.2968	39.0667
90	1.9297	41.7250	0.3281	40.9208
100	1.9362	46.3063	0.1980	45.0192

Figure 5: Accuracy and performance experiment results of the proposed TSP filter and general particle filter. The accuracy is measured by mean square error and the unit is pixel. The performance is measured by milliseconds pre frame.

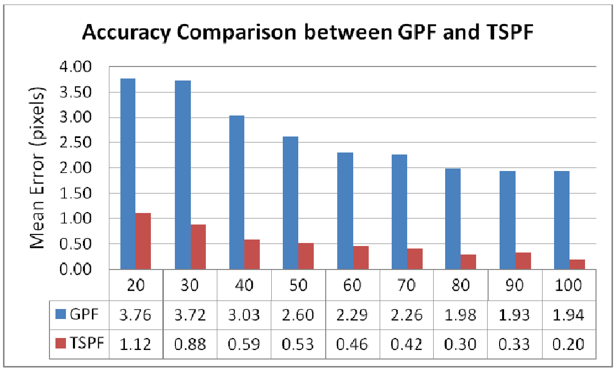

Figure 6: Bar graph representation of the accuracy comparison results between the proposed TSP filter and generic particle filter.

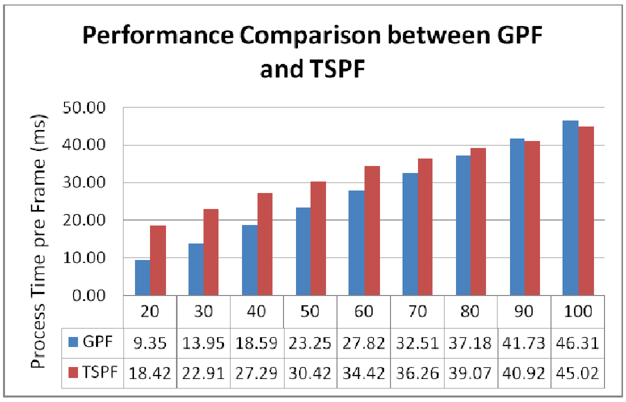

Figure 7: Bar graph representation of the performance comparison results between the proposed TSP filter and generic particle filter.

ID	GPF			TSPF		
	Particle No.	**error**	**time**	**Particle No.**	**error**	**time**
1	**100**	1.94	46.31	**10**	1.82	11.47
2	**30**	3.72	13.95	**10**	1.82	11.47
3	**40**	3.03	18.59	**20**	1.12	18.42
4	**60**	2.29	27.82	**40**	0.59	27.29
5	**70**	2.26	32.51	**50**	0.53	30.42
6	**80**	1.98	37.18	**70**	0.42	36.26
7	**90**	1.93	41.73	**80**	0.30	39.07
8	**90**	1.93	41.73	**90**	0.33	40.92
9	**100**	1.94	46.31	**100**	0.20	45.02

Figure 8: A re-organized view of the original data.

V. CONCLUSION

The filtering process of a sequential Monte Carlo method is improved by the proposed TSP filter, which is based on the hybridization of the generic particle filter and the population based probabilistic tabu search optimization algorithm.

Quantitative evaluation illustrates that the proposed TSP filter achieves better tracking accuracy with much smaller particle population and shorter processing time than the widely used generic particle filter. For example, in the human tracking experiments, the proposed TSP filter achieves better tracking accuracy with merely 10% of the particle population and only 24.77% of the processing time than the generic particle filter. Furthermore, the experiment also proves that with the same particle population, for example 100 particles, the proposed TSP filter achieves 9.78 times better accuracy than the generic particle filter in less processing time.

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