

Path Relinking Particle Filter for Human Body Pose Estimation

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Abstract. This paper introduces the Path Relinking Particle Filter (PRPF) algorithm for improving estimation problems in human motion capture. PRPF hybridizes both Particle Filter and Path Relinking frameworks. The proposed algorithm increases the performance of general Particle Filter by improving the quality of the estimate, by adapting computational load to problem constraints and by reducing the number of required evaluations of the weighting function. We have applied the PRPF algorithm to 2D human pose estimation. Experimental results show that PRPF drastically reduces the MSE value to obtain the set of markers with respect to Condensation and Sampling Importance Resampling (SIR) algorithms.

1 Introduction

Automatic visual analysis of human motion is an active research topic in Computer Vision and its interest has been growing during last decade [1][2][3]. Biomechanics of Human Movement is an interdisciplinary area, supported by Biomedical Sciences, Mechanics and other different technologies, that studies the human body behavior subject to mechanical loads [4]. This area has evolved into three main fields [4]: medical, sports and occupational.

A typical biomechanical study involves four phases: (i) defining a suitable theoretical model, (ii) obtaining relevant point (marker) coordinates, (iii) performing the kinematic analysis, and (iv) determining parameters of interest. Manual digitizing is generally used to obtain the marker coordinates. These procedures are slow and require the supervision of specialists in human anatomy. Automated marker-based systems [5] permit to automatically obtain the set of marker coordinates, although they are intrusive and force the use of expensive specialised hardware. Therefore, the goal of research in human motion capture is the development of an automatic full-body tracking system, which runs under conventional hardware, and oriented to processing realistic applications.

Most of human motion analysis studies are based on articulated models that properly describe the human motion [1][6][7][8]. Recent research in human motion

analysis makes use of the particle filter framework. The Particle Filter (PF) algorithm, (also termed as Condensation algorithm) enables the modelling of a stochastic process with an arbitrary probability density function (pdf), by approximating it numerically with a set of points called particles in a state-space process [9]. Deutscher [5] developed an algorithm termed Annealed Particle Filter (APF) for tracking people using articulated models.

The principal contribution of this paper is the development of the Path Relinking Particle Filter (PRPF) algorithm. The algorithm is inspired by the Path Relinking metaheuristic proposed by Glover [10][11] as a way to integrate intensification and diversification strategies in the context of combinatorial optimization problems. PRPF hybridizes both Particle Filter (PF) and Path Relinking (PR) frameworks in two different stages. In the PF stage, a particle set is propagated and updated to obtain a new particle set. In PR stage, a selected elite set from the particle set is selected, and new solutions are constructed by exploring trajectories that connect each of the particles in the elite set. PRPF algorithm significantly improves the performance of both general and other optimized particle filters.

2. Particle filter

General particle filters (PF) are sequential Monte Carlo estimators based on particle representations of probability densities which can be applied to any state-space model [12]. The state-space model consists of two processes: (i) an observation process $p(\mathbf{Z}_t|\mathbf{X}_t)$, where \mathbf{X} denotes the system state vector and \mathbf{Z} is the observation vector, and (ii) a transition process $p(\mathbf{X}_t|\mathbf{X}_{t-1})$. Assuming that observations $\{\mathbf{Z}_0, \mathbf{Z}_1, \dots, \mathbf{Z}_t\}$ are sequentially measured in time, the goal is to estimate the new system state $\{\chi_0, \chi_1, \dots, \chi_t\}$ at each time. In the framework of Sequential Bayesian Modelling, posterior pdf is estimated in two stages:

(i) Prediction: the posterior pdf $p(\mathbf{X}_t|\mathbf{Z}_{t-1})$ is propagated at the time t using the Chapman-Kolmogorov equation:

$$p(\mathbf{X}_t | \mathbf{Z}_{t-1}) = \int p(\mathbf{X}_t | \mathbf{X}_{t-1})p(\mathbf{X}_{t-1} | \mathbf{Z}_{t-1})d\mathbf{X}_{t-1} \quad (1)$$

A predefined object motion model is used to obtain an updated particle set.

(ii) Evaluation: the posterior pdf is computed using the observation vector \mathbf{Z}_t :

$$p(\mathbf{X}_t | \mathbf{Z}_t) = \frac{p(\mathbf{Z}_t | \mathbf{X}_t)p(\mathbf{X}_t | \mathbf{Z}_{t-1})}{p(\mathbf{Z}_t | \mathbf{Z}_{t-1})} \quad (2)$$

The aim of the PF algorithm is to recursively estimate the posterior pdf $p(\mathbf{X}_t|\mathbf{Z}_t)$, that constitutes the complete solution to the sequential estimation problem. This pdf is represented by a set of weighted particles $\{(\mathbf{x}_t^0, \pi_t^0) \dots (\mathbf{x}_t^N, \pi_t^N)\}$, where the weights $\pi_t^n \propto p(\mathbf{Z}_t | \mathbf{X}_t = \mathbf{x}_t^n)$ are normalised. The state χ_t can be estimated by the equation:

$$\chi_t = \sum_{n=1}^N \pi_t^n \mathbf{x}_t^n \quad (3)$$

A pseudocode of a general PF is shown in Figure 1. PF starts by setting up an initial population \mathbf{X}_0 of N particles using a known pdf. The measurement vector \mathbf{Z}_t at time t , is obtained from the image. Particle weights Π_t are computed using weighting function. Weights are normalized and a new particle set \mathbf{X}_t^* is selected. As particles with larger weight values can be chosen several times, a diffusion stage are applied to avoid the loss of diversity in \mathbf{X}_t^* . Finally, particle set at time $t+1$, \mathbf{X}_{t+1} , is predicted by using the motion model.

```

algorithm          PARTICLE_FILTER          ((IN)M:          video_sequence;
(IN)N:number_of_particles; (OUT) $\mathbf{X}_t$ : estimates_set)
var  t: time;
       $\Pi_t$ : weight_set;
       $\mathbf{X}_t, \mathbf{X}_t^*, \mathbf{X}_{t+1}$ : particle_set;
       $\mathbf{Z}_t$ : measurement_vector;
begin
t := 0;
 $\mathbf{X}_t$  := Initialize(N);
repeat
   $\mathbf{Z}_t$  := ObtainMeasures(S, t);
   $\Pi_t$  := Evaluate( $\mathbf{X}_t, \mathbf{Z}_t$ );
  [ $\mathbf{X}_t, \Pi_t$ ] := Normalize( $\mathbf{X}_t, \Pi_t$ );
   $\mathbf{X}_t$  := Estimate( $\mathbf{X}_t, \Pi_t$ );
   $\mathbf{X}_t^*$  := Select( $\mathbf{X}_t, \Pi_t$ );
   $\mathbf{X}_t^*$  := Diffuse( $\mathbf{X}_t^*$ );
   $\mathbf{X}_{t+1}$  := Predict( $\mathbf{X}_t^*$ );
  t := t+1;
until (termination_condition)
end.

```

Fig. 1. General Particle Filter Algorithm

Several optimized algorithms from the general PF approach, which use different strategies to improve its performance have been proposed [5][10][12]. For example, the Sampling Importance Resampling (SIR) algorithm [12] reduces the effects of the degeneracy phenomenon. The goal of SIR algorithm is to eliminate those insignificant particles and to consider the contribution of those ones with larger weight values. Reference [5] presents an Annealed Particle Filter (APF) to track human motion using a proposal articulated body model. APF is applied to searching in high dimensionality spaces. This filter works well for articulated models with 29 DOFs. Partitioned Sampling (PS) [12] is a statistical approach to tackle hierarchical search problems. PS consists of dividing the state-space into two or more partitions, and sequentially applying the stated dynamic model for each partition followed by a weighted resampling stage. The advantages of this technique are that the number of required weighting function evaluations is reduced.

3. Path Relinking

Path Relinking (PR) [10][11] is an evolutionary metaheuristic in the context of the combinatorial optimization problems. PR constructs new high quality solutions by combining others obtained solutions by exploring paths that connect these solutions.

To yield better solutions than the original ones, PR starts from a given set of elite solutions obtained during a search process, called *RefSet* (short for “Reference Set”). These solutions are ordered according to their quality, and new solutions are then generated, by exploring trajectories that connect solutions in the *RefSet*. The metaheuristic starts with two of these solutions x' and x'' , and it generates a path: $x' = x(1), x(2), \dots, x(r) = x''$, in the neighbourhood space that leads towards the new solution sequence. In order to produce better quality solutions, it is convenient to add a local search optimization phase. Figure 2 sketches a pseudocode of the PR metaheuristic.

```

algorithm  PATH_RELINKING  ((IN)Solutions:  Solution_set;  (IN) $\Pi_s$ :
weight_set;  (IN)b:  RefSet_size;  (IN)NumImp:  Integer;  (IN) $Z_c$ :
measurement_vector;  (OUT)RefSet:  Solution_set;  (OUT) $\Pi_R$ :  weight_set)
var   $\Pi_P, \Pi_{RN}$ :  weight_set;
      RefSetNew, Path:  Solution_set;
      NewSubSets:  Pairs_of_Solutions;
      NewSolutions:  Boolean;
begin
  [RefSet,  $\Pi_R$ ] := MakeRefSet(Solutions,  $\Pi_s$ , b);
  [RefSet,  $\Pi_R$ ] := Order(RefSet);
  NewSolutions := TRUE;
  while (NewSolutions) do
    NewSubSets := MakeNewSubsets(b);
    NewSolutions := FALSE;
    while (NewSubSets =  $\emptyset$ ) do
      Path := MakePath(NewSubSets(1));
       $\Pi_P$  := Evaluate(Path,  $Z_c$ );
      [Path,  $\Pi_P$ ] := Improve(Path,  $\Pi_P$ , NumImp);
      [RefSetNew,  $\Pi_{RN}$ ] := Update(RefSet,  $\Pi_R$ , Path,  $\Pi_P$ );
      if (RefSetNew  $\neq$  RefSet) then
        NewSolutions := TRUE;
      end if
      NewSubSets := Delete(NewSubSets, 1);
    end while
    RefSet := RefSetNew;
     $\Pi_R$  :=  $\Pi_{RN}$ 
  end while
end.

```

Fig. 2. Template of the Path Relinking metaheuristic

4. Path Relinking Particle Filter

The Path Relinking Particle Filter (PRPF) algorithm is introduced in this paper to be applied to estimation problems in sequential processes that can be expressed using the state-space model abstraction. As pointed in section 1, PRPF integrates PF and PR frameworks in two different stages. The PRPF algorithm is centered on a delimited region of the state-space in which it is highly probable to find new better solutions than the initial computed ones. PRPF increases the performance of general PF by improving the quality of the estimate, by adapting computational load to constraints and by reducing the number of required evaluations of the particle weighting function.

Figure 3 shows a graphical template of the PRPF method. Dashed lines separate the two main components in the PRPF scheme: PF and PR optimization, respectively.

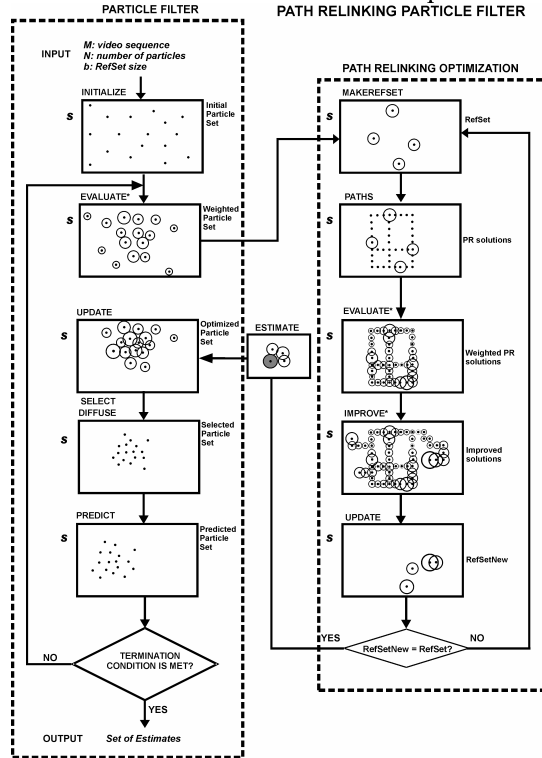


Fig. 3. Path Relinking Particle Filter scheme. Actual frame measures are required during EVALUATE and UPDATE stages (*)

PRPF starts with an initial population of N particles drawn from a known pdf. Each particle represents a possible solution of the problem. Particle weights are computed using a weighting function and a measurement vector. PR stage is later applied to improve the best obtained solutions of the particle filter stage. A Reference Set ($RefSet$) is created selecting the b ($b \ll N$) best particles in particle set. New solutions are generated and evaluated, by exploring predefined trajectories that connect all possible pairs of particles in the $RefSet$. Paths are generated following those directions according to the state-space axes. In order to improve the solution fitness, a local search from some of the generated solutions within the PR procedure is performed. Worst solutions in the $RefSet$ are replaced when there are better performance new ones. PR stage ends when new generated solutions $RefSetNew$ do not improve the quality of the $RefSet$. Once the PR stage is finished, the “worst” particles are replaced with the $RefSetNew$ solutions. Then, a new population of particles is created by selecting the individuals from particle set with probabilities according to their weights. In order to avoid the loss of diversity, a diffusion stage is applied to the particles in new set. Finally, particles are projected into the next time step by making use of the update rule. The proposed pseudocode of PRPF algorithm for visual tracking is shown in Figure 4.

PRPF system estimator quality is improved and the required number of evaluations for the weighting function is also reduced. Therefore, PRPF search in state-space is not performed randomly like in a general particle filter. PRPF is time-adaptive since the number of evaluations of the weighting function changes in each time step. If the initial solutions in the *RefSet* are far away one from each other, then paths connecting solutions are long, and the number of explored solutions increases. It is not possible to have any estimate of the previous state of the system at the beginning of the visual tracking, thus the particle filter is usually randomly initialized. The number of individuals in the particle filter does not change during the algorithm execution. PRPF algorithm reduces the total required number of evaluations of the weighting function when increasing the number of total time steps.

```

algorithm PRPF((IN)M: video_sequence; (IN)N: number_of_particles;
(IN)b: RefSet_size; (IN)NumImp: Integer; (OUT) $\chi_t$ : estimate_set)
var t: integer;
 $\Pi_t, \Pi_p, \Pi_R, \Pi_{NR}$ : weight sets;
 $\mathbf{X}_t, \mathbf{X}_t^*, RefSet, RefSetNew, Path$ : particle sets;
NewSubSets: Pairs of Particles;
NewSolutions: Boolean;
 $\mathbf{Z}_t$ : measurement vector;
begin
t := 0;
 $\mathbf{X}_t$  := Initialize(N);
repeat
 $\mathbf{Z}_t$  := ObtainMeasures(M, t);
 $\Pi_t$  := Evaluate( $\mathbf{X}_t, \mathbf{Z}_t$ );
[RefSet,  $\Pi_R$ ] := PATH_RELINKING( $\mathbf{X}_t, \Pi_t, b, NumImp, \mathbf{Z}_t$ ); {See fig. 2}
 $\chi_t$  := Estimate(RefSet,  $\Pi_R$ );
[ $\mathbf{X}_t, \Pi_t$ ] := Update( $\mathbf{X}_t, \Pi_t, RefSet, \Pi_R$ );
[ $\mathbf{X}_t, \Pi_t$ ] := Normalize( $\mathbf{X}_t, \Pi_t$ );
 $\mathbf{X}_t^*$  := Select( $\mathbf{X}_t, \Pi_t$ );
 $\mathbf{X}_t^*$  := Diffuse( $\mathbf{X}_t^*$ );
 $\mathbf{X}_{t+1}$  := Predict( $\mathbf{X}_t^*$ );
t := t+1;
until (termination_condition)
end.

```

Fig. 4. Path Relinking Particle Filter Algorithm

5. Considered Upper-Body Model for Pose Estimation

The automatic computation of marker coordinates is the aim of human pose estimation system. Our proposed PRPF system is applied to determine the position and orientation of body segments in the global frame. The set of particles describe complete solutions for the tracking problem. The particle structure in an eight-limbs model is:

$$\left[x_1, y_1, \theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7, \theta_8, \dot{x}_1, \dot{y}_1, \dot{\theta}_1, \dot{\theta}_2, \dot{\theta}_3, \dot{\theta}_4, \dot{\theta}_5, \dot{\theta}_6, \dot{\theta}_7, \dot{\theta}_8 \right] \quad (4)$$

where x and y are the spatial positions, θ is the angle and \dot{x} represents the first derivative of magnitude (velocity).

A geometrical model is used to represent the human upper-body in a 2D space as a hierarchical set of articulated limbs. It stores time-independent parameters describing the body components. On the other hand, each particle stores time-dependent values relating to limbs position and orientation. Therefore, it is possible to build blobs and edges pixel maps combining the particle state prediction and the geometrical model. Figure 5(a) shows the proposed blobs and edge models for upper body tracking.

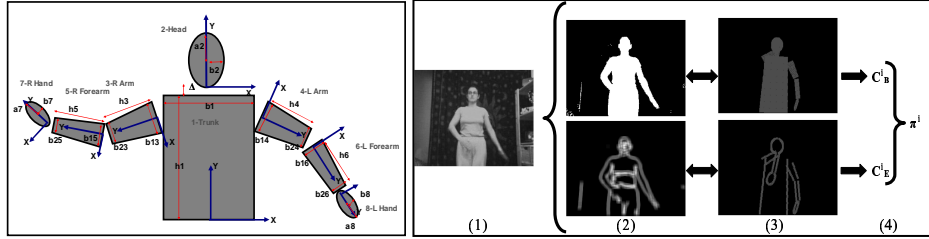


Fig. 5. (a) Proposed human upper-body model. (b) Measurement process: (1) initial image, (2) feature extraction, (3) particle prediction and (4) particle weight computation

Figure 5(b) represents the measurement process to obtain the particle weights. To construct the weighting function it is necessary to use adequate image features. Continuous edges extracted from a human image usually provide a good measure of visible body limbs. Canny edge detection method can be used to extract edges. Edges outside from human silhouette are removed using background subtraction. The resulting edges are then smoothed using a convolution operation. This produces a pixel map E^M which assigns each pixel a value related to its proximity to an edge. Another pixel map E^P is built using edges produced by the geometrical model of the configuration predicted by the i th particle, for each pixel (j) in the pixel map. Differences between these two pixel maps are computed by:

$$C_E^i = \sum_j |E_j^M - E_j^P| \quad (5)$$

Similarly, background subtraction was used to obtain human silhouette. Two pixel maps B^M and B^P are built and compared to compute the corresponding values of C_B^i . Finally, edges and blobs coefficients are combined to obtain i th particle weight using the following weighting function:

$$\pi^i = e^{-\alpha(C_E^i + C_B^i)} \quad (6)$$

where α is an experimental parameter.

6. Results

To demonstrate the advantages of proposed PRPF algorithm, three different particle filter algorithms (Condensation, SIR and PRPF) were implemented using MATLAB 6.1. We tested the developed algorithms for tracking people who performed planar movements in different scenes. A Pentium 4 1.7 GHz. computer and a webcam were

used for the experiments. Performance of Condensation using 4000 particles, SIR using 2000 particles (at each sampling stage) and PRPF using 200 particles in the particle set and four solutions in the *RefSet* were evaluated. Manual digitizing was performed to take a reference in order to evaluate the qualitative performance of the different algorithms. Different estimations of the x coordinate for the right wrist marker over a 50 frames video sequence using PRPF, SIR, Condensation and manual digitizing are shown in figure 6. The required number of evaluations of the weighting function related to each frame in the video sequence of figure 7 was 4000 for SIR particle filter algorithm and 2838 for the PRPF algorithm.

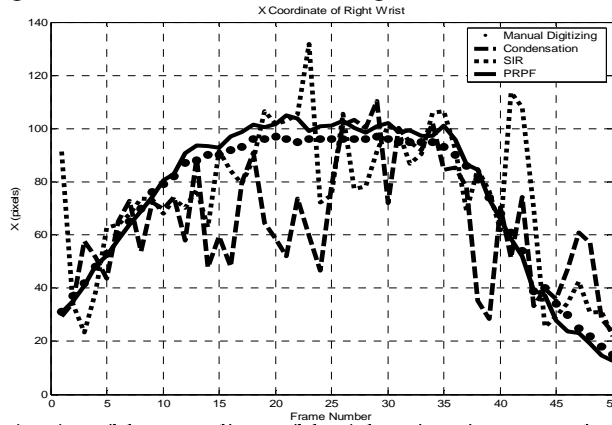


Fig. 6. (a) Estimation of the x coordinate of the right wrist using a manual procedure, the Condensation, SIR and PRPF algorithms

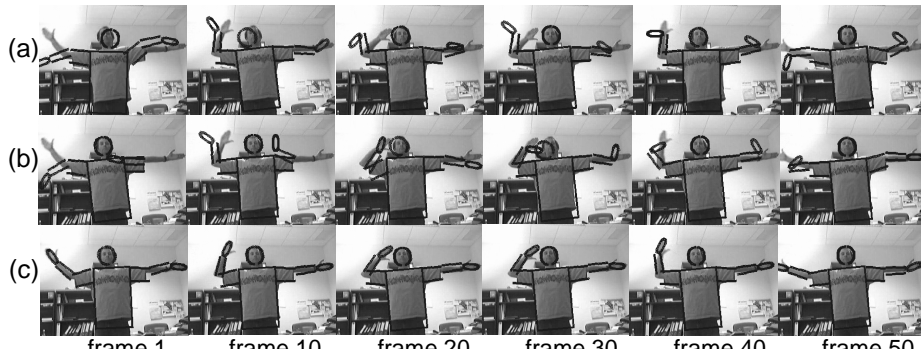


Fig. 7. Estimates in different frames using: (a) Condensation (b) SIR and (c) PRPF

Figure 7 shows the achieved experimental model configuration results using the Condensation, SIR and PRPF algorithms for the same video sequence. Table 1 shows the deviations from manual digitizing of the estimates using the considered algorithms. The Mean Square Error (MSE) deviation for the set of all markers averaged by the two sequences was 26.34 using PRPF, 224.57 using SIR and 288.92 using Condensation algorithm respectively. Note that MSE has decreased to 11.73% of the SIR error and to 9.12% of the Condensation error. This is due to a drastic improvement of the *RefSet* quality after Path Relinking optimization.

Table 1. MSE respect to manual digitizing of Condensation, SIR and PRPF for two sequences.

Marker	Image Sequence 1			Image Sequence 2		
	Condens	SIR	PRPF	Condens	SIR	PRPF
X Vertex	3.19 e+001	4.92 e+001	1.26e+001	1.17e+002	1.26e+002	7.65e+001
Y Vertex	6.49 e+001	9.52 e+001	1.20e+001	6.07e+001	6.47e+001	3.04e+001
X Neck	3.26 e+001	2.93 e+001	2.83e+001	2.23e+001	2.68e+001	1.16e+001
Y Neck	3.00 e+001	2.48 e+001	1.04e+001	2.78e+001	2.66e+001	1.19e+001
X R Shoulder	2.59 e+001	2.10 e+001	1.31e+001	2.15e+001	2.11e+001	7.10e+000
X L Wrist	3.12 e+002	1.69 e+001	5.71e+000	1.37e+003	1.19e+003	9.37e+001
Y L Wrist	8.29 e+002	4.54 e+002	8.69e+000	2.18e+003	9.64e+002	1.76e+001
Mean	152.15	107.52	15.31	425.69	341.62	37.38

7. Conclusion

The main contribution of this work is the Path Relinking Particle Filter (PRPF) algorithm, developed for estimation problems in sequential processes that are represented by the state-space model abstraction. Experimental results have shown that PRPF appreciably increases the performance of general and SIR particle filters. We have applied the proposed PRPF algorithm to the 2D human pose estimation problem. PRPF increases the accuracy for automatically obtaining the marker coordinates with a more reduced particle set in 2D biomechanical analysis. As future work the PRPF will be applied to perform the tracking of 3D images for human pose estimation in biomechanics applications. In addition, a study of PRPF properties oriented to reduce execution time of the proposed algorithm is necessary.

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