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Reducing Particle Filtering Complexity for 3D Motion Capture using Dynamic Bayesian Networks

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Abstract

Particle filtering algorithms can be used for the monitoring of dynamic systems with continuous state variables and without any constraints on the form of the probability distributions. The dimensionality of the problem remains a limitation of these approaches due to the growing number of particles required for the exploration of the state space. Computer vision problems such as 3D motion tracking are an example of complex monitoring problems which have a high dimensional state space and observation functions with high computational cost. In this article we focus on reducing the required number of particles in the case of monitoring tasks where the state vector and the observation function can be factored. We introduce a particle filtering algorithm based on the dynamic Bayesian network formalism which takes advantage of a factored representation of the state space for efficiently weighting and selecting the particles. We illustrate the approach on a simulated and a realworld 3D motion tracking tasks.

1 Introduction

Complexity and uncertainty are two common problems that arise when dealing with realworld monitoring applications. Markerless 3D motion tracking is an example of a high dimensional problem with partial observability. Partially observable Markov processes are a formal framework that allow probabilistic reasoning on dynamic systems.

Dynamic Bayesian networks are a graphical formalism that can be used to model dynamic processes such as Kalman filter, hidden Markov Model and more generally any kind of Markov process over a set of variables. Exact or approximate deterministic inference algorithms are always based on assumptions over the form of the probability laws that govern the system. It is not the case for particle filtering that has the advantage of working with any kind of probability distributions. Particle filtering is known to perform exact inference asymptotically (for an infinite number of particles). In practice, particle filtering is used to perform approximate inference with a limitation due to the dimensionality of the problem. In this article we focus on reducing the number of particles for problems that can be factored. We introduce a factored particle filtering inference algorithm for dynamic Bayesian network and its application on a simulated and a realworld 3D motion tracking problem.

2 Markov processes and particle filtering

In partially observable Markov processes, we assume that the probability distribution over the state space which is called the belief state is conditionally independent from the past sequence given the previous state.

$$P(X_t|X_{1:t-1}) = P(X_t|X_{t-1})$$

In the same way, the observation is conditionally independent of the past given the current state. The belief state can be computed recursively using the Bayes rule.

$$\alpha_t(x_t) = P(X_t = x_t|y_{1:t})$$

$$\alpha_t(x_t) = \frac{P(y_t|x_t) \sum_{x_{t-1}} P(x_t|x_{t-1})\alpha_{t-1}(x_{t-1})}{P(y_t|y_{1:t-1})}$$

The idea behind particle filtering is to represent the probability distribution over the state space by a weighted set of particles $\{x_t^i\}_{i=1..N}$ sampled from a proposal distribution.

$$\alpha_t(x_t) \approx \sum_{i=1}^N w_t^i \delta(x_t, x_t^i)$$

where δ is the Dirac delta function.

The particles are resampled and weighted in order to maintain the estimation of the belief state over time given the previous observations. The required number of particles grows as an exponential function of the dimensionality of the state space [4].

Condensation algorithm introduced by Isard et al. [3] is described in 3 steps.

- The resampling step where a selection occurs among the particles associated to α_{t-1} .
- The diffusion step which consists in estimating

$$P(x_t|y_{1:t-1}) = \sum_{x_{t-1}} P(x_t|x_{t-1})\alpha_{t-1}(x_{t-1})$$

by moving the particles according to the dynamics of the system (described by $P(x_t|x_{t-1})$ used as a proposal distribution).

- The measure step in which the weight of the particles are updated using the observation $P(y_t|x_t^i)$ and normalized. The normalization factor corresponds to $\frac{1}{P(y_t|y_{1:t-1})}$.

3 Working with a small number of particles

Particle filtering in a continuous state space is an example where the exploration exploitation dilemma occurs. The resampling step in the condensation algorithm ensures that more exploration effort will be spent on more likely state space areas at the cost of less precision in less likely areas. The difficulty here, particularly when working with multi-modal distribution, is to keep a sufficient exploration potential in order to find the global maximum. Reducing the number of particles is therefore a delicate matter, although it is often necessary for applications with high computational cost such as vision problems. In [1] the authors have used simulated annealing in order to simplify and incrementally refine the form of the state probability distribution and be able to keep track of the global maximum. In [6], the authors have used a modified particle filtering algorithm based on a deterministic exploration of parts of the state space. It shows the efficiency of deterministic distribution sampling when working with a small number of particles. In this article we propose to take advantage of the factorization of the probability distribution in order to reduce the number of particles. This factored approach can be combined with the previously mentioned methods.

4 DBN

Bayesian networks (BN) are a graphical formalism for reasoning about variables independence. A BN gives a graphical representation of the joint probability distribution of a set of variables. Each variable is described by a local probability law so that the joint probability distribution can be written as the product of the local laws. When working with a time-evolving set of variables X_t , we call the BN a Dynamic Bayesian Network (DBN). A DBN [5] is a temporal probabilistic model which is based on a factored representation of the probability distributions $P(X_t|X_{t-1})$ and $P(Y_t|X_t)$ where X_t and Y_t are decomposable into several variables: $X_t = (X_t^1, \dots, X_t^N)$ and $Y_t = (Y_t^1, \dots, Y_t^M)$. The factored representation of $P(X_t, Y_t|X_{t-1})$ is given by a directed acyclic graph in which each node is associated to a variable X_t^i or Y_t^j .

$$P(X_t, Y_t|X_{t-1}) = \prod_i P(X_t^i|Pa(X_t^i)) \times \prod_j P(Y_t^j|Pa(Y_t^j))$$

where $Pa(X_t^i) \in (X_{t-1}, X_t), Pa(Y_t^j) \in (X_t)$ are the parents of X_t^i, Y_t^j in the directed acyclic graph.

Several exact and approximate deterministic inference algorithms exist for Bayesian networks according to the nature of the conditional probability distributions (discrete,

continuous linear gaussian, hybrid). In this article we propose a particle filtering algorithm for making inference in DBNs in the case of continuous variables with no constraints on the form of the probability distribution. With this algorithm we intend to reduce the number of particles required for finding the most likely values of the hidden variables given an observation sequence.

5 Factored Particle Filtering

A critical issue in high dimensional particle filtering is that a majority of the particles get 'killed off' during resampling step, meaning that a lot of the exploration effort is wasted. The main idea behind this work is to use the factorization of the process for hierarchically resampling the components of the state vector. Our proposal is inspired by the likelihood weighting procedure [2][7] in which the elements of the state vector are sampled in a topological order. We denote as x_t^i the i^{th} particle at time t which is an instantiation of the whole set of variables of the DBN. The n^{th} variable of the DBN being denoted as X_t^n , the particle x_t^i is an instantiation of (X_t^1, \dots, X_t^N) . By searching the graph in a topological order, we propose to resample the particles every time an observed node is encountered. Thus, the particles can be eliminated without being fully instantiated and the early resampling improves the efficiency of the exploration effort.

- If the node corresponds to a state variable X_t^n , each particle x_t^i is completed with a sample from the proposal distribution $P(X_t^n | Pa(X_t^n) = u_i)$ where u_i is the value of $Pa(X_t^n)$ in the particle x_t^i or its predecessor at time $t - 1$.
- If the node corresponds to an observation function. The weight w_t^i of the particles x_t^i is updated by the rule :

$$w_t^i = w_t^i * P(Y^k = y_t^k | Pa(Y^k) = u_i)$$

where u_i is the value of $Pa(Y^k)$ in particle x_t^i . If necessary the particles x_t^i are resampled according to their weight w_t^i .

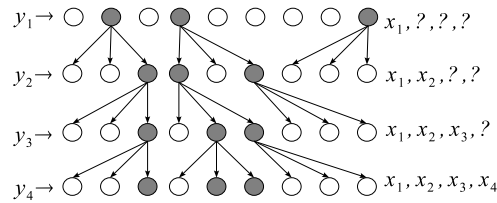


Figure 1: Hierarchical resampling: Grey nodes correspond to particles with higher weight after introduction of observation Y_i .

Figure 1 is an illustration of the resampling process. The algorithm is detailed in figure 2.

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 $Pa(x_t^i)$  : parent particle at time  $t - 1$  of particle  $i$ .
 $Z_t=(X_t, Y_t)$  denotes the set of observed and hidden variables.
 $N$  is the total number of particles.

For each node  $n$  in topological order
  case  $n$  hidden
    for each particle  $i$ 
      :  $u_i = \text{value of } (Pa(Z_t^n)) \text{ in } (x^i, Pa(x_t^i))$ 
      : Complete  $x_t^i$  with a sample from  $P(Z_t^n | Pa(Z_t^n) = u_i)$ 
    case  $n$  observed ( $Z^n=y_t^k$ )
      for each particle  $i$ 
        :  $u_i = \text{value of } (Pa(Z_t^n)) \text{ in } (x^i, x_{t-1}^i)$ 
        :  $w_t^i = w_t^i * P(Z^n = y_t^k | Pa(Z_t^n) = u_i)$ 
      resample the particles according to their weight  $w_t^* = 1/N$ 

```

Figure 2: Factored particle filtering algorithm.

6 3D Motion tracking

In this section we show how we can use factored particle filtering in an application of 3D motion tracking. 3D motion tracking can be viewed as a Markov monitoring task in which we search the most likely state sequence of the 3D model knowing an observation sequence given by video feeds.

6.1 Factored representation of a kinematic chain

A kinematic chain is defined by a set of joints between segments $S^i_{i=1..N}$ allowing relative motion of the neighboring segments. The state of the chain can be described by the relative positions of the neighboring segments which we denote as $\{R^1, \dots, R^N\}$. The dimensionality of the each relative position R^i depends on the degrees of freedom of the corresponding joint. In an open loop chain, every segment of the chain is connected to any other segment by one and only one distinct path and the chain takes the form of a tree. We can define a hierarchy between the joints by taking one of the segments as the root of the structure. We denote the absolute 3D position of the segments in topological order as $\{X^0, \dots, X^N\}$ and $Pa(X^i)$ refers to the position of the parent of the i^{th} segment.

The position of the i^{th} segment $X^i = f_i(Pa(X^i), R^i)$ can be calculated knowing the absolute position of its parent and the configuration R^i of the joint linking X^i and $Pa(X^i)$. Thus, the structure of the kinematic chain induce a factored representation of the joint probability distribution $P(X^0, \dots, X^N) = \prod_{i=0}^N (P(X^i | Pa(X^i)))$. The dimensionality of each factor $P(X^i | Pa(X^i))$ is the same as the dimensionality of the corresponding joint R^i . This factored representation is a Bayesian network in which each node corresponds to a segment position and each arc is associated with a joint

dynamics.

6.2 Factored observation function

Our observation function is simply based on the video feeds. The basic idea is to compare the video inputs which are the projections of the 'real' observed object to the projections of our 3D model. This doesn't provide a direct observation of the segments. Nevertheless, we will show that the evaluation function can be factored. We can indeed evaluate the matching of the segments, not independently, but one after the other. The first segment S^1 is compared to the reference image provided by the camera. The common pixels between the projection of S^1 and the silhouette are marked as masked and the resulting image is used as a reference for the next segment. This chain process for evaluating the state vector allows us to write the observation function as $P(Y|X) = \prod_{i=1}^N P(Y^i|X^i, pre(Y^i))$ where $pre(Y^i)$ is the observation function that precede Y^i in our evaluation process.

7 Simulated hand gesture tracking

This section presents an experiment that we used for the validation of the algorithm. We developed a 3D articulated hand-like model which was used for the generation of motion sequences recorded by several virtual cameras. Performing this 'simulated motion tracking' presents the advantage of knowing the corresponding exact state sequence and provides the possibility to compare the 3D filtered positions to the exact 3D positions. It also allows us to avoid some image processing tasks (such as shadow filtering or silhouette extraction) as the sole evaluation of the algorithm itself is done in this part.



Figure 3: 3D hand-like model

The used model contains 15 degrees of freedom represented by 15 variables. The only presumed dynamic constraints are angular speed limits for each joint. Therefore, the conditional density distributions are uniform laws on intervals centered on the relative position of the joints a time $t - 1$.

Combining factored particle filtering with deterministic interval sampling [6], we used a simple particle resampling method which consists in keeping at each rank the 5 most fitting particles and copy them 5 times for diffusion without uniformizing their weight so that the sum $\sum_{i=1}^N w_t^i \delta(x_t, x_t^i)$ remains proportional to $\alpha_t(x_t)$. For particle

diffusion we sampled the uniform laws deterministically taking 5 samples equally distributed on the interval. As a result, the number of particles oscillates between 5 and 25 and the total number of particles evaluated for each time step is $15 \times 25 = 375$. This way of diffusing the particles, which differs from the method used in the condensation algorithm, ensures a minimum exploration potential which is needed in compensation to the reduction of the number of particles.

The animated scene was recorded from different view points by 3 virtual cameras. The results of the tracking performed using 375 particle estimations per frame were visually satisfying. We measured the error relatively to the amplitude of the movements by dividing the euclidean distance between the tracked 3D positions and the true 3D positions of each joints by the amplitude of their movement. The error calculated for each joint was then averaged over time. Using factored particle filtering, we obtained a 4% average error calculated over all the 3D points. As a comparison, the condensation algorithm using the same number of particles (375) resulted in a 13% average relative error. An example of a comparison between condensation and factored particle filtering is given on figure 4. The true 3D position of the tracked point is given as a reference. Even using a relatively small number of particles, condensation manages to keep track of the finger movement but it is clearly outperformed by the factored approach. On the forefinger tip, the reconstruction average error is 2% for the factored approach while it is 19% in the case of condensation.

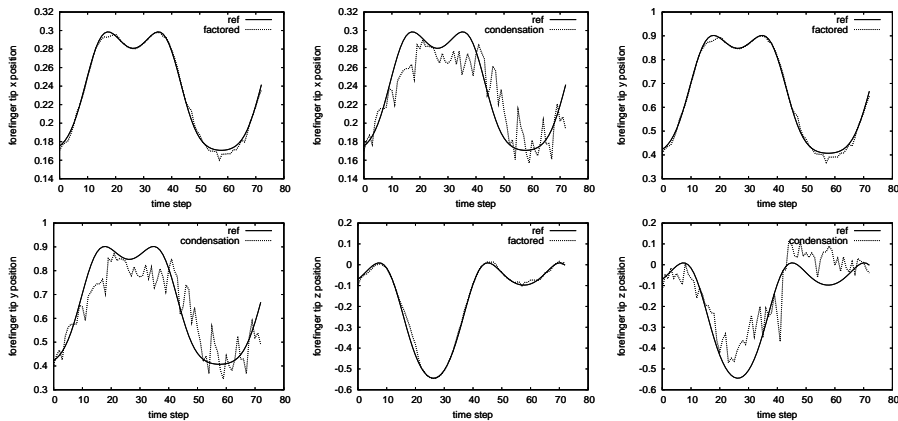


Figure 4: 3D reconstruction: comparison between forefinger tip reference and tracked positions using factored particle filtering (on left) and using condensation (on right).

8 Human motion tracking

3D human motion capture systems are based on an estimation of the 3D movements of some points of the body. Marker-based systems have been widely used for years with applications found in biometrics or animation. These approaches implicate the use of expensive specialized equipments and require a footage taken in a specially arranged

environment. Using video feeds from conventional cameras and without the use of special hardware, implicates the development of a marker less body motion capture system. Research in this domain is generally based on the articulated-models approach. This section shows the feasibility of applying factored particle filtering to 3D human motion capture.

8.1 The articulated body model and the likelihood function

The 3D articulated human body model we use simulates the human movement through the configuration of 31 degrees of freedom. These degrees of freedom represent rotations of 19 joints of the body (neck, elbows, knees etc..). The body parts form an open loop kinematic chain composed of four branches starting from the torso.

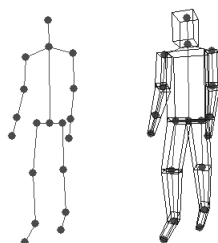


Figure 5: 3D articulated human body model composed of 19 joints each represented by a 3D point.

In addition to defining a model, we define a function to evaluate its configuration (31 parameters values) likelihood to the real image. A silhouette image of the tracked body is constructed by subtracting the background from the current image and then applying a threshold filter. This image will then be compared to the synthetic image representing the model configuration (2D projection of the 3D body model) to which we want to assign a weight. This evaluation can be made in a factored manner as explained before by projecting the body parts sequentially and masking previously observed segments on the real image.

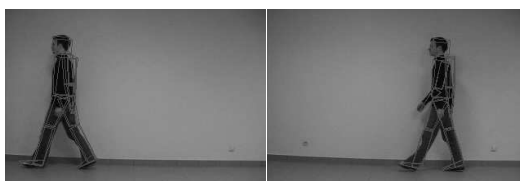


Figure 6: Projection of articulated 3D model on sample images

8.2 DBN for human motion capture

The corresponding dynamic Bayesian network is adapted from the kinematic chain representation of the model by choosing the torso position as the root variable for directing the edges. Edges have also been added between the observed nodes Y_k to show the dependences (hierarchical order) between the observation functions. In order to take advantage of the factored representation of the state vector, the hierarchy of the observations has to follow the one of the hidden variables. For separate branches (right leg, left leg,...) an order is defined arbitrarily. The dynamics of the different joints are specified by temporal links between variables at time $t - 1$ and variables at time t . A partial representation of the DBN is shown on figure 7.

No dynamic nor trained walking models were used, which makes this approach simple and generic. The only dynamic constraints used are those of the human body joints (amplitude and speed limits). For each joint, the proposal distribution is a uniform probability density function covering an interval centered on the previous position of the joint. The width of the interval depends on the physiological joint speed limit.

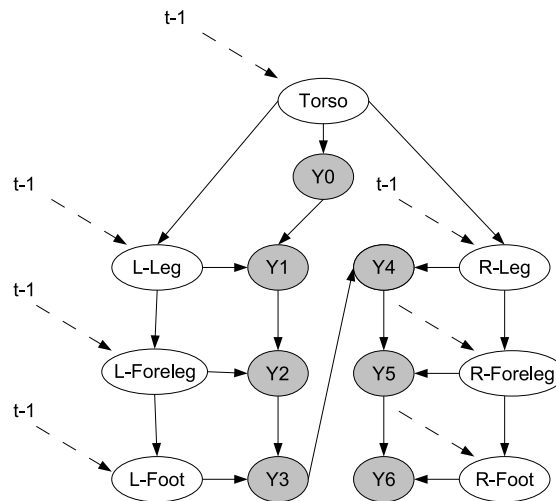


Figure 7: A (partial) DBN for gait analysis, based on the kinematic chain of a 3D articulated body model. Grayed nodes (Y_i) correspond to observation functions. The parts of the kinematic chain corresponding the arms are missing on this representation for simplification reasons.

8.3 Recovering from ambiguous situations

There are several sources of ambiguities when working on real-world motion tracking. The limited number of different viewpoints results in sequences where certain part of the body are occluded. The enlightenment of the scene is usually not uniform. The background color may produce imperfect silhouette extraction. The capacity of the

algorithm to recover from these ambiguities is related to its capacity to represent the uncertainty about the state variables. This capacity closely depends on the number of surviving particles at each resampling step.

In [6], the authors used a simple method for ensuring occlusion recovery while reducing the number of particles. The idea is to ensure a minimum exploration effort by injecting static particles in the state space. This method can be adapted to the factored approach by injecting complete configurations or variable configurations. Particle injection can compensate the risk of using a small number of particles.

On figure 8, we have compared the evolution of the algorithm from a single misplaced particle. On the left, the algorithm evolves using the uniform proposal distribution based on the joint speed limits. On the right, a few static particles (2%) are added. In the two cases, the five best particles were kept after each resampling step.

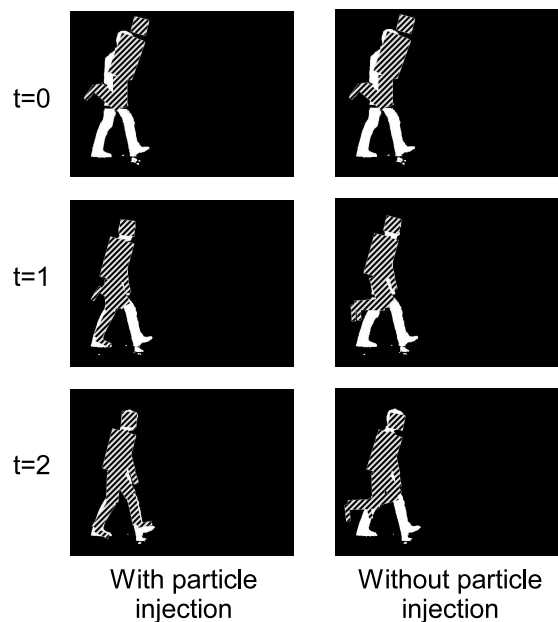


Figure 8: Recovering from a misplaced particle.

8.4 Discussion

In our experiments we used two video cameras with a resolution of 780×580 working at 25Hz. The factored approach allows visually satisfying motion tracking with a reduced number of particles. Less than 800 particles were necessary for the tracking of the 17 degrees of freedom on which gait movement is based. 2000 particles are necessary for the full 31 degrees of freedom motion tracking. This constitutes a significant improvement in comparison to the original Interval Particle Filtering [6] using 6000 particles.

The observation function is rather simple and the whole motion tracking process rely on the quality of silhouette extraction (shadow removal, thresholding, ...). The number of video feeds used is also a critical element for eliminating occlusion problems. In our experiments, only the five best particles were kept after each resampling step. We used static particles injection in order to ensure that the tracking did not diverge in the case of ambiguous observations for which keeping only five particles at resampling step may not be sufficient.

9 Conclusion

We have presented a new approach for 3D motion estimation using the formalism of dynamic Bayesian networks and a modified particle filtering algorithm for taking advantage of the factorization of the state space. The observation at time step t is used for the generation of the particles at time t which allows to search the state space more efficiently by reducing the exploration of unlikely areas. The particle economy rely on the capacity for the observation function to be factored in accordance with the state vector. We showed that the structure of a kinematic chain induced a factored representation of the probability distribution over its configurations which is based on dynamics of its joints. We saw that the likelihood function in an articulated-model approach could be factored. Using these results we were able to address a 15 degree of freedom problem using 15 layers of 25 particles each which represents only 375 particles estimations. On real human motion tracking, the number of particles was significantly reduced due to the use of factored particle filtering.

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