A Particle Filter Based Approach of Visualizing Time-varying Volume

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ABSTRACT

Extracting and presenting essential information of time-varying volumetric data is critical in many fields of sciences. This paper introduces a novel approach of identifying important aspects of the dataset under the particle filter framework in computer vision. With the view of time-varying volumes as dynamic voxels moving along time, an algorithm for computing the 3D voxel transition curves is derived. Based on the curves which characterize the local data temporal behavior, this paper also introduces several post-processing techniques to visualize important features such as curve clusters by k-means and curve variations computed from curve gradients.

1 INTRODUCTION

Time-varying volumetric datasets are ubiquitous in many scientific disciplines such as fluid simulations and medical imaging measurements. These datasets have the properties of being large and dynamic, which creates new challenges for developing efficient techniques to visualize and analyze the data. In previous studies, one way of viewing the data is to treat it as a series of static scalar volumes. With this interpretation, a number of techniques have been proposed based on showing animations of the data volume or presenting key volumes along a timeline [4]. These methods have the disadvantages of only revealing part of the whole dataset, which makes the user lose the global picture. Another way of understanding time-varying volumes is to view it as dynamic 3D volume where each voxel is a time-dependent series. Researchers have proposed many solutions to summarize the voxel temporal behaviors and visualize the whole dataset as a single aggregated volume, for example, the time-activity curves [2] and importance curves [5]. These techniques not only increase the efficiency of viewing the data but also preserve the overall temporal information.

However, the previous research under the dynamic volume concept mostly focuses on temporal behaviors at fixed coordinates, i.e., the voxels. This is adequate for certain datasets where the object geometry is stable across the time, such as medical images, whereas for some other time-varying volumetric datasets, such as hurricane simulations, the shape of object is changing all the time, reflecting that the meaning of each voxel is varied. In other words, a particular part of the hurricane data represented by a voxel may move to other locations as time evolves. Therefore the proposed techniques, which do not take such movement information into account, may not be able to reveal the key underline characteristics of the dataset.

In this paper, a novel visualization technique is proposed, based on a well-known object tracking framework in computer vision called particle filter [3]. This technique first extracts the motion information of voxels as a group of transition curves, and then visualizes the time-varying volumetric data with transfer functions developed by clustering transition curves and summarizing curve properties. With this approach, users can efficiently identify voxels with similar temporal behaviors or abnormal regions in the volume.

2 METHOD

2.1 Particle Filter

Particle filter, also known as a sequential Monte Carlo method [3], is a famous framework for object tracking. It is an iterative algorithm that can be used to estimate Bayesian models in which the latent variables are connected in a Markov chain. Given an initial probability distribution of the object position, the algorithm tracks the object in a three step process at each iteration (time frame) including *sampling*, *propagation*, and *observation*. In the sampling step, a set of weighted samples (called particles) is created from the probability distribution of the object position of the previous time frames. The more the sample's weight is, the more likely the object is there. Next in the propagation step, these samples are applied with predefined movement dynamics, which makes them drift to new positions served as predictions of the possible object positions in current frame. In the observation step, the propagated samples are evaluated based on some computer vision features from the current frame to estimate their probabilities (or weights). Then the mean position of all the samples is viewed as the predicted object position and these samples, representing the new probability distribution of the object position, are passed to next iteration. Canton-Ferrer et al. [1] applied this approach for tracking human body gestures using voxel information, which is similar to our idea. But our goal is to reveal the underline temporal characteristics of voxels rather than using them as feature vectors.

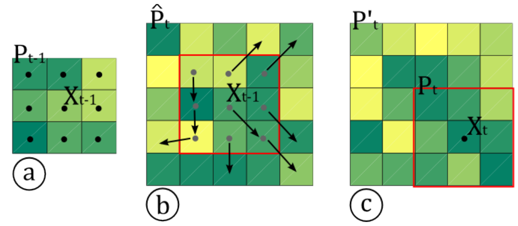

Figure 1: One iteration of the algorithm computing the transition curve of one voxel, including steps: (a) sampling, (b) propagation and (c) observation. The probability distribution is presented as the grid background in a yellow-to-green colormap.

2.2 Transition Curves

Under the aforementioned concept, we develop an algorithm to track the movements of voxels according to the volume data at each time frame. There are two basic assumptions: 1) at each time frame, a voxel can only move one unit far, i.e., to its 26 neighbor locations, or stay at the same position and 2) the volume of current time frame is only affected by the previous frame (i.e., a first-order Makov chain).

Let $x_i = [x'_i, y'_i, z'_i]^T$ be the coordinates of the volume lattice whose index is i. For ith voxel whose initial position is x_i, we want to track its movement along time, forming a path (i.e., voxel transition curve) in the volume, $C_i = \{X_1, X_2, \dots, X_T\}, X_t \in \{x_1, x_2, \dots, x_N\}$, where T is the number of time frames and N is the total number of data points in the volume. At each iteration, given the previous voxel position X_{t-1} and its probability distribution P_{t-1}, we want to estimate its current position X_t and distribution P_t. The distribution expresses the uncertainty of the voxel position, i.e., the likelihood of the voxel residing at that location. According to the first assumption, the possible voxel positions are within the $3 \times 3 \times 3$ neighbor cube centered at X_t, thus the probability beyond this scope is zero.

Next we describe the algorithm of computing transition curves using the concept of particle filters. A simple illustration with the 2D volume case is shown in Figure 1.

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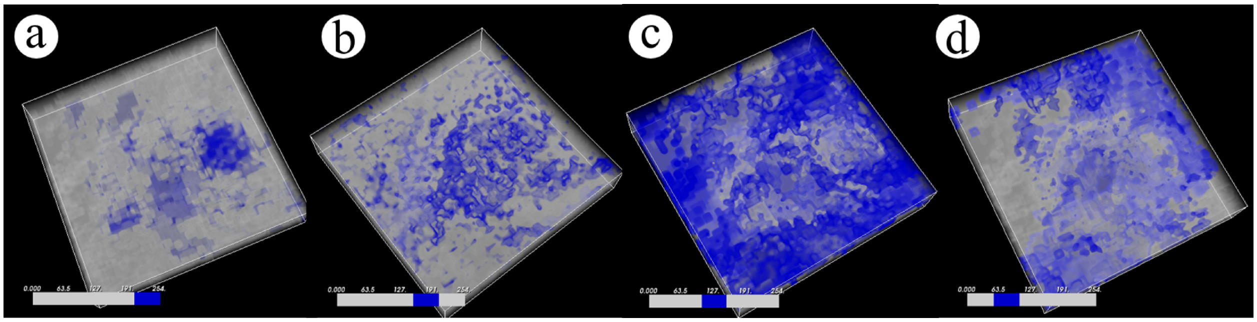

Figure 2: Results of highlighting voxels of different curve clusters in the volume.

Sampling First we sample all the points located within the neighbor region of the voxel, $\Omega(X_{t-1})$, which in our case is the cube of 27 points centered at X_{t-1}, and each selected point has the weight (probability), $P_{t-1}(x_i)$, where $x_i \in \Omega(X_{t-1})$ and $\sum_{x_i} P_{t-1}(x_i) = 1$.

Propagation With the sampled location x_i, we estimate its current position according to the movement dynamics,

$$\hat{x}_i = x_i + A(X_{t-1} - X_{t-2}) + B, \quad x_i \in \Omega(X_{t-1}), \tag{1}$$

where A and B are movement parameters. The first item of the equation represents the determinant part, assuming the point is moving at speed A and at the same direction as in last iteration, and the second item represents the random part, in which B is a noise factor, e.g., in normal distribution $B \sim \mathrm{N}(0, \sigma_m^2)$. According to our assumption, after the propagation, these sampled points initially in region $\Omega(X_{t-1})$ moved within the boundary of region $\Omega^2(X_{t-1})$ that is a $5 \times 5 \times 5$ neighbor cube centered at X_t.

Next we can compute the estimated distribution at current time frame, $\hat{P}_t$, in region $\Omega^2(X_{t-1})$. Thus we have

$$\hat{P}_t(x_j) = \frac{\sum_i w(x_j, x_i) P_{t-1}(x_i)}{\sum_i w(x_j, x_i)}, w(x_j, x_i) = \exp(-\frac{\|x_j - \hat{x}_i\|}{2\sigma_x^2}),$$
$$x_i \in \Omega(X_{t-1}), x_j \in \Omega^2(X_{t-1}) \tag{2}$$

where the weight $w(x_j, x_i)$ measures how other sample points affect the probability at the position x_j.

Observation In this step we want to adjust the estimated distribution $\hat{P}_t$ according to the real (observed) volumetric data and identify the most likely movement of the voxel with the adjusted probability distribution. Let $V_t(x_i)$ be the scalar value of the volume data at position x_i at time frame t. Similarly, we can use the above weights to compute the estimated volume data values,

$$\hat{V}_t(x_j) = \frac{\sum_i w(x_j, x_i) P_{t-1}(x_i) V_{t-1}(x_i)}{\sum_i w(x_j, x_i) P_{t-1}(x_i)} \tag{3}$$

Thus we adjust the distribution according the estimated and observed volume data values,

$$P'_t(x_j) = \hat{P}_t(x_j) \exp(-\frac{\|V_t(x_j) - \hat{V}_t(x_j)\|}{2\sigma_v^2}) \tag{4}$$

Because of the movement, we compute $P_t(x_j)$ in region $\Omega^2(X_{t-1})$. In order to predict X_t, we simply find a $3 \times 3 \times 3$ region that has the maximum probability,

$$X_t = \arg\max_{x_j} \sum_{x \in \Omega(x_j)} P'_t(x) \tag{5}$$

Thus the center of the selected region is the predicted voxel position X_t. To compute P_t, we normalize the probability distribution P'_t in $\Omega(X_t)$. Then X_t and P_t are passed to next iteration.

3 Volumetric Visualization with Transition Curves

This section presents two ways of utilizing the transition curves to visualize key aspects of the time-varying volume. The dataset used here is the water vapor value of the hurricane simulation data in the IEEE Vis2004 contest, containing a volume of dimension $500 \times 500 \times 100$ with 48 time frames. In practice, when computing the transition curves, the time-varying volume can be block-wised, i.e., dividing the volume into spatial blocks and averaging the data values in each block. This approach is more suitable than voxel-wise method when the data size becomes too large to be handled efficiently [5]. The performance of computing the transition curves with block dimension $100 \times 100 \times 20$ on a desktop of Intel Dual Core 2.4GHz, 4GB memory is 39 min.

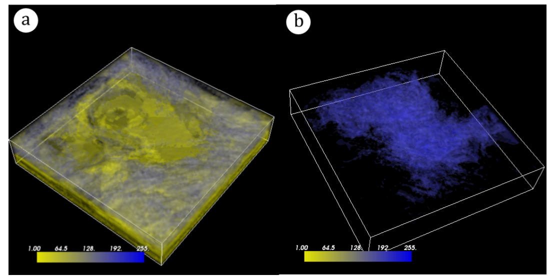

Figure 3: The visualization of transition curve variations.

The first approach is highlighting curve clusters with similar temporal behaviors in the time-varying volume. Figure 2 shows the results of clustering transition curves into 5 groups using k-means algorithm, from which we can clearly see that (a) the eye region, (b) the middle area, (c) peripheral space of the hurricane, and (d) area closed to the ground are identified.

The second approach is to visualize the properties of the transition curves starting at each voxel, for example, the variations of curves. In this paper, the curve variation is measured by computing the sum of the lengths of curve gradients at each point. The results show that the curve variation values can clearly indicate the more stable region (Figure 3a) and severe movement region (Figure 3b).

4 Conclusions

This paper has introduced a novel approach of visualizing time-varying volumetric data based on tracking the movement of dynamic voxels along time. An algorithm of computing such transition curves is described based on the framework of the particle filter. The results indicate that visualizations of characteristics of transition curves have captured important features of the data.

References

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