**Tracking Objects in Video Using Particle Filters**

AUTHOR

Frolovskaya Elena. IU7-29

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КЛЮЧЕВЫЕ СЛОВА

Отслеживание объектов, фильтр частиц, метод Монте-Карло.

ABSTRACT

The problem of tracking football players in video sequence is considered. State, motion and measurement models are defined. The common probabilistic approach is described. The particle filter algorithm is introduced.

АННОТАЦИЯ

Рассматривается проблема отслеживания футболистов в видеопотоке. Определены модели состояния объектов, заданы уравнения движения и наблюдения. Описан общий вероятностный подход к решению проблемы. Представлен алгоритм, основанный на фильтре частиц.

INTRODUCTION

The tracking of moving non-rigid objects in the video sequence is frequently solved task in the computer vision systems. It plays a key role in several applications, particularly in visual surveillance, gestural human-machine inter-face and smart environments, video editing and compression, augmented reality and visual effects, motion capture, medical and meteorological imaging, etc. Typical examples include face tracking, security monitoring, traffic flow measurement etc. However, despite of the research efforts and attention to the issue visual tracking still remains a challenging problem. Small target size, background clutter, low contrast with the background and appearance changing are the most common problems that make reliable tracking difficult to achieve.

In my graduation work tracking methods are applied to track football players in American football video. This problem is extremely challenging due to the erratic movement of players, the complexity of interactions that sometimes involve upwards of five or ten players, and the strong dependence of player behavior on the player’s type and the stage of the play. There have been many efforts devoted to player tracking in sports video. Some approaches use single camera, while others attempted to track players from the video from multiple cameras.

In this work a tracking approach based on particle filter technique will be applied. Particle filtering is a widely used framework for visual object tracking. One aspect of particle filters which makes them specially useful in that area is their ability to simultaneously maintain multiple hypotheses of the state of a tracked object.

PROBABILISTIC TRACKING

The goal of any tracking system is to estimate the state of an object at discrete time , given a set of noisy observations up to this point . The goal is therefore to estimate – the posterior state distribution at each time step. This can be accomplished in two steps: prediction and filtering, or updating.

Suppose that the required distribution at time is available. The prediction stage obtains the prior probability density function (pdf) of the state at time via the Chapman-Kolmogorov equation :

At time step a measurement becomes available and may be used to update the prior on the filtering stage via Bayes’ rule:

where the normalizing constant

depends on the likelihood function . In the update stage the measurement is used to modify the prior density to obtain the required posterior density of the current state.

PARTICLE FILTER

The particle filter is the algorithm based on the probability measure, which do not use the probability density function directly, but approximates it by weighted set of particles:

Each particle is associated with its weight, which is the certain measure of probability. Such approximation is called a sequential Monte Carlo method as well. The particle filter algorithm is recursive in nature and comes through three stages: evolution, re-sampling and propagation. After every computation each particle is newly modified and propagated based on the latest measures and the motion model. During the re-sampling process, the particles with the smallest weights are eliminated.

At every time step set of samples is approximately distributed according to . Then new samples are generated from a suitable proposal distribution, which may depend on the previous state and the new measurements i.e. . The new importance weights are set to

where . The new particle set is then approximately distributed according to . In order to eliminate particles with small weights and concentrate on those with large ones re-sampling step is implemented. This step involves generating one more set of particles by re-sampling with replacement times from , so that .

A recursive filtering approach means that received data can be processed sequentially rather than as a batch so that it is not necessary to store the complete data set nor to reprocess existing data if a new measurement becomes available.

MOTION AND MEASUREMENT MODELS

Generally speaking, particle filter is based on a system of model and measurement time-dependent equations:

where is the state vector, describing target state at discrete time moment k, and is measurement at that time. The first one is the system update equation, it represents the evolution of the state of the object from time to time . The state depends on previous state and stochastic error that represents the uncertainty in the state update. Since is a random variable of known statistics, the equation implicitly defines a prior pdf . The second equation is called measurement equation. It defines the dependency of the measure on the current unknown value of the state and the error term , representing the uncertainty in measuring the state. In the similar fashion, since is a stochastic variable, this equation implicitly defines a probability density function .

Following [reference here], in the graduation work random walk model currently is chosen for implementing. Objects are described by reference color histogram q\*. is video sequence, where denotes the image at discrete time .

State vector is given by , where denotes the center of the image region used for the color histogram computation. The state dynamics is described by a linear model:

where F is a transition matrix, (for random walk model F equals to identity matrix) and s the process noise, assumed to be white, zero-mean, Gaussian, with a covariance matrix .

The color histogram computed inside the image region, specified by state vector, serves as a measurement at time step . The pdf is given by:

where is the distance between the reference histogram of object to be tracked and the histogram computed from the current frame .

As proposal distribution the state evolution model is used.

It should be also mentioned, that particles have the same structure, as the state vector.

CONCLUSION

At the moment of writing this text the graduation work is under development, so there are no novel results yet. The plan of future work is firstly to try to repeat the results of other researches and then try to add some new features to improve them.

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