Slide 1. 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 interface 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.

In the graduation work I have chosen football players as the targets for tracking. 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. The tracking methods in my work are based on particle filters technique. So, that’s the issue coming up next.

Slide 2. Models

The first thing should be done is to determine model of moving object. This includes state vector, motion and measurement models. The state vector at frame k of a single object typically consists of kinematic and region (or shape) parameters. For example, coordinates (x,y) define the center of object region (see the picture) and can be used to describe the target’s position in the image, while h and w are region parameters, which denote its size.

Let’s look at the motion equation. It represents the evolution of the state of the object from time to time . Here xk is the state vector, and stochastic error represents the uncertainty in the state update. Since is a random variable of known statistics, the equation implicitly defines a prior probability density function . 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 .

Slides 3,4 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 . At time step a measurement becomes available and is used to modify the prior density to obtain the required posterior density of the current state on the updating stage.

The problem here resides in the fact, that models using to build all these probabilities in general are nonlinear. It is here, where the particle filter algorithm comes.

Slide 5 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.

Slide 6 Steps

Assuming it is known that particles set from the previous step is distributed according to posterior density on that step. Then new samples are generated from a suitable proposal distribution, which may depend on the previous state and the new measurements. It is very important to correctly choose the proposal distribution, since the efficiency of the whole algorithm depends on it. For example, the state evolution model, defined by motion equation, may be used as proposal distribution.

After new particles are generated the new weights are to be computed. You can see the formula in the slide. The weights should be normalized, so that their sum must be equals 1. So we got a new weighted set of particles, distributed according to proposal distribution on time step k.

Slide 7.

The left figure shows us the main drawback of particle filter: its degeneracy. It means, that after a few steps one or two particles get all the weight, while others have very low weights and are no more meaningful. To eliminate the particles with low weights re-sampling step is implemented. This step involves generating one more set of particles by re-sampling with replacement times from the last given set of samples. The particle falls into new set with the probability equal to its weight.

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.

Slide 8. Here we can see particle filter technique implemented to tracking football players.