Research on Moving Target Tracking and Information Filtering in Complex Building Environment

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Abstract. An algorithm of target tracking based on information filteringBook and particle filter is proposed in this paper. Accurate foreground region through the fusion of neighbour-information is segmented and features of foreground are extract to build an initial template for particle filter. The experimental results show that this algorithm can overcome the interference of target intersection and complex background environment to track the target stably and better than the particle filter algorithm in literature on the accuracy, robustness and real-time performance.

Introduction

Particle filter realizes the bayesian filter with the parameterized monte carlo simulation method, which is widely used in target tracking within nonlinear and non-gaussian noise space. The standard particle filter needs pre-built observation model to initialize the tracking system, and the observation of the targets template usually do not change in the tracking process. Because of the interference of target scale changes, occlusion and intersection or complex background, the pre-built observation model was difficult to update with the changing state in the tracking process, then created tracking errors. Meanwhile, due to the randomness of particles sampling, a large number of particles were wasted in calculation of a non-target area for sampling, resulting in praticle emission and particles degradation. To improve tracking accuracy, there are a lot of research have studied on the detection of observation model to improve particle filter. A tracking framework of Tracking - by – Detection was proposed in literature, in which continuous credible detector and particle filter was used to detect and track. Though the accuracy was improved, the algorithm complexity was also higher and the real-time performance was poorer. In literature, Adaboost detector was used for target detection to set the classification samples as particle filter model and realized the off-line tracking of moving target, but it required a large number of training samples as a precondition of particle filter, which was not conducive to track diversity targets.

In order to establish an effective prior state observation model, an improved particle filter was proposed. At first, neighbor-information Code Book was used to overcome the interference of light and noise to get accurate foreground region of moving target and extracted features, then combined with particle filter to realize target tracking under environment of occlusion and intersection or complex background.

Algorithm of Neighbor-Information Code Book Background Modeling

The standard Code Book proposed by Kim ignores the relevance of pixels between background and foreground, which cannot cope with the uncertainty of changes of the neighborhood space, and also cannot accurately reflect the actual situation of the current pixel. In this paper, neighbor-Information CodeBook background modeling was proposed to improve the Markov local information CodeBook modeling by Wu M. The relevant algorithm steps are as follows:

Step1. Initialize the CodeBook，set $C \to \varnothing, L \to 0$;

Step2. Train sequence of every pixel in video: $x_t = (R,G,B)$, $I = \sqrt{R^2 + G^2 + B^2}$, Find out codeword c_i matched with x_t as following conditions: brightness$(I, < \check{I}_i, \hat{I}_i >) = \text{true}$, colordist$(x_t, v_i) \le \varepsilon_1$;

If $C = \varnothing$ or unmatched, then $L = L + 1$ and create a new codeword c_l, $v_l = (R,G,B)$,

$\text{aux}_l = (I, I, 1, t-1, t, t)$;

Else, update the codeword c_i: $v_i = (\frac{f_i \bar{R}_i + R}{f_i + 1}, \frac{f_i \bar{G}_i + G}{f_i + 1}, \frac{f_i \bar{B}_i + B}{f_i + 1})$,

$\text{aux}_i = (\min\{I, \check{I}_i\}, \max\{I, \hat{I}_i\}, f_i + 1, \max\{\lambda_i, t - q_i\}, p_m, t)$;

Step3. Eliminate the redundant codeword. In $C = \{c_i, 1 \le i \le L\}$, we set temp $\lambda_i = \max\{\lambda_i, N - q_i + p_i - 1\}$;

Step4. Input the pixels to be detected $x_t = (R,G,B)$;

Step5. Find out codeword c_i matched with x_t as following conditions:

brightness$(I, < \check{I}_i, \hat{I}_i >) = \text{true}$, colordist$(x_t, v_i) \le \varepsilon_1$ (usually $\varepsilon_1 < \varepsilon_2$);

Step6. If codeword c_i matches with x_t, then $x_t = background$, and update the codeword c_i;

Else, $x_t =$ *foreground*, at the same time, make the following operation:

Step6.1 In the 8-adjacent areas of the codebook of x_t, if c_i matches, $count++$;

Step6.2 If $count++ \ge K$ (K is threshold)，then $x_t = background$; Else， $x_t =$ *foreground*.

Improved Particle Filter Tracking Algorithm Based on Neighbor-Information CodeBook

The searching space of Particle filter in literature was random sampling, which easily caused tracking errors by noise or complex background. Meanwhile, in the tracking process, a large number of particles were wasted in the noise calculation and the searching sapce spreaded more and more widely, causing the degeneration of particles. In this paper, the target foreground region was extracted in foreground detection，so that the particle sampling outside of the area was meaningless. We set this area as the limited particle sampling sapce and get the feature extraction to reduce unnecessary particles sampling. The relevant algorithm steps are as follows:

Step1. Foreground detection. Extract the precise region of moving target by neighbor-information CodeBook, then set around (x_0, y_0) as sampling region of particles;

Step2. Features extraction and particle initialization. Extract HSV color histogram $\{q\}$ of foreground regions as template of particle filter, and establish initial sample sets $\{X_0^{(i)}, \frac{1}{N}\}_{i=1}^N$ in sequential importance sampling;

Step3. State transition. Transfer state of particles through random motion model $X_{k+1} = X_k + G_k$ (X_k is vector of position coordinates, G_k is gauss random noise), and calculate HSV color histogram of particle $\{X_k^{(i)}\}_{i=1}^N$;

Step4. Features matching. Calculate the similarity of particles $X_k^{(i)}$ $\{p\}$ and the template of target $\{q\}$ with Bhattacharyya factor: $\rho(p,q) = \sum_{u=1}^{m} \sqrt{p_u q_u}$ and get Bhattacharyya distance $d = \sqrt{1 - \rho(p,q)}$;

Step5. Normalization of particles weight. Set particles weight $\omega^{(i)}$ as $\omega_k^{(i)} = \omega_{k-1}^{(i)} \frac{1}{\sqrt{2\pi}\sigma} \exp(-d^2/2\sigma^2)$, when Bhattacharyya distance is lower the particle weight is higher. Normalize all of the particle weights: $\omega_k^{(i)} = \omega_{k-1}^{(i)} \frac{1}{\sqrt{2\pi}\sigma} \exp(-d^2/2\sigma^2)$;

Step6. Position prediction. Particle weight represents the possibility of the target‘s position, so that the largest particle weight represents the target’s real position;

Step7. Particles resampling. As the prediction of location going on, the number of particles with higher weight will drop down. At this point particles need resampling. Calculate the number of particles which can effectively describe the system status $N_{eff} = \frac{1}{\sum_{i=1}^{N} (\omega_k^{(i)})^2}$, and determine the number of effective particles N_{eff}. When $N_{eff} \le N_{th}$, resample particles $N_{th} = \frac{2}{3} N$.

The experimental results and analysis

To verify the stability and robustness of particles sampling under the foreground restraint, and the effectiveness of tracking under complex background with neighbor-information CodeBook feature extraction, we make experiments with algorithm of literature [6] and improved particle filter with two videos. Coped with the combination of neighbor-information CodeBook, the improved algorithm reduces the searching range of particles, so particles only to search around the target, which has a precise and stable tracking result.

According to the tracking result of 144th frame of this video, we set the pixel distance of No.1 to 100 sampling particles rectangle and the real position of target to describe the sampling status of particles. Statistics of sampling status contrast are shown in Fig.1.

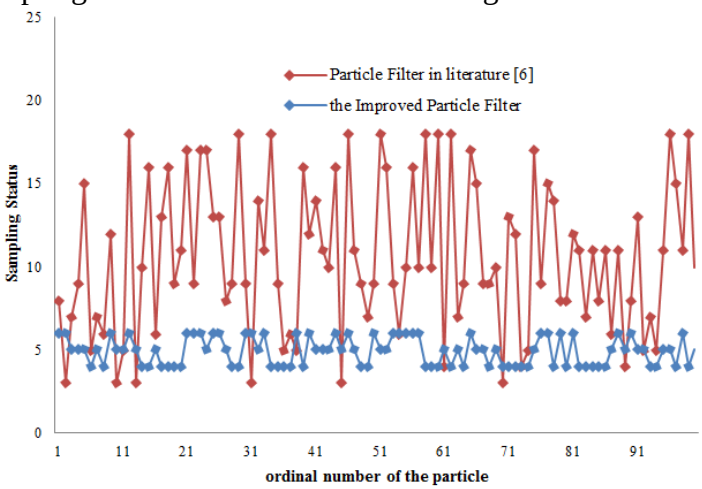

Fig.1. sampling status of 1-100th particles

We set the pixel distance of the final tracking result and the real position to describe the tracking errors. Statistics of tracking errors comparison are shown in Fig.2.

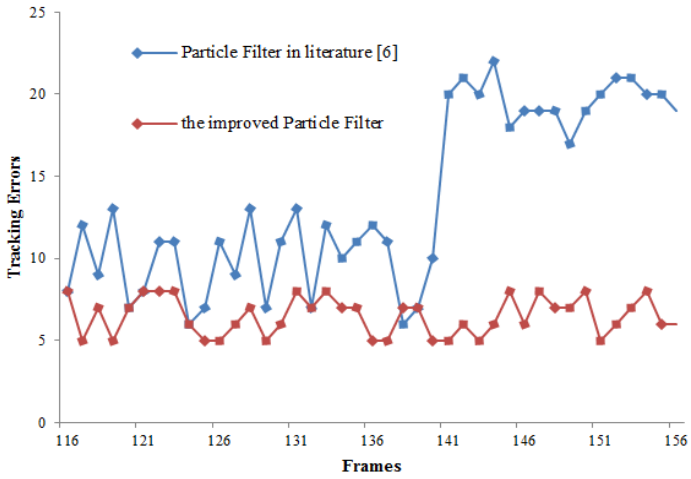

Fig.2. Errors of final tracking result

Conclusions

In order to overcome the tracking failure caused by the accumulation of errors in particle filter, an algorithm of target tracking based on information filteringBook and particle filter was proposed. Firstly, in the process of CodeBook background modeling, the CodeBook of targets' current pixels were combined with its 8-neighbourhood pixels to overcome the complex background noise and get the precise foreground of target; Then, the HSV colour features of foreground regions were extracted as the initial prior distribution of particle filter to track. The experimental results show that this algorithm can reduce the sampling errors caused by the particle emission and can effectively track moving target under complex background, moreover, the real-time and accuracy are superior to the other particle filter algorithm.

References

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