다중 특징 기반 입자필터를 이용한 강건한 영상객체 추적

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Multiple Cues Based Particle Filter for Robust Tracking

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Abstract

The main goal of this paper is to develop a robust visual tracking algorithm with particle filtering. Visual Tracking with particle filter technique is not easy task due to cluttered environment, illumination changes. To deal with these problems, we develop an efficient observation model for target tracking with particle filter. We develop a robust phase correlation combined with motion information based observation model for particle filter framework. Phase correlation provides straight-forward estimation of rigid translational motion between two images, which is based on the well-known Fourier shift property. Phase correlation has the advantage that it is not affected by any intensity or contrast differences between two images. On the other hand, motion cue is also very well known technique and widely used due to its simplicity. Therefore, we apply the phase correlation integrated with motion information in particle filter framework for robust tracking. In experimental results, we show that tracking with multiple cues based model provides more reliable performance than single cue.

1. Introduction

There are many methods which have been proposed for object tracking. Recently, Particle filter provides a robust tracking framework as they are neither limited to linear systems nor require the noise to be Gaussian [1,2,3]. In order to develop an efficient object tracking algorithm with particle filter, we represent the target object with multiple cues.

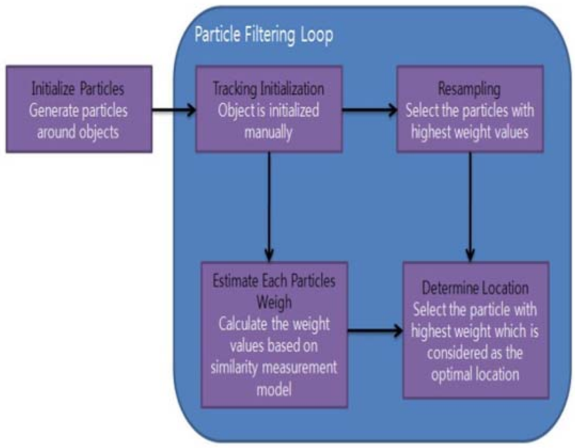
Target Representation is mostly a bottom-up process which has also to cope with the changes in the appearance of the target. The main contribution of this paper is to introduce a new framework for efficient tracking of non-rigid objects. In this work for target representation use the Motion combined with Phase correlation algorithm.

Phase correlation is a method of image registration, and uses a fast frequency-domain approach to estimate the relative translative offset between two similar images, which is based on the well-known Fourier shift property. Phase correlation has the advantage that it is not affected by any intensity or contrast differences between the two images. Motion information takes the differences between two frames. It used for it's simplicity and computationally efficient. Therefore, Combination of Phase Correlation and Motion information can track the object efficiently rather than individual cue.

The rest of the paper organized as follows: section 2, describes describe the basic framework of this work; 3, introduce the particle filter technique; section 4, describes the Propose work of this research; experimental results presented in section 5, finally, in section 6 we draw the conclusions.

2. Basic Framework

There are major four steps for particle filter based object tracking such as initialization of particles, weight calculation, determine the optimal location based on weight value and Resampling. In the initialization step it randomly generates some number of particles around the target object. In weight calculation step, it calculates every weight based on observation model. After calculating the weight values, it determines the optimal location of next state. Finally, in Resampling step, the system eliminates the particle with lower weight. Figure 1 show the basic frame work of particle filter based tracking



(Figure 1) The Basic four step of tracking

3. Particle Filter

Particle filter are effective for solving state space estimation when the state equation is non-linear and the posterior density is non-Gaussian. It is a technique for implementing recursive Bayesian filter by Monte Carlo sampling. The key idea is to represent the posterior density by a set of random particles with associated weights and to compute estimates based on these samples and weights [6]. For any filtering theory there are two major steps one is prediction and another one is update. The particle filter also consists of these two steps [4,5].

In order to develop the details of the algorithm, let assume given observations $Y_{1:t-1} = \{Y_1, \dots \dots \dots, Y_{1:t-1}\}$ up to time t-1, the prediction uses transition model to predict the posterior at time t as

$$p(X_1|Y_{t-1}) = \int p(X_1|X_{t-1})\, p(X_1|Y_{1:t-1}) dX_{t-1} \quad (1)$$

And update as follows:

$$p(X_t|Y_{1:t}) = \frac{p(Y_t|X_t)p(X_t|Y_{1:t-1})}{p(Y_t|Y_{1:t-1})} \quad (2)$$

Where $p(Y_t|Y_{1:t-1}) = \int p(Y_t|X_t)p(X_t|Y_{1:t-1})dX_t$ and X_t is object location. The basic idea of particle filter is to approximate $p(X_t|Y_{1:t})$ using a set of random sampling (particle) $\{X_t^i, i = 1, \dots N\}$ with associate weights $\{w_t^i, i = 1, \dots N\}$. The candidate samples $X_t^{\sim i}$ are drawn from an important distribution $p(X_t|X_{1:t-1}, Y_{1:t})$ and the weight of the samples are-

$$w_t^i = w_{t-1}^i \frac{p(Y_t|X_t^{\sim i})p(X_t^{\sim i})|X_{t-1}^i}{q(\widetilde{X_t}|X_{1:t-1})} \quad (3)$$

The weights are assigned according to the similarity of target object and reference object. In resampling step, the system eliminates particles with lower weight and chooses more particles in more probable regions.

4. Propose Approach of This Research

We develop a visual tracking algorithm with Particle filter based framework. In this section, describe the propose technique and the experimental results for several video sequences. In our research, we develop a similarity measurement model with multiple cues such as Phase Correlation and Motion information.

A. Phase Correlation Based Model

Phase correlation provides straight-forward estimation of rigid translational motion between two images, which is based on the well-known Fourier shift property [7]. Let given 2D functions $I_1(x, y)$ and $I_2(x, y)$ representing two images related by a simple translational shift (α,β). Then we can write this by the following relation

$$I_2(x, y) = I_1(x - \alpha, y - \beta)) \quad (4)$$

The Corresponding Fourier Transforms (FT) of both images can be denoted by $\widehat{I_1}(u, v)$ and $\widehat{I_2}(u, v)$. Thus we can be expressed it by the following equation

$$\widehat{I_2}(u, v) = \widehat{I_1}(u, v) \exp\{-i(\alpha u + \beta b)\} \quad (5)$$

Therefore, a shift in the spatial domain will produce a phase difference in the frequency domain. The phase correlation is defined as the normalized cross power spectrum between $\widehat{I_1}$ and $\widehat{I_2}$ which can be written by the following equation

$$S(u, v) = \frac{\widehat{I_2}(u,v).\widehat{I_1}(u,v)^*}{|\widehat{I_2}(u,v).\widehat{I_1}(u,v)^*|} = \exp\{-i(\alpha u + \beta b)\} \quad (6)$$

The Phase Correlation function is finally obtained by taking the Inverse Fourier Transform (IFT) of the cross-power spectrum. The Phase-Correlation algorithm is briefly explained in papers [7,8].

Phase-based local features perform better than some others approach when dealing with common illumination changes, 2D rotation, and sub pixel translation [9]. Therefore, we use this technique in our work to develop robust visual tracking algorithm. Let the reference template image and the target input image can be written as α_0 and α_t^i respectively. Equation can be written by

$$\varphi\left(\alpha_T,\ \alpha_t^i\right) = \sum_{i=1}^{N} (\alpha_T - \alpha_i^t)^2 \quad (7)$$

Particle i^* with the maximum total similarity is determined as:

$$i^* = arg_i max\ \varphi\left(\alpha_T, \alpha_i^t\right) \quad (8)$$

Where, Particle i^* with maximum total similarity score is considered the optimal location of current target object.

B. Motion Based Model

Many algorithms have been suggested to solve the problem of motion detection, In this paper, the moving pixels are identified with thresholding the temporal difference between the frames.

In our approach, to measure the amount of change in some time interval is the variance. Further, we apply an exponentially decaying weight (window) to the pixel values to save computation and memory. This is easily computed by the recursive filter

$$m(i, j, t) = \alpha m(i, j, t - 1) + (1 - \alpha)x(i, j, t) \quad (9)$$

$$m_2(i, j, t) = \alpha m_2(i, j, t - 1) + (1 - \alpha)x^2(i, j, t) \quad (10)$$

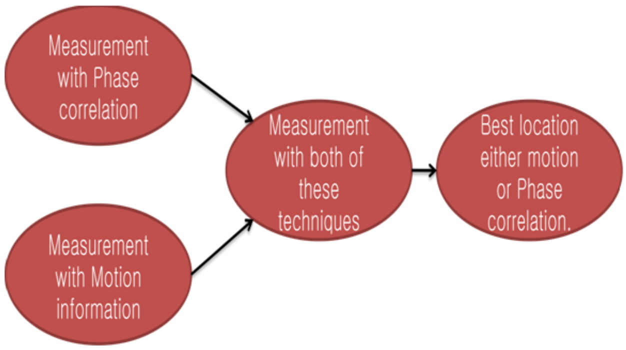
$$\sigma^2(i, j, t) = m_2(i, j, t) + m^2(i, j, t) \quad (11)$$

Where: where: $x(i, j, t)$ is the intensity, $m(i, j, t)$ is the first moment, $m_2(i, j, t)$ is the second moment and $\sigma^2(i, j, t)$ is the variance at pixel (i, j) at time t, α is the decay rate, that can be rewritten with respect to the filter window size N as:

$$\alpha = \frac{N-1}{N} \text{ and } N = \frac{1}{1-\alpha}$$

Moving target detection can be achieved by thresholding this variance. The briefly description of this approach can found in paper [10][11].

C. Integrated Framework



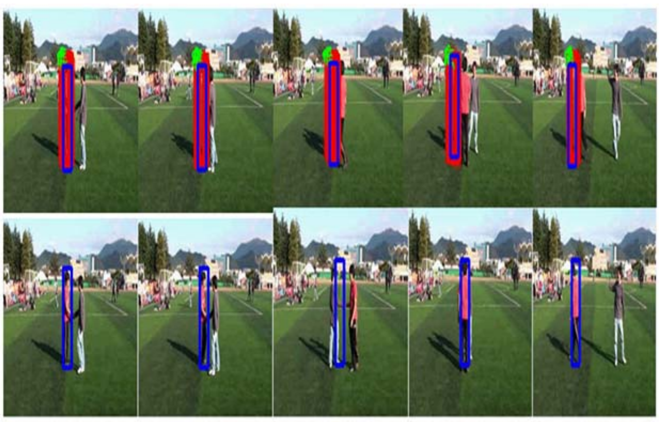
(Figure 2) Diagram of Integrated Frame work

The motivation for integrated framework comes from the inability of a single cue to fully describe the object and therefore its inability to achieve accurate and robust results. A general framework is introduced for the integration of multiple cues such as Phase Correlation and Motion information in our work. The final equation for integrated framework can be written as follows:

$$Y = S(u,v) + \sigma^2(i,j,t) \qquad (10)$$

Y is the best location; obtain by both Phase correlation and Motion information. $S(u,v)$ and $\sigma^2(i,j,t)$ are the phase different between a images and variance at pixel (i,j) at time t.

5. Experimental Results



(Figure 3) The first raw represent the only Phase Correlation based Particle filter and the second raw represent the Phase Correlation integrated with Motion based Particle filter.

In the experimental results as shown in figure 3, the background is quite complex and two persons walk together and cross each other several times. In our first experiment as shown in figure 3, we use this video sequence to compare between the individual cue phase correlation based model and Phase Correlation integrated with Motion based model. From this figure we can see, Phase Correlation integrated with motion based model are tracking well compare to the individual cue phase Correlation based model.

6. Conclusion

In this paper, we have formulated the framework for moving object tracking with particle filter based tracker. The visual tracking has been implemented with particle filter due to its non-linear and non Gaussian properties

The performance of particle filter based object tracking algorithm is depended with object representation or observation model because the occlusion problem is correlated with the observation model. So, we propose a model to represent the object for efficient tracking. The multi-feature benefits from its complementary characteristic rather than single feature. That is, as one feature is not reliable, the tracker can rely on other features. Therefore, in our system the motion information is also consider as a secondary cue to develop an observation model. Adopting multi-feature to represent objects along with gathering Phase correlation and motion information improves distinctiveness of object between backgrounds.

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