# Change detection of image sequence based on belief propagation algorithm

*Fengqin Yu, Yijia Zhu and Ying Chen*
*Information technology department,Jiangnan University,China*
*yufq@jiangnan.edu.cn*

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## Introduction

Change detection of image sequence is a technique for detect changes from the scene which has unknown target prior knowledge, by contrast image sequences at different times taken at a certain scene. In most case, the technique is to separate foreground objects of interest from the relatively static background [1]. In many automated monitoring applications, change detection can lay the foundation for such as target tracking, image classification and scene understanding [2]. Energy optimization method is a relatively new change detection method, which is proposed in recent years. It's mainly through optimization of the objective function to solve the global energy optimal solution. Common energy optimization methods include graph cut, belief propagation, simulated annealing and so on [3]. Kohli used highly efficient graph cut algorithm to detect a moving target in MRF[4]. Reference [5] used Kalman filter to predict the target pixels adaptive update node of graph cut model to extract moving targets.

Because of changes in the target and the similar background color will cause target missed or incomplete detection problem, proposed belief propagation and energy optimization method used for target detection. Belief propagation algorithm can achieve information exchange between the pixels among temporal and spatial domain. Then calculate the amount of information for each pixel, so it is possible to extract the changing target by comparing correlation between the to-be-detected pixels and background pixels. According to the slowly varying characteristics of background in the time domain, record the change of background in time matrix and adjust the time information in order to improve the accuracy of the time-domain information. Simulation results show that the belief propagation algorithm can effective transfer information between pixels, the algorithm can adjust to the complex scene, track changes in the background and detect change target in the complex scenes effectively.

## The principle of belief propagation algorithm with spatial and temporal information

A. Belief propagation principle

Belief propagation algorithm is an energy function optimization method based on Markov random field for solving probability inference problem in probabilistic graphical model. Each node in the MRF regards as a belief variable, message propagation include messaging and message updates, the paper messaging process mainly in the temporal and spatial. Each node needs to transmit the message to its neighbor in the belief propagation process, the neighbor update immediately after receiving the message until the algorithm converges, which is after receiving the message the node does not change the information.

Definition of variables $m_{i\to j}^{t}\left(x_j\right)$ represents the $t$ time iteration of the message from node $i$ to its neighboring node $j$, whose value represents the probability of the node $j$ in a certain state, $i$ and $j$ are mutual neighbor, and the message values are very close. The probability of node $i$ is defined as

$b_i(x_i)$, representing the probability of node $i$ in the state $x$, also be interpreted as the information in $i$ during the belief propagation process, the information can be expressed as follows:

$$b_i(x_i) = k\left\{\phi_i(x_i) + \sum_{k\in N(i)} m_{k\to i}(x_i)\right\} \tag{1}$$

Where $N(i)$ represents the neighboring nodes of $i$, the probability of node $i$ in the state $x$ constitute of partial evidence $\phi_i(x_i)$ and the sum of all neighboring nodes $\sum_{k\in N(i)} m_{k\to i}(x_i)$, $k$ is the normalization constant to make the probability equal to 1. Each message is calculated as follows:

$$m_{i\to j}^t(x_j) = \min_{x_i}\left\{\psi_{i,j} + b_i(x_i)\right\} \tag{2}$$

The message updating formula as follows:

$$m_{i\to j}^t(x_j) = \min_{x_i}\left\{\phi_i(x_i) + \psi_{i,j} + \sum_{k\in N(i)\backslash j} m_{k\to i}^{t-1}(x_i)\right\} \tag{3}$$

Where, $\psi_{i,j}$ and $\phi_i(x_i)$ represent the spatial and temporal information respectively.

B. Spatial and temporal information

Generally in static background scene, the higher the frequency of appearance of a pixel is considered the greater the probability that it belongs to the background pixels. When faced with more complex scenes, that spatial is not so smooth, the larger the value of the correlation function, such as dynamic scenes, harsh environment, and camera jitter. Using only the spatial information between pixels has great errors, by combining the temporal information can effectively improve the detection performance, because the background interference set of pixels tend to have a certain periodicity and regularity, such as flying banner, fluctuations in the water and playing in the display. The background pixels have slowly changing characteristics over time, it can be used to compensate for the defect that spatial information is susceptible to interference. In such cases, the correlation function of change pixels is greater than background pixels, so the joint of spatial and temporal can improve detection accuracy.

Joint spatial and temporal information to separate background pixel, the background pixel are recognized by the pixels round it. Spatial correlation function is the relative difference $\psi_{i,j}^t(I_i^t, I_j^t) = \left|I_i^t - I_j^t\right| / I_j^t$ in this psper.

Temporal correlation function, denoted as $\phi_i^{t,T}$, is as follows:

$$\phi_i^{t,T} = \tau\left(I_i^t - B_i^t\right)^2 \tag{4}$$

$0 < \tau < 1$, $B_i^t$ is the estimated background at pixel $i$ and update as following formula.

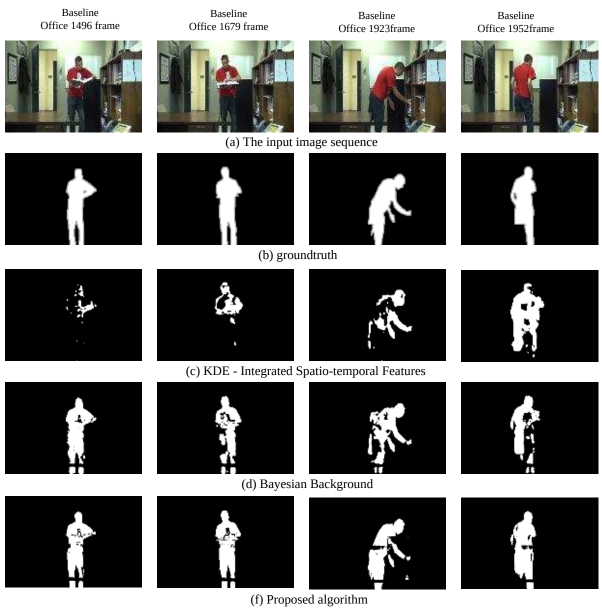
$$B^t = I^t M^t + B^{t-1}\left(E - M^t\right) \tag{5}$$

Which $\mathrm{E}$ is a unit matrix, $M^t = \begin{cases} 1, T^t < 0 \\ 0, T^t \geq 0 \end{cases}$, $M^t$ recording sign change of time matrix $T^t$, $T_i^0 = \mathrm{O}$.

## Results and Discussion

The simulation objects use change detection database updated in 2014 [3], experimental subjects have four image sequences, namely Baseline Office, Baseline Pedestrians. The simulation results compare the results of KDE Features algorithm [6] with Bayesian Background algorithm [7] in quantitative performance.

Baseline Office image sequence constituted by 2050 image. The image sequence is the scene of images of indoor office, the scene contains the target person to go and out, intermittent opening book and similar color between target and background, the test results obtained by the image sequence shown in Fig. 1. The first line in Figure 1 represents the input image sequence, the second line is the hand-labeled ground truth, the third to the fifth rows are the test results of KDE algorithm based on temporal and spatial characteristics, Bayesian Background algorithms and proposed algorithm.



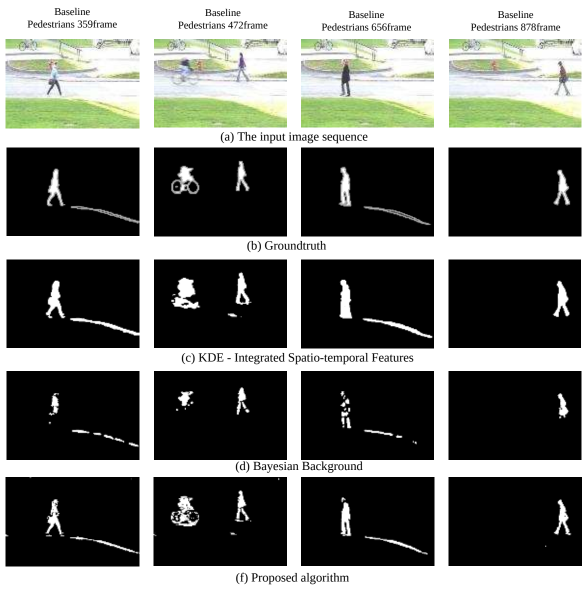




Fig. 1 Contrast results of Baseline Office image sequence

Fig. 2 Contrast results of Baseline Pedestrians image sequence

Baseline Pedestrians image sequence composed of 1099 images. The image sequence is the scene of images of outdoor pedestrian, the scene contains the pedestrian, moving objects at different speeds, the light gradient and shadow gradient, the detection result obtained by the image sequence as shown in Fig.2.

As can be seen from Fig.1 and Fig.2, the test results of KDE algorithm to moving targets for intermittent are unsatisfactory, the results appear missed a lot of target pixels and there have been many internal voids within the target, the change region is not complete. Because the algorithm selects only partial information for spatial and temporal characteristics, it is lack of background information on long-term changes, when the target residence longer, the algorithm based on time-domain characteristics within a small range is difficult to separate goals and background. The detection results obtained by the Bayesian Background algorithm have good effect and a certain degree of shadow inhibitory effect, but the target edges are not smooth enough. There are some internal voids in the detection targets. The algorithm uses a Bayesian learning mechanism to establish a multi-layer background model, because of the diversity of scene mode, the number of layers is limited by a fixed threshold. The algorithm has no high flexibility. In addition, the algorithm in the case of multiple targets repeatedly missed, and showed the capability to detect interior light areas is weak.

In order to objectively evaluate proposed algorithm, using Recall, Precision and F-measure metrics for the three algorithms to be compared, the comparing results shown in Tab. 1.

Tab. 1 Change detection method comparison of Office and Pedestrians image sequence

| Algorithm | Baseline_Office | | | Baseline_Pedestrians | | |
|---|---|---|---|---|---|---|
| | Recall | Precision | F-Measure | Recall | Precision | F-Measure |
| KDE–Spatio-temporal | 0.3036 | 0.8154 | 0.4425 | 0.9972 | 0.7372 | 0.8477 |
| Bayesian Background | 0.8737 | 0.9681 | 0.9185 | 0.6581 | 0.9628 | 0.7818 |
| Proposed algorithm | 0.9114 | 0.9495 | 0.9301 | 0.9934 | 0.8094 | 0.8920 |

As can be seen from Tab. 1, the overall performance F-measure of the proposed algorithm is superior to the other two algorithms, but inadequate in terms of precision.

## Conclusion

In this paper, a change detection based on the belief propagation algorithm is proposed. The belief propagation iterative updates the pixel information among all the pixels, then use the spatial and temporal information of input image sequence to calculate the amount of information for each pixel, by comparing the degree of correlation between the pixels to effectively detect change targets. Simulation results show that the belief propagation algorithm can effectively deliver information in spatial and temporal, the algorithm which can adapt to the complex scenarios, simulation results fully verify the validity and reliability.

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