LPT Optimization Algorithm in the Nuclear Environment Image Monitoring

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Abstract—**Image analysis is an important means of the the nuclear environment monitoring. In this paper, a novel moving target detection called Local Trinity Patterns which is based on Local Binary Patterns algorithm is presented, Based on The standard LBP proposed by Ojala3, it mainly captures the texture information, and in some circumstances it results in misidentification. The proposed LTP feature, in contrast, captures the gradient information and some texture information. Moreover, the proposed LTP are easy to implement and computationally efficient, which is desirable for real-time applications. Experiments show that the algorithm is effective, can significantly improve the nuclear environment detection performance and produce state of the art performance.**

Index Terms—**moving target detection, local trinity patterns, image analysis, Environmental monitoring**

I. INTRODUCTION

Monitoring of discharges nuclear site operators are required to control the amount of radioactivity released into the environment. The national regulator puts controls on the amount and type of radioactivity released into the environment, including imposing upper limits on radioactive discharges. The national regulators require nuclear facility operators to assess the potential radiological impact through regularly monitoring of the environment surrounding the nuclear site. In addition to this monitoring, national radioactivity monitoring programmed are carried out by state bodies such as the national regulators or national environmental laboratories. Environmental monitoring programmer may include measurement of general radiation levels (called ‘ambient dose’) as well as radioactivity levels in air, soil, vegetation, food and water[1-2].

The ability to detect moving target in images has a major impact on applications such as video surveillance, smart vehicles, robotics. Changing variations in moving target such as clothing, combined with varying cluttered backgrounds and environmental conditions, make this problem far from being solved[4-5].

The proposed method has a simple flow: every pixel at every frame is encoded as a short string of ternary digits(trits) by a process which compares this frame to the previous and to the next frame. The encoding process itself is based on comparing nearby patches, in a manner inspired by the self-similarity approach. For every pixel of every frame, a small patch centered at this pixel is compared to shifted patches in the previous and in the next frame. In a manner pertaining to the Local Binary Pattern approach, one trite of information is used to describe the relative similarity of the two patches to the patch in the central frame: the shifted patch in the previous frame is more similar to the central one, the patch in the next frame shifted by the same amount is more similar, or both are approximately comparable in their similarity.

II. COMPARISONS OF MOVING TARGET DETECTION METHOD

Target detection is divided into "background subtraction" technologies and detection methods based on target features, "Background subtraction" technology is the first to obtain different patterns of moving target , more stable, not easily changed background image , and then extract the target area by comparing the current image with the background image. Detection methods based on target features, is to use the information of the target features (such as shape, color, texture, motion information, etc.) ,it is the method of extracting the target area in each frame of the video sequence .These rules are based on background features of the scene, or the priori knowledge of target feature , they come from specific requirements of varieties application. Viewing from the published literature at home or abroad, the main methods of moving object detection include optical flow method, temporal difference method and background difference

Manuscript received date: April 20,2012;revised date:
Supported by the grant from Scientific research plan projects of Jiangxi Education Department(No. GJJ11495) and Key Laboratory of Nuclear Resources and Environment (East China Institute of Technology) of Ministry of Education of China(No. 101112).
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doi:10.4304/jsw.8.3.659-665

method. However, each algorithm has advantages and disadvantages, there has not a generic algorithm. Therefore, this article develops a comprehensive study by dividing moving target detection method into " background subtraction " technologies and detection methods based on target features,and explores the methods of video target detection based on the specific target.

A." Background Subtraction" Technology of Moving Target Detection

"Background subtraction" technologies include four steps : preprocessing, background modeling, foreground detection and post-processing. Preprocessing is a simple video data in space or time filtering in order to eliminate camera noise and transient noise; Background modeling is to build background image or to represent the background by constructing a model, this is the heart of various Background subtraction algorithms; Foreground detection is the threshold segmentation, refers to using the differences of the current video frame and the background model to detect the pixels in foreground region ; Post-processing is to remove the pixels which do not belong to the real moving target in foreground region, in order to obtain the interested target region. Eliminating noise and shadows are all belonging to post-processing.

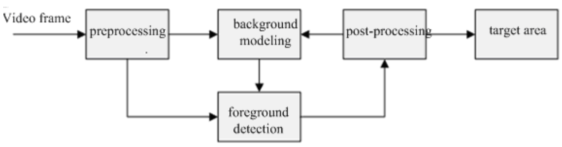


Fig. 1 Principle of background subtraction technology

(1) Temporal Difference Method

Temporal difference method [1] (Temporal Difference Method) uses the difference from the current two frame or the current frame in video sequence with a frame before to extract the movement area. The method by using the t-1 video frame directly as the t background frame is known as Frame Difference method (Frame Difference), (1) gives the formula of background subtraction of the frame difference method , Ta is the pre-specified threshold, the pixels meet (1) belong to the foreground area.

$$|I_t(x,y)-I_{t-1}(x,y)|>T_a \tag{1}$$

Temporal difference method has a strong ability to adapt to scene changes, the background does not accumulate over time and the speed of updating is fast. But because it gets the two pixels in the same location, therefore, it may not be able to detect relatively large, the same color pixels within the moving target, as well as produce empty phenomenon in internal of the moving target. Therefore, in order to get good performance, the selection of background frame must take into account the speed and frame rate of moving target . For fast moving target, background frame should be close to the current frame , even the before one, or there is likely to detect the same target as the two targets.

(2) Median filtering method

As the Average filter and median filter [2] [3] (Average / Median Filtering) have the same theories, so they are classified as a class, which are the most used method to build up a background image. The main idea of algorithm is first to create a Video stream sliding window using to cache L sheets of video frame, and then takes the average or median value of pixels with the position in all the video frame in buffer as the value of the pixel in background. (2) and (3) show the formulas of average filter and median filter to build up background model , which take the median value for the operation, (4) gives the background subtracion formula, Tb as pre-given threshold, the pixels meet (4) belong to the foreground area.

$$B_t(x,y)=\frac{1}{L}\sum_{i=1}^{L}I_{t-i}(x,y) \tag{2}$$

$$B_t(x,y)=median(I_{t-1}(x,y),...,I_{t-L}(x,y)) \tag{3}$$

$$|I_t(x,y)-B_t(x,y)|>T_b \tag{4}$$

Obviously the average filter and median filter require L times frame size of memories, they suit the scene target which is not large and continuous movement. For detecting large and slow moving target , which requires to increase the sliding window. To reduce the memory, another improved method called run-time average method (Running Average), the idea is to introduce the learning rate λ, which reflects the response from background image to the scene changes , λ usually takes 0.03, the lower the λ is , the less changes in prospects will affect the background, (5) gives the formula for building up its background model.

$$B_t(x,y)=\lambda I_{t-1}(x,y)+(1-\lambda)B_{t-1}(x,y) \tag{5}$$

(3) W4 method

W4 method [4] record the maximum brightness values $I_t^{max}(x,y)$ 、the minimum brightness value $I_t^{min}(x,y)$ and the maximum value of brightness difference $D_t(x,y)$ between two adjacent frames of pixel in the period of time in the same position, by observing the current video sequence in near period of time.Then, we can use these three values to represent the background model.

Then $|I_t(x,y)-I_t^{max}(x,y)|>D_t(x,y)$ or $|I_t(x,y)-I_t^{min}(x,y)|>D_t(x,y)$ as foreground pixels.

$W4$ method can detect the multi-moving targets in outdoor scenes, but only adapt to light conditions that slowly changed, but it is more sensitive to light background mutations and leaves disturbances , and is not suitable for detection of slow moving target .

(4) GMM(Gaussian Mixture Model)

For the outdoor environment, for often existing shaking leaves (tree trunk), all these conditions make the background that is not completely static. For example, in the case of absence of moving target, to the pixels in the same location in the video sequence , some frames express the ground, but in some other frames express leaves. Such background model can use Gaussian mixture model GMM (Gaussian Mixture Model) to model. Grimson and Stauffer gives the principle of GMM, the model used K Gaussian to statistic the brightness value $\{X_1, X_2, ..., X_t\}$ of pixels in the same location in the current t frame, then it can get the probability density function of the pixel brightness values in the current frame :

$$P(X_t) = \sum_{i=1}^{K} \omega_{i,t} . \eta(X_t, \mu_{i,t}, \sigma_{i,t}^2) \quad (6)$$

Among the function, $\eta(X_t, \mu_{i,t}, \sigma_{i,t}^2)$ expresses the i Gaussian distribution in t moment(simplified $\eta_{i,t}$), $\omega_{i,t}$ expresses $\{X_1, X_2, ..., X_t\}$ rate that falls the first i of Gaussian distribution $\eta_{i,t}$, $\mu_{i,t}$ and $\sigma_{i,t}^2$ are expectations and variance for the Gaussian distribution. In order to express conveniencely, we assume $\omega_{i,t} / \sigma_{i,t}$ ($i = 1, 2, ...K$)that are arranged in descending order. The model has two important parameters α and H : $1/\alpha$ is sample numbers that train $P(X_t)$ in maximum sample space, $\alpha = 1/t$, H is used to determine the distribution of B as the background model.

$$B = \arg\min_b (\sum_{i=1}^{b} \omega_{i,t} > H) \quad (7)$$

To each new sample X_{t+1} of the pixel,we must judge the existing the K pixels with the Gaussian distribution in which it can match. If $|X_{t+1} - \mu_{i,t}| \le 2.5\sigma_{i,t}$, then X_{t+1} and $\eta_{i,t}$ match. If X_{t+1} does not match any one of the former s Gaussian distribution, but matches the $s+1$ Gaussian distribution,then $M_{s+1,t+1} = 1$ and $M_{i,t+1} = 0$ ($1 \le i \le K$ 且 $i \ne s+1$),and the $s+1$ Gaussian distribution updates its weights, the expected value and variance by the following formula.Others update only theirs weights ,but expected value and variance not changed.

$$\omega_{i,t+1} = (1-\alpha) \cdot \omega_{i,t} + \alpha \cdot M_{i,t+1} \quad (8)$$

$$\mu_{i,t+1} = (1-\rho) \cdot \mu_{i,t} + \rho \cdot X_{t+1} \quad (9)$$

$$\sigma_{i,t+1}^2 = (1-\rho) \cdot \sigma_{i,t}^2 + \rho \cdot (X_{t+1} - \mu_{i,t+1})^2 \quad (10)$$

$$\rho \approx \alpha / \omega_{i,t+1} \quad (11)$$

If X_{t+1} and the K Gaussian distribution do not match, then ω / σ the exprected value of minimum Gaussian distribution $\eta_{K,t+1}$ is substituted by X_{t+1} and variance sets a larger value, the weight sets a smaller value. According to equation (7) B distribution,we know $\eta_{1,t}, \eta_{2,t}, \cdots, \eta_{B,t}$ obey the Gaussian distribution of the background model, so X_{t+1} matches any one ,then it belongs to the background area, or belongs to the foreground area.

GMM is sutable to disturbances background scene that often exists leaves (tree trunk) outdoor, but its convergence speed is very slow, and the time complexity is high.Improved model from the convergence rate [6] [7], can only improve the initial convergence speed, since the initialized model is independent with the Gaussian mixture model ,in the process of target detection after initialization , when the light mutation changed background, these improved model effects less to the convergence speed of the Gaussian mixture model .Improved model in time complexity that can reduce the time complexity mainly uses adaptive of each pixel corresponding to the number of Gaussian distribution to adjust.

B. Moving Target Detection Methods based on Target Features

In addition to "background subtraction" technology, we can also use the feature information of the target to detecte moving target, these features usually include color, texture, edge, shape and motion information. Moving targets in video sequences are usually different from the disturbanced motion ,such as leaves (tree trunk) and other target motion. so we can use the motion information in video image sequences to detecte the target.Optical flow method (Optical flow) is commonly used . Optical flow is generally used to describe successive motion the point features in frames. Motion segmentation based onOptical flow use the features of vector stream of moving targets over time to detect the changed area in image sequence .

Moving target detection methods based on Optical flow method uses the optical flow features that a moving target changes over time. Its advantage is albe to detect the independence moving target, without konwing priorly any knowledge of scene information , and it can also be used for the case of camera motion. Its disadvantage is computationally intensive, and it is difficult to apply to real-time scenaries. Optical flow model shown in Figure 2.

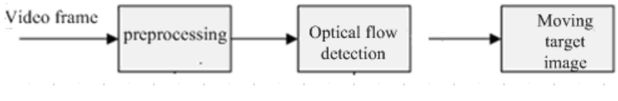


Fig. 2 Model of optical flow

The basic method is as follows: record gray value $P(x, y, t)$ of the point (x, y) on the image at the t time, this point's motion from time $t + \Delta t$ to $(x + \Delta t, y + \Delta t)$, so at the time $t + \Delta t$ record gray value $P(x+\Delta t, y+\Delta t, t+\Delta t)$ of the point on the image, assuming it's value equal to $P(x,y,t)$,that is:

$$P(x+\Delta t, y+\Delta t, t+\Delta t) = P(x,y,t) \tag{12}$$

Start at the point (x,y,t) with Taylor's formula using the type (3.12) on the left , the quadratic terms of the brief was to:

$$P(x,y,t) + \frac{\partial P}{\partial x}\cdot\frac{\Delta x}{\Delta t} + \frac{\partial P}{\partial y}\cdot\frac{\Delta y}{\Delta t} + \frac{\partial P}{\partial t} + \mathrm{O}(dt^2) = P(x,y,t)$$
(13)

record:

$$\mu(x,y,t) = \frac{\Delta x}{\Delta t} = \frac{dx}{dt} \tag{14}$$

$$v(x,y,t) = \frac{\Delta y}{\Delta t} = \frac{dy}{dt} \tag{15}$$

Among the formula , $\mathrm{O}(dt^2)$ represents high-end items who's order is greater than or equal to 2, eliminate $P(x,y,t)$ and ignore $\mathrm{O}(dt^2)$,we can get the optical flow constraint equation:

$$\frac{\partial P}{\partial x}\cdot u + \frac{\partial P}{\partial y}\cdot v + \frac{\partial P}{\partial t} = 0 \tag{16}$$

The target detection method based on the target's features usually involves matching, optical flow analysis and other complex operations.It is difficult to apply to real-time processing, and it usually depends strongly on a priori knowledge.That will cause robust methods be affected. "Background subtraction" technology can only identify those changed pixels,compared with target detection methods which based on the target features. "Background subtraction" technology can provide better detection results, and small time complexity.Therefore, in order to achieve real-time automatic detection of moving targets, wd should chose "Background subtraction" technology or use it mainly. And we can use the method by integrating a priori knowledge of target features to finish detecting and extracting moving target.

III. FOUNDATION OF LBP ALGORITHM

The local binary pattern (LBP) operator is defined as a gray-scale invariant texture measure, derived from a general definition of texture in a local neighborhood. Through its recent extensions, the LBP operator has been made into a really powerful measure of image texture, showing excellent results in many empirical studies. The LBP operator can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Perhaps the most important property of the LBP operator in real-world applications is its invariance against monotonic gray level changes. Another equally important is its computational simplicity, which makes it possible to analyze images in challenging real-time settings. The LBP method and its variants have already been used in a large number of applications all over the world[3-5].

The basic idea for developing the LBP operator was that two-dimensional surface textures can be described by two complementary measures: local spatial patterns and gray scale contrast. The original LBP operator (Ojala et al. 1996) forms labels for the image pixels by thresholding the 3 x 3 neighborhood of each pixel with the center value and considering the result as a binary number. The histogram of these 28 = 256 different labels can then be used as a texture descriptor. This operator used jointly with a simple local contrast measure provided very good performance in unsupervised texture segmentation (Ojala and Pietikäinen 1999). After this, many related approaches have been developed for texture and color texture segmentation.

The standard version of the LBP feature of a pixel is formed by thresholding the neighborhood of each pixel with the center pixel's value. Let be the center pixel graylevel and (i=0,1,…7) be the graylevel of each surrounding pixel. If is smaller than ,the binary result of the pixel is set to 0, otherwise to 1. All the results are combined to a 8-bit binary value. The decimal value of the binary is the LBP feature. See Fig.1for an illustration of computing the basic LBP feature.

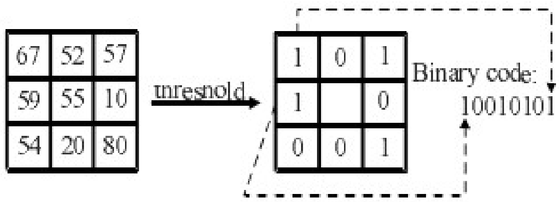


Fig.3. Illustration of the basic LBP operator

In order to be able to cope with textures at different scales, the original LBP has been extended to arbitrary circular neighborhoods by defining the neighborhood as a set of sampling points evenly spaced on a circle centered at a pixel to be labeled. It allows any radius and number of sampling points. Bilinear interpolation is used when a sampling point does not fall in the center of a pixel. Let $LBP_{p,r}$ denote the LBP feature of a pixel's circular neighborhoods, where r is the radius of the circle and p is the number of sampling points on the circle. The $LBP_{p,r}$ can be computed as follows:

$$LBP_{p,r} = \sum_{i=0}^{p-1} S(g_i - g_c)2^i, S(x) = \begin{cases} 1 \text{ if } x \ge 0 \\ 0 \text{ otherwise.} \end{cases} \tag{17}$$

Here g_c is the center pixel's graylevel and g_i (i=0,1,….,7) is the graylevel of each sampling pixel on the circle. See Fig.2 for an illustration of computing the LBP feature of a pixel's circular neighborhoods with $r=1$ and $p=8$. Ojala et al. proposed the concept of "uniform patterns" to reduce the number of possible LBP patterns while keeping its discrimination power. An LBP pattern is called uniform if the binary pattern contains at most two bitwise transitions from 0 to 1 or vice versa when the bit pattern is considered circular. For example, the bit pattern 11111111(no transition),00001100(two transitions) are uniform whereas the pattern 01010000(four transitions) is not. The uniform pattern constraint reduces the number of LBP patterns from 256 to 58 and is successfully applied to face detection in [3,5].

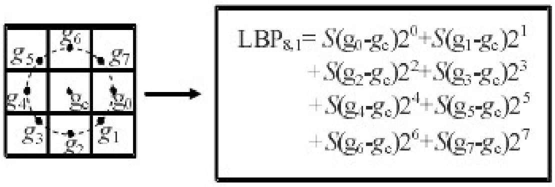


Fig.4. The LBP operator of a pixel's circular neighborhoods with r=1, p=8

IV. LTP Algorithm Structure And Process

Although the local texture character can be described efficiently and the whole image character description can be easily extended[7-9]. Due to the single transform and mapping, namely in the calculation of mapping around the neighborhood point and center pixel size relations, only consider threshold value 0, when the value of surrounding pixel points minus the center point pixel is greater or equal to 0, denoted by 1, or 0 vice versa. Thus the local texture character can be described efficiently, but focus only on texture background environment detail varies, in some dramatic changes will brought by mistake, and these details identify a plethora of information for classification may lead to a information redundancy or fitting. Thus in order to make LBP less sensitive to noise, particularly in near-uniform image regions, Tan and Triggs[5-7] extended LBP to 3 valued codes, called local trinary patterns(LTP). If each surrounding graylevel g_i is in a zone of width $\pm t$ around the center graylevel g_c, the result value is quantized to 0. The value is quantized to $+1$ if g_i is above this and is quantized to -1 if g_i is below this. The $LTP_{p,r}$ can be computed as:

$$LTP_{p,r}=\sum_{i=0}^{p-1}S(g_i-g_c)3^i, S(x)=\begin{cases}1 \text{ if } & x\geq t\\ 0 \text{ if } & |x|<t\\ \text{-}1 \text{ if } & x\leq t\end{cases}, \quad (18)$$

Here is a user-specified threshold. Fig.3. shows the encoding procedure of LTP. For simplicity, Tan and Triggs[5]used a coding scheme that splits each ternary pattern into its positive and negative halves as illustrated in Fig.4,treating these as two separate channels of LBP codings for which separate histograms are computed, combining the results only at the end of the computation.

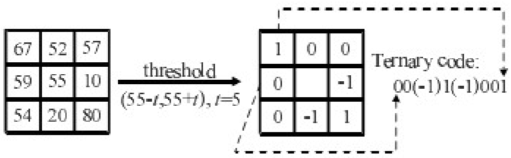


Fig.5. Illustration of the basic LTP operator

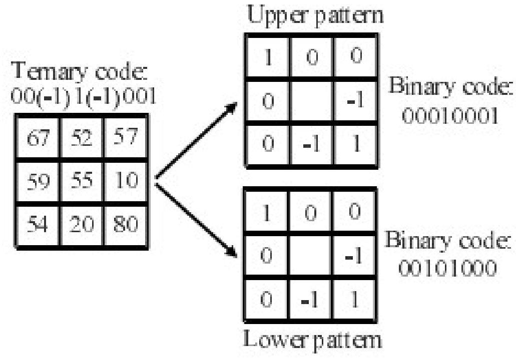


Fig.6. Splitting the LTP code into positive and negative LBP codes

V. Encoding Motion In The Frame

The various flavors of Local Binary Patterns use short binary strings to encode simple properties of the local micro texture around each pixel[9,10.] Here we propose an LBP like descriptor which captures the effect of motion on the local structure of self-similarities. Consider a small image patch moving from left to right. During its motion it will pass through a certain image location $(x-\Delta x, y)$ at time $t-\Delta t$, and continue to location (x, y) to the right at time t .This motion is probably going to induce image similarity between a patch of appropriate dimensions centered at location $(x-\Delta x, y)$ at time $t-\Delta t$ and the patch with the image center (x, y) at time t.

By itself, the increase of image similarity caused by the motion depends on the intensities of the moving patch and the appearance of the rest of the image. It may be difficult to distinguish between similarity caused by motion and similarity caused by similar static textures, without incorporating further statistics. Here we suggest to examine the similarity between a patch centered at (x, y) at time t and the patch around $(x-\Delta x, y)$ at time $t+\Delta t$ as the background statistic. One trit is used to encode whether one of the two similarities is significantly higher than the other or whether the two similarities are approximately the same. If the previous frame patch is more similar to the central patch -a value of -1 is assigned, if the patch in the next frame is more similar -a value of +1 is assigned. If both similarities are within a predefined threshold from each other, a value of 0 is assigned.

Note that in the absence of significant image motion the similarities of the patch at center location (x, y) at time t to the patches at location $(x-\Delta x)$ at times $t-\Delta t$ and $t+\Delta t$ are about equal, and the value of the encoding trit is zero. This implies that no appearance information is encoded in the absence of motion.

The full 8 trit encoding is described in Figure 5. Patches at eight shifted locations at times $t-\Delta t$ and $t+\Delta t$ are compared to a central patch at time t to produce 16 similarities. Due to its computational simplicity the SSD(sum of square differences)score as the basic distance between the patches. The lower the SSD score, the larger the similarity.

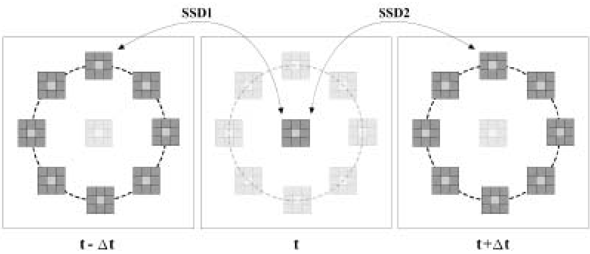
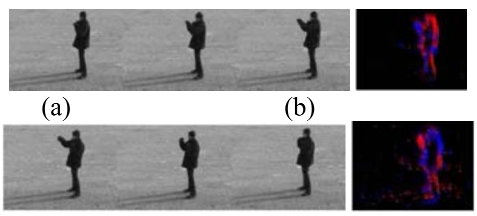


Fig.7. An illustration of the encoding process.

For each of 8 different locations at time $t-\Delta t$ and the same locations at time $t+\Delta t$ SSD distances of 3 × 3 patches to a central patch at time t are computed. SSD1 and SSD2 are computed patch distances at one of the eight locations. One trinity bit is used to encode if $SSD1 < SSD2 - TH$ (value of -1), $|SSD1 - SSD2| < TH$ (value of 0),or $SSD2 < SSD1 - TH$ (value of +1). We define gray values are between 0 and 255,and TH is set to 0.097. Also Δt is set to 3 frames, and the patches are spread around as close as possible using integer values to distance of 4 pixels from the center of the central patch.

VI. Simulation and Analysis

We perform the experiments under Mat lab platform. The first group image is from one boxing sequence of the KTH dataset, the rest are from two typical AVI file: intelligent_room.avi, highway_raw.avi, the detection result are as follows:



(a) (b)

(c) (d)

Fig.8. Two groups of nearby frames from one boxing sequence of the KTH dataset.(a) Three frames from the beginning of the boxing motion.(b) One trinary digit encoding of the sequence in (a). Blue pixels indicate patches which are significantly more similar to the patch on the left in the next frame than to the patch on the left in the previous frame. Red indicates patches that are more similar to the patch of the previous frame. (c) Three frames from the end of the boxing motion, in which the hand returns. (d) The analog trit encoding of (c)

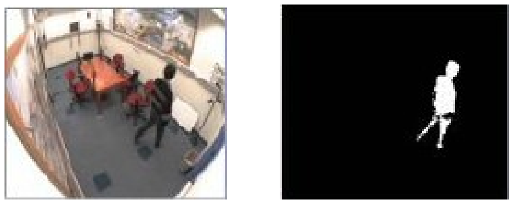


Fig.9. intelligent_room

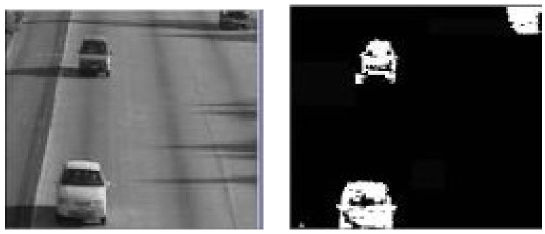


Fig.10. highway_raw

From the result, we can see this method aims to extract features of a target for moving targets detection, and have a good combination of local texture information and edge mutations gradient information so that improve the measuring accuracy.

VII. Conclusion

In short, moving target detection is the most basic core technology in intelligent video surveillance system , which is the basic of the follow-up advanced processing, such as behavior analysis, event detection, behavior recognition, intelligent pre-warning , the video image compression encoding semantic and other high video processing and application-level understanding. At the same time, it is the key of video surveillance technology automatically and real-time applications.

This article present a novel moving target detection called Local Trinity Patterns which is based on Local Binary Patterns algorithm, the detection result shows that it can combine local texture information and edge mutations gradient information, and can significantly improve the detection performance and produce state of the art performance.

Acknowledgment

This work was supported by the grant from Scientific research plan projects of JixiangXi Education Department (No. GJJ11495) and Key Laboratory of Nuclear Resources and Environment (East China Institute of Technology) of Ministry of Education of China (No. 101112).

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2. A new three-Dimensional Reconstruction Algorithm for Micro-surface based on image fusion, finished in 2008, 2009 International Conference on Industrial and Information Systems, 2009.5

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