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THE OCCLUDED MULTI-TARGET TRACKING BASED ON LOCAL ANALYSIS OF GRAY&EDGE

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Abstract. *For the cross-occlusion issue in multi-target tracking, an adaptive multi-target tracking algorithm based on local analysis of Gray&Edge (G&E) is proposed in this paper. The strong gradient direction around the edge and the corresponding gray value of the inner pixel point are considered as the tracking feature to establish the block model. When occlusion occurs, cross-occlusion is firstly analyzed by Kalman prediction to screen out the effective local features for tracking, and then the overall information is predicted by the local features. The proposed algorithm is tested on tracking multi-target in some fixed monitor scenes, and the experiment results demonstrate that the proposed algorithm can effectively solve the cross-occlusion problem in multi-tracking.*
Keywords: Cross-occlusion multi-tracking, Local analysis, G&E feature

1. **Introduction.** Target tracking [1,2] technology has become one of the hot topics in computer vision, and is a novel technique blended with image processing, pattern recognition and automatic control. It has been widely used in video surveillance [3,4], human-computer interaction, product testing, medical diagnostics and many other fields. However, the progress of the technology is closely related to the research results of the physiological characteristics of human perception, so a robust object tracking algorithm must be considered to solve a lot of difficult issues, such as illumination, size and other changes, particularly occlusion occurrences between targets, which can result in the loss of information so that the tracking becomes more difficult.

To solve the occlusion problem, scholars have done a lot of researches and made a variety of effective algorithms in recent years, for example, center-weighted method [5], probability method [6], learning model [7] and block model [8-13]. Center-weighted method means that the center region of the target has a larger weight, but its edge areas share smaller weights. When a slight occlusion occurs, it has less impact on the result since the edge has small weight. However, if the occlusion is serious, the failure of central feature can result in the algorithm to be failed. Probability method is a class of algorithms based on probability analysis and has been used to solve the occlusion problem in multi-tracking, such as particle filter, in which some discrete random sampling points (particles) approximate the probability density function of the state variables to assess the probability of the target's best position for target tracking. Learning model was used to establish the target model by samples learning. By using the integral histogram, Adam et al. [8] established the fixed block model to solve the occlusion problems, but the target's feature was affected by the other obscured targets easily in update procedure. Wang et al. [9] improved the timeliness of the traditional mean shift algorithm by using the block model, but the single feature makes the algorithm not robust. Gunes et al. [10] divided the targets into the head, left upper body, right upper body, left lower body and right lower body according to the proportion of pedestrians, with six common features for tracking; however, the algorithm used too much features and the computation complexity was high, so it is only suitable in single target rather than multi-target. Chang et al. [11] proposed tracking algorithm based on correlation matching characteristics, which used the characteristic analysis of target's gray value to decide either edge feature or block gray feature as the tracking feature. However, since the main research object of this algorithm is rigid object, it is difficult to adapt the changes of size and posture for the algorithm. Zhou et al. [12] established a block model based on edge direction histogram and RGB color histogram, so the algorithm has good anti-occlusion ability but it still cannot deal with the target with complete occlusion. In the existing block models, the use of block is varied, including fixed block [8] and flexible block [11,13]. Fixed block divides the target using the fixed template, for example, a grid. However, the flexible block means that the blocks in each frame are changed with the feature, and it is more flexible but difficult to achieve and also very slow.

For characteristic instability problems that appear in the above algorithm, an adaptive multi-target tracking algorithm based on local analysis of G&E features is proposed in this paper. A fixed block model based on the combination of the direction of strong gradient around the edge and the gray values of the corresponding inner pixel points is established and then the Kalman prediction to predict overall by local information is applied to achieving tracking.

This paper is organized as follows, Section 2 is an introduction about the established model, and Section 3 is the realization of target tracking. Section 4 provides the experimental results and analysis, and Section 5 draws the conclusion.

2. Block Model Based on G&E Feature.

2.1. **Local analysis.** When occlusion occurs, the only valid information about the target is the local information that is unobstructed, so we must use the local information to complete the match on the overall target. Block is the most usual way to describe the local information of the target, since block can obtain some valid information of the target and the effective information is used to achieve tracking target when it is obstructed [8-13]. The block way usually includes fixed block and flexible block. Figure 1(a) shows a flexible block which is changed according to the feature. Adam et al. [8] used the fixed block similar to that shown in Figure 1(b). Because of the quasi-rigid objects (e.g., pedestrians) in occlusion, the local information's position relative to the whole is fixed, so if we use the flexible block, we may break the relationship of position between local and whole. And when occlusion occurs, the unobstructed part always appears in the non-central region. Therefore, when we use Figure 1(b)'s method it will inevitably lead to tracking failure. Based on the above analysis, we choose the block way in Figure 1(c) in this paper.

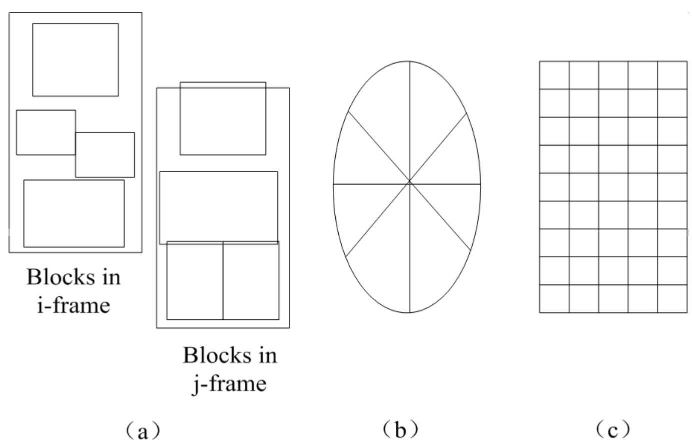

FIGURE 1. Block model

2.2. **G&E feature.** Feature selection plays a very important role in target tracking, and it directly affects the performance of the tracking algorithm. In target tracking algorithm, the target can be expressed with different features, such as the color [13], the gradient [11]. However, in the quasi-rigid objects tracking (e.g., pedestrian), the phase difference in the sub-blocks will exist due to the changes of size and shape. As shown in Figure 2, when the size or position of the sub-block is changed, the feature of the sub-block will produce the phase shift. And if we choose the color or gray value as the tracking feature, we will calculate all pixels in the sub-block, so the phase shift will lead that the feature becomes rather unstable and result failure. While the edges only occupy a part of the sub-block, the phase shift has less effects on overall statistical results, so the feature of sub-block is relatively stable.

Since the number of edges is small in edge detection, the statistical results will be unstable. Therefore, we choose the strong gradient as the tracking feature in block model after threshold processing. As shown in Figure 3, when we calculate the gradient of target in sub-block, the gradient information of the background will be counted also, so it will produce serious impact on the statistical results. However, we observed that when the target moves in the background, although the background in the external of edge constantly changes, the gray value of the target is relatively stable. Therefore, in order to make the feature of the target more stable, we go along the strong gradient direction to the search center and pass the number of dis pixels to get an inner point (G), and then combine the gray value of the inner point and the strong gradient direction as G&E feature. And the edges of background have strong randomness, but we can weaken its interference to the target feature by learning and make the G&E feature more stable.

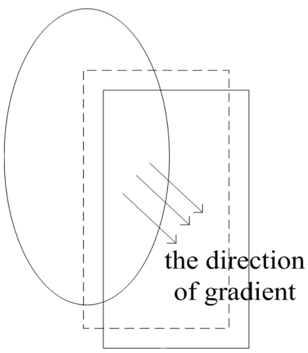

Figure 2. Phase difference

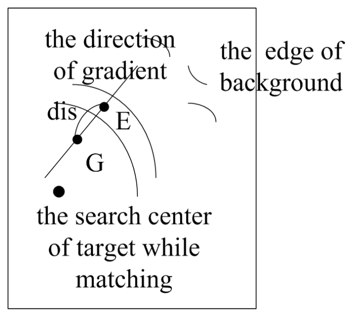

Figure 3. The G&E feature of sub-block

To achieve the tracking algorithm in this paper, feature construction steps are provided as follows.

(1) Firstly, calculate the gradient of the target by Sobel, and then obtain the strong gradients after threshold processing, and the threshold is a third of the largest gradient magnitude.
(2) Go along the strong gradient direction to the search center and pass the number of dis pixels to get an inner point (G), dis usually takes 3 to 5 based on empirical values, and then combine the gray value of the inner point and the strong gradient direction as G&E feature.
(3) Divide the direction of gradient (0 180) and the gray value (0 255) into 8 and 16 levels to analysis.
(4) Quantize the feature of sub-block through the barycenter of the gradient direction histogram and gray value histogram. The feature in construction is shown in Figure 4.

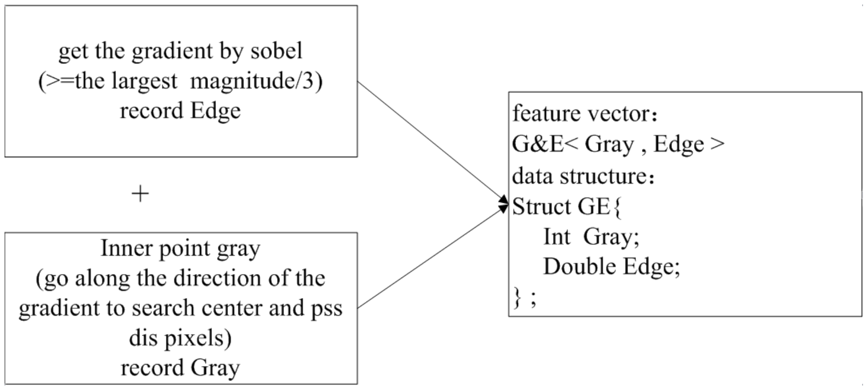

FIGURE 4. Feature construction

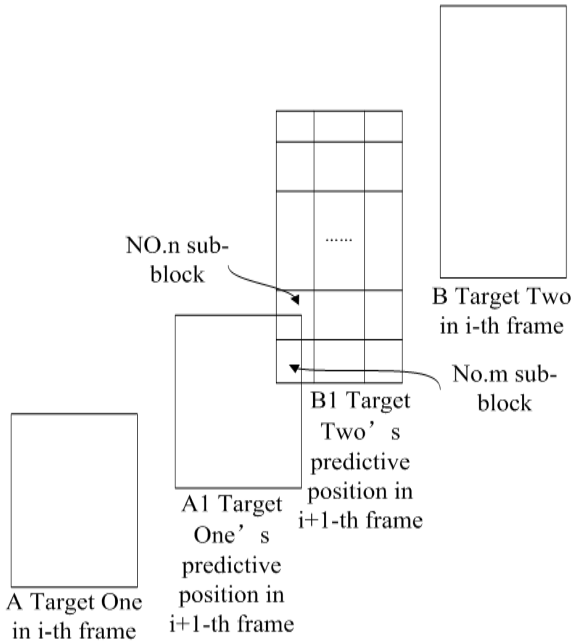

FIGURE 5. Position prediction

2.3. **Sub-block selection.** When occlusion occurs between the targets, the information of the occluded part of the target becomes invalid, at this time, using the information for tracking will lead to failure, so sub-block selection is also an important part of the algorithm. In this paper, we study the case of occlusion between single targets shown in Figure 5. When occlusion happens, we can screen out the effective sub-block of the target as local feature by analyzing the occlusion. Firstly, we can predict the target's relative position in next frame using Kalman filter in order to determine whether occlusion occurs between targets or not. As shown in Figure 5, A and B are the positions of target 1 and target 2 in the i-th frame respectively, and A1 and B1 are the predictive position in the $i+1$-th frame by the Kalman prediction. By the principle of perspective and position A1 and B1, we can judge that the m-th and n-th sub-blocks of the two targets are occluded, so when tracking is in the $i+1$-th frame, the two sub-block's feature must be removed. If there is a serious occlusion, almost all sub-blocks are occluded, so we can only get the position by prediction. When three or more targets are occluded, we will all turn into two targets as shown in Figure 5.

3. **Tracking and Matching.** In order to achieve the multi-target tracking algorithm in this paper, we must establish a reasonable framework and tracking strategies based on

the G&E block model. During the video moving, the posture and feature of target are always changed, so we cannot track only according to the feature of previous frame. The feature of single frame is extremely unstable, which easily leads to failure. In order to improve the stability of feature, we learn the feature by calculating mean value of the G&E features of 10 frames before the current frame. However, when occlusion happens, since some local information has lost, we do not need to learn the sub-block's G&E feature. Based on the G&E block model and feature learning, in order to analyze the occlusion, we detect the moving foreground by the Gaussian mixture model [14], and then establish the relationship between detection and the target of previous frame. As shown in Figure 6, we do pairwise analysis on the occlusion and get the valid information by Kalman prediction, and then search target around the moving detection area. Finally, to obtain the target's final position, we need to assess all possible candidates for position. In this paper, we choose Euclidean distance as the assessment criteria: the Euclidean distance between each sub-block is regarded as the assessment result. Generally, the smaller assessment result means the better matching position. In the actual implementation, in order to save computing time, the Euclidean distance without square root is used in this paper.

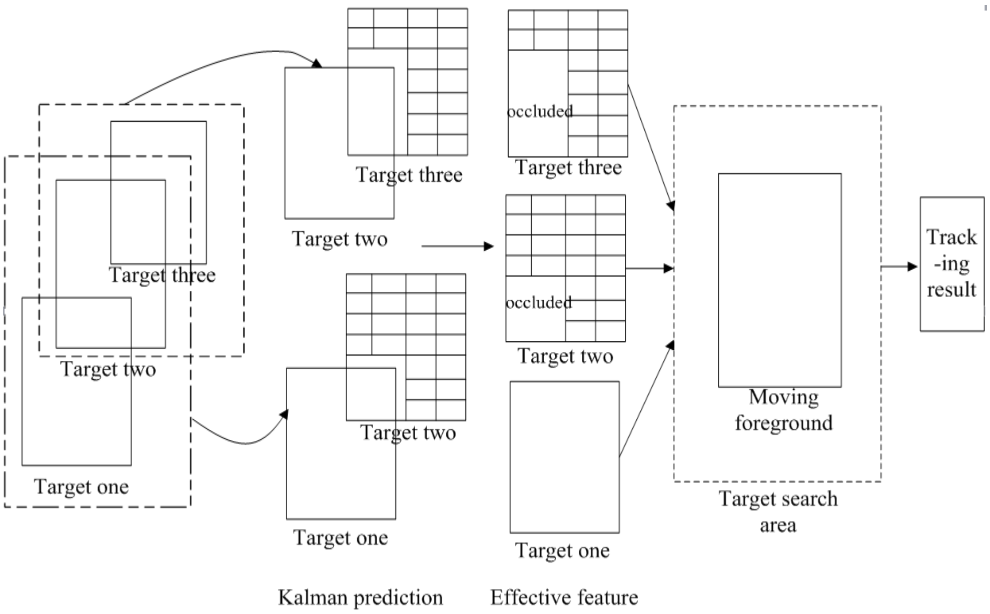

Figure 6. Cross-occlusion tracking

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The algorithm in this paper as follows:
The Multi-target Tracking Algorithm Based on G&E
Program
  Input: Sequence of video frames, F;
  Output: Sequence of video frames with the tracking result, R;
  Begin
    Step1: Extract moving foreground by Gaussian mixture model, fm;
    Step2:
      for each fm do
        if first frame
           Establish new target according fm, T;
           Establish G&E feature of T's every sub-block, TS;
           Update T's kalman, TK;
           Update T's study vector, TSV;
           Output T's tracking result, TR;
        else
```

```
        Study T's size and feature, TSR;
        Establish the relation between fm and T, REL;
        if REL = one to one
        Search T's best match position around T, find the position
        where |TS - search.G&E| is minimum;
        else if REL = one to many
        Screen sub-block by kalman prediction, TSK, and then search
        the Best match position where |TSK - search.G&E| is minimum;
        else
        Establish new Target, T;
        end if
        end if
      end if
Step3: Save and output R;
```

4. **Experimental Results.** In this paper, we have completed the experiment in four scenes, and the experimental results are provided in Figures 7-12. In the experimental

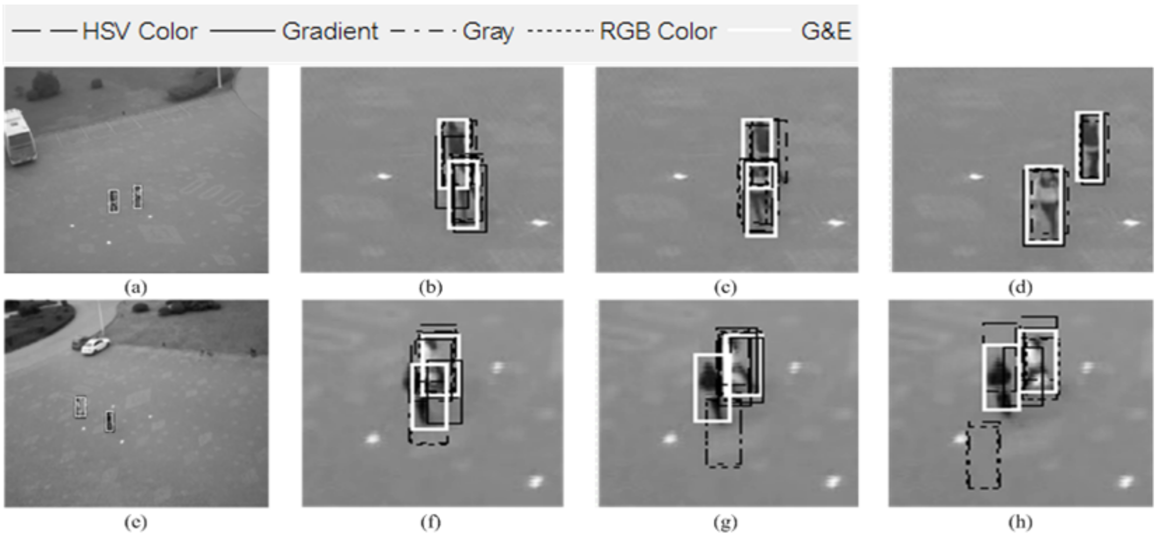

FIGURE 7. Scene one

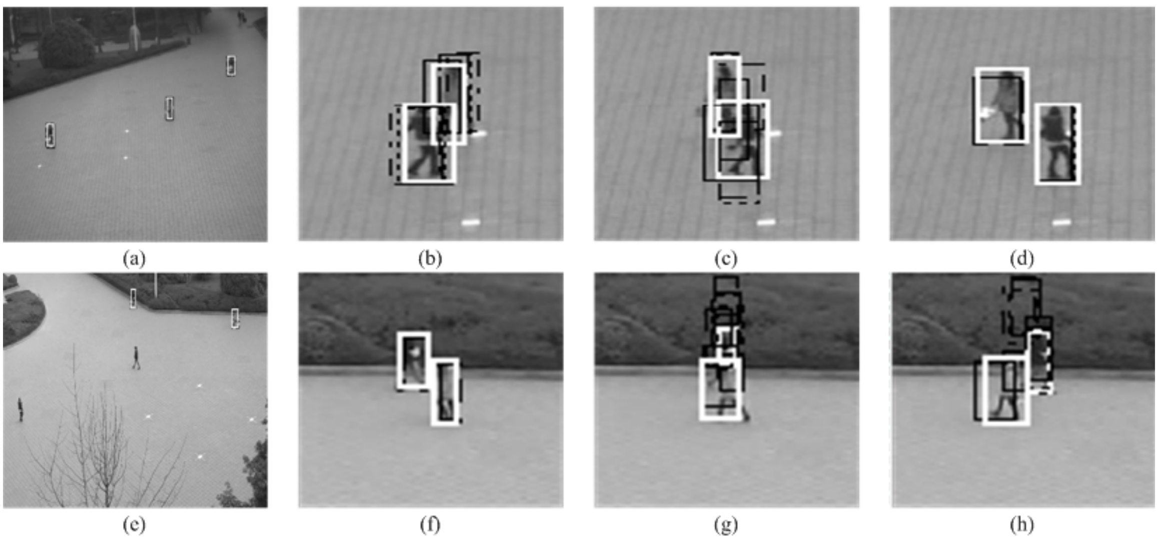

FIGURE 8. Scene two

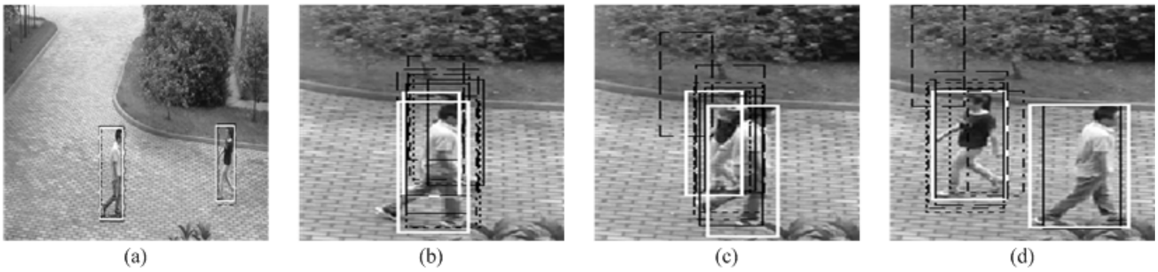

Figure 9. Scene three

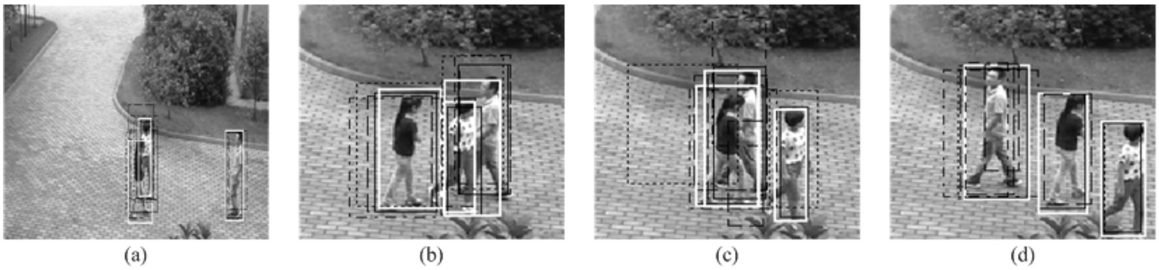

Figure 10. Multi-target (one)

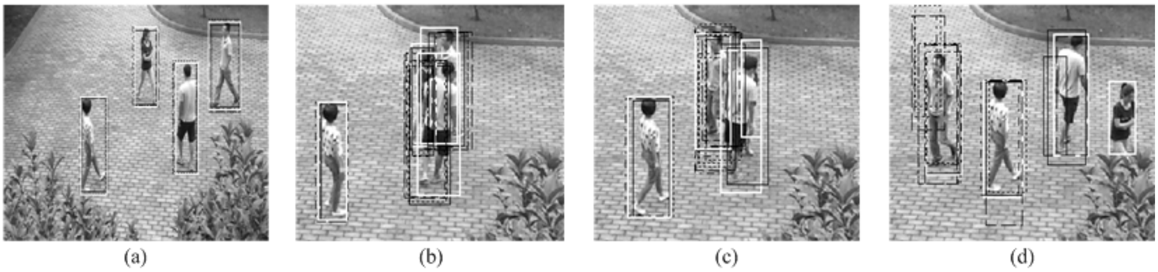

Figure 11. Multi-target (two)

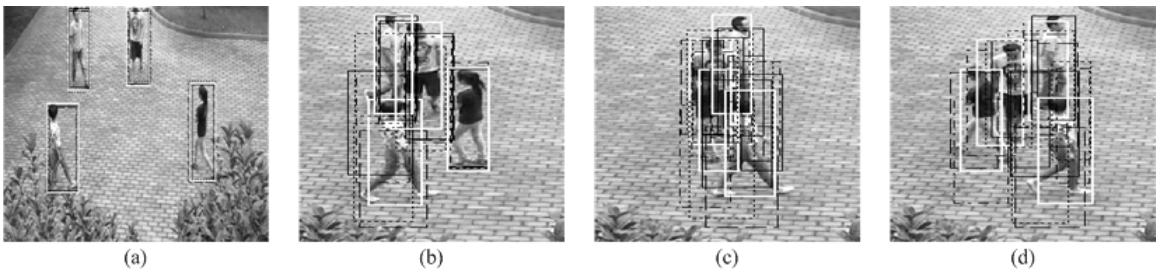

Figure 12. Multi-target (three)

results, the first piece is the actual scene, and the following three are enlarged for easy view. Figure 7 shows the results in scene of the third teaching building: (a)-(d) and (e)-(h) get at the same time with two cameras; due to the purpose of the cameras, in the same weather conditions, (a)-(d) are darker but (e)-(h) are brighter, but in the two data sets the algorithm has got very nice results. Figure 8 gives the results of the fourth teaching building. Figure 9 is in a small corner behind the fifth teaching building. This scene is smaller than the above two scenes and the camera is farther, so the target is bigger. Figures 10-12 are tracking between three and four targets occlusion. The algorithm all has got very nice results in these scenes.

5. **Conclusion.** To solve the cross-occlusion issue in multi-target tracking, an adaptive algorithm based on local analysis was proposed in this paper. We established a reasonable algorithm framework and conducted series experiments on four scenes. Experiment results showed that the algorithm's performance is good on these scenes, and it can solve the issue in some situations. However, the algorithm only plays on the single target that enters the scene, and it is able to handle for the case that more than one target first time enter the scene in parallel. So, our further work is to consider the difficult case.

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