

# An Enhanced Human Activity Prediction at Rainy and Night Times



Manju D, Radha V

**Abstract:** Human activity prediction aims to recognize an unfinished activity with limited motion and appearance information. A generalized activity prediction framework was proposed for human activity prediction where Probabilistic Suffix Tree (PST) was introduced to model causal relationships between constituent actions. Then, each kind of activity in videos was predicted by modeling interactive object information through Spatial Pattern Mining (SPM). This framework mined the temporal sequence patterns. For efficient human activity prediction a Spatio-Temporal Frequent Object Mining (STOM) was proposed in which the spatial, size and motion correlation among objects information were collected along with the temporal information. After the collection of this information, the objects were identified by using Modified Histogram Of Gradient (MHOG) and then the objects were tracked by particle filter technique. The frequent action of detected objects were identified by using Frequent Pattern-growth (FP-growth) which predicted the infrequent action as abnormal human activity in videos. However, MHOG based Object Detection and Tracking-STOM (MHOGODT-STFOM) based human activity prediction is not more effective at night time and rainy time. So in this paper, Enhanced Object Detection and Tracking- STFOM (EODT-STFOM) and Removing Rain Streaks-EODT-STFOM (RSR-EODT-STFOM) are proposed for human activity prediction even at night time and rainy time. In EODT, a modified Contrast Model is used which combined the contrast information and local entropy information to detect object contents present in the current image frame. Then, the objects are tracked by Kalman filter. In RSR-EODT, the rain streaks in the images are removed based on the deep Convolutional Neural Network (CNN). Then the objects are detected and tracked by modified Contrast Model and Kalman filter respectively. After the object detection and object tracking by EODT and RSR-EODT, the frequent actions are obtained by applying STFOM. The frequent actions are considered as normal activities and the infrequent actions are considered as abnormal activities. Thus the proposed EODT-STFOM and RSR-EODT- STFOM methods predict the human activities even at night time and rainy time.

**Keywords :** Human activity prediction, Object detection, Object tracking, Removing rain streaks, Spatio-Temporal Frequent Object.

## I. INTRODUCTION

Many large cities face crime and antisocial behavior problems such as breaking and entering shop windows, fights, vandalism, etc. Even though these cities have video cameras to monitor activities, it is lacking in the automatic analysis of the video data. Such analysis could detect unusual events, such as patterns of running people, converging people or stationary people, and then alert security staff. Due to increasing the amount of video data collected daily by surveillance system [1], the need for automatic systems to detect and recognize the suspicious activity performed by people and objects is also increasing.

Human activity prediction [2] is a probabilistic process of inferring ongoing activities from videos only containing onsets of the activities. The main intention of human activity prediction is to enable early recognition of unfinished activities as opposed to the after-the-fact classification of completed activities. Activity prediction techniques are particularly necessary for surveillance systems which are required to prevent crimes and dangerous activities from occurring. A generalized framework [3] was proposed for human activity prediction by discovering temporal sequence patterns. The interactive object information was modeled through a Sequential Pattern Mining (SPM) where Apriori algorithm was used to find frequent activities.

In order to improve the human activity prediction, a Spatio-Temporal Frequent Object Mining (STFOM) [4] was proposed where spatial, temporal, size and motion correlation among objects were considered. In STFOM, objects were detected by Modified Histogram Of Gradient (MHOG) and the detected objects were tracked by particle method. Finally, Frequent Pattern-growth (FP-growth) was used to find the frequent activities in videos. The frequent activities were considered as normal activities and the infrequent activities were considered as abnormal activities. However, this method is not more effective during night time and rainy time.

So, in this paper human activity prediction methods are proposed to predict the human activities even at night time and rainy time. An Enhanced Object Detection and Tracking- STFOM (EODT-STFOM) is proposed to detect the human activities at the night time. In this method, objects in the videos are detected based on MHOG feature, contrast information and local entropy information. The detected objects are tracked by using Kalman filter because the particle filter is computationally more expensive than Kalman filter. In order to predict the human activity at rainy condition, a Rain Streaks Removal-EODT-STFOM (RSR-

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EODT-STFOM) is proposed. A deep Convolutional Neural Network (CNN) is used to remove the rain streaks in the video. After the removal rain streaks, the objects are detected and tracked for human activity prediction. Finally, FP-growth is applied to find the frequent activities and those are considered as normal activities.

## II. LITERATURE SURVEY

A human activity prediction approach [5] was proposed for temporally weighted generalized time wrapping. In this approach, each activity video was decomposed into a sequence of short video by the local spatial-temporal statistics. Then a temporally weighted generalized time wrapping was developed for the activity prediction problem. Finally, the obtained similarity from temporally weighted generalized time wrapping was integrated with the k-nearest neighbor algorithm to predict the activity class of an input sequence. However, this approach face problem while searching corresponding part between different activity videos which leads to high prediction error.

A human activity prediction [6] method was proposed which predicted human activity by mapping grouplets to Self-Organizing Map (SOM). The detection efficiency was improved by extracting dense spatio-temporal interest points (STIPs) from streaming videos as low level descriptors. A scale-adaptive mean shift method was proposed to find out the grouplet number and it was scaled to each frame adaptively. The located grouplets were successively mapped to Recurrent SOM (RSOM) for learning the sequentiality in videos. In RSOM, a combination of Dynamic Time Wrapping (DTW) and edit distance measure was used which found the dissimilarity between RSOM trajectories. However, it doesn't perform well in noisy environment.

Partial entropy [7] was introduced for detection of abnormal crowd behavior. The partial entropy represented crowd distribution information which was very helpful to detect abnormal behavior. An unstable foreground extraction process was avoided in the partial approach which minimized the computational complexity of abnormal behavior detection. A Gaussian Mixture Model (GMM) was used in this approach which determined the crowd speed information. Both the crowd distribution information and crowd speed information were used to predict the abnormal behavior. However, this approach was not more suitable for complex datasets.

Hierarchical abnormal event detection [8] was proposed for detection of abnormal human activities in the outdoor. A trajectory based abnormal event detection method was processed in the real time outdoor videos. From the video storage server Video On Demand data was taken and a video analysis algorithm was applied on the extracted data to detect the abnormal event. Then abnormal event detection method was explored to confirm the detected abnormal event was triggered by human or not. It reduced false alarm of abnormal event detection. However, it takes high computation time for abnormal event detection.

A unified framework based on deep convolutional neural network [9] was proposed for detection of abnormal behavior in video surveillance system. It solved the problem of separating object entities by human subject detection and

discrimination module. Then, a posture classification module was employed to extract the spatial features. Finally, Long Short Term Memory (LSTM) was proposed as an abnormal behavior detection module. However, this framework is difficult to distinguish the similar pattern motions.

A novel dictionary learning algorithm [10] was proposed for abnormal event detection in video surveillance. A new concept called reference was introduced in sparse representation framework to define the intrinsic event patterns in normal video events. The intrinsic event patterns in normal video events were integrated with sparse representation framework by using a clustering based constraint. In the learned dictionary, normal events can be approximately represented as sparse linear combinations of bases. However, it was failed to use more structural information for abnormal detection which reduced the accuracy of abnormal event detection.

## III. PROPOSED METHODOLOGY

In this section, Enhanced Object Detection and Tracking-Spatio-Temporal Object Mining (EODT-STOM) and Rain Streaks Removal-EODT-STOM (RSR-MHOGODT-STOM) are described in detail for human activity prediction event at night time and rainy time.

### A. Enhanced Object Detection and Tracking-Spatio-Temporal Object Mining

Initially, a patch based training method is applied in the collected videos to learn the normal patterns in video sequence. When a blob sequence does not fit the normal pattern, then it is detected as a candidate sequence. In this process, MHOG feature is used to identify the objects in the videos. For human activity prediction even at night time, a modified contrast model is introduced in object detection process. In the modified contrast model, contrast information and local entropy information of each image patch are combined together and it is used as additional features for object detection. The contrast is defined as the local standard deviation  $\sigma_L$  of the image intensities divided by the local mean intensity  $\mu_L$  and the contrast information  $C_L$  is given as follows:

$$C_L = \frac{\sigma_L}{\mu_L} \quad (1)$$

The local mean intensity  $\mu_L^{(p,q)}$  of a  $(2p+1) \times (2q+1)$  block of pixels is

$$\mu_L^{(p,q)} = \frac{1}{(2p+1) \times (2q+1)} \sum_{i=p}^{i+p} \sum_{j=q}^{j+q} I(i,j) \quad (2)$$

The local standard deviation  $\sigma_L^{(p,q)}$  of the block is calculated as,



$$\sigma_L^{(p,q)} = \left( \frac{1}{(2p+1) \times (2q+1)} \times \sum_{i=p}^{i+p} \sum_{j=q}^{j+q} [I(i,j) - \mu_L^{(p,q)}(i,j)]^2 \right)^{1/2} \quad (3)$$

Using Eq. (1), the contrast information on each image is calculated. Along with the contrast information, entropy information of local patch is calculated based on Shannon's estimation formula which is given as follows,

$$E_L = \sum_{i=1}^n P_i \log\left(\frac{1}{P_i}\right) \quad (4)$$

In Eq. (4),  $P_i$  is the probability of a given image. A modified contrast model is formed by combining the contrast information and entropy information and the modified contrast model is given as follows:

$$C_{Lmod} = C_L \times E_L \quad (5)$$

Along with the MHOG, the contrast and entropy information is given as input to the CNN classifier to detect the objects in the video. To track the detected object in a 2D image frame depends on the robust system modeling. Kalman filter is used for simultaneous prediction and filtering of measurement of object position and motion. The standard Kalman filter trying to estimate the state  $s$  of detected objects in which transition is from  $t$  to  $t+1$  can be expressed as,

$$s_{t+1} = As_t + w_t \quad (6)$$

with a measurement  $z$  that is,

$$z_t = Hs_t + v_t \quad (7)$$

In Eq. (7),  $A$  represents the state transition matrix and  $H$  is an  $m \times n$  matrix which relates the state to the measurement.  $w_t$  and  $v_t$  are the random variables that represent the process and measurement noise respectively.

The overall processes of the Kalman filter can be divided into two steps are time update step and measurement update step. The time update step determines the expected value of  $s_{t+1}$  and the associated covariance matrix  $P_{t+1}$ . The prediction for  $z_{t+1}$  can be then calculated from the expected value of  $s_{t+1}$ . The measurement update step uses the measured  $z_{t+1}$  to determine  $s_{t+1}$  and  $P_{t+1}$  in preparation for the next recursive step. The mean of  $s_{t+1}$  conditioned on  $z_0, z_1, \dots, z_t$  is written as  $\hat{s}_{t+1|t}$  and similarly the covariance matrix is denoted as  $P_{t+1|t}$ . Therefore, the measurement

update step determines  $\hat{s}_{t+1|t+1}$  and  $P_{t+1|t+1}$  since the measurement of  $z_{t+1}$  has been made at that point.

In the time update step, the expected state at  $t+1$  can easily be determined by applying the state transition matrix to  $\hat{s}_{t|t}$ . This is possible due to the assumption that the process noise has zero mean. Hence the expected mean can be expressed as,

$$\hat{s}_{t+1|t} = A\hat{s}_{t|t} \quad (8)$$

The  $P_{t+1|t}$  can be derived with:

$$P_{t+1|t} = AP_{t|t}A^T + Q \quad (9)$$

The main intention of this calculation is to determine the distribution of  $s_{t+1}$  given  $z_0, z_1, \dots, z_{t+1}$ . The values of  $\hat{s}_{t+1|t+1}$  and  $P_{t+1|t+1}$  can be obtained with:

$$\hat{s}_{t+1|t+1} = \hat{s}_{t+1|t} + K_{t+1}(z_{t+1} - H\hat{s}_{t+1|t}) \quad (10)$$

$$P_{t+1|t+1} = P_{t+1|t} - K_{t+1}HP_{t+1|t} \quad (11)$$

In Eq. (12),  $K_{t+1}$  called Kalman gain matrix which is calculated as,

$$K_{t+1} = P_{t+1|t}H^T(HP_{t+1|t}H^T + R) \quad (12)$$

After the object detection and object tracking, combine the blobs which have large overlapping areas, similar MHOG features, similar modified contrast model and large difference of state and covariance matrix. That is,

$x_t^w$  and  $x_{t-1}^y$  blobs will be associated if:

$$\begin{aligned} & \frac{\text{size}(x_t^w \cap x_{t-1}^y)}{\text{size}(x_t^w \cup x_{t-1}^y)} > 0.5 && \& \\ & \text{Sim}_H(MHOG(x_t^w), MHOG(x_{t-1}^y)) > 0.5 && \& \\ & \text{Sim}_H(C_{Lmod}(x_t^w), C_{Lmod}(x_{t-1}^y)) > 0.5 && \& \\ & \text{Dif}(s(x_t^w), s(x_{t-1}^y)) == \text{high} && \& \\ & \text{Dif}(P(x_t^w), P(x_{t-1}^y)) == \text{high} && \end{aligned} \quad (13)$$

In Eq. (13),  $x_t^w$  and  $x_{t-1}^y$  denotes the  $w$ -th and  $y$ -th blob in frame  $t$  and frame  $t-1$  respectively,  $MHOG(x)$  is modified HOG feature for blob  $x$ ,  $\text{Sim}_H(MH(x_t^w), MH(x_{t-1}^y))$  denotes the histogram intersection similarity between blobs  $x_t^w$  and  $x_{t-1}^y$ ,  $\text{Sim}_H(C_{Lmod}(x_t^w), C_{Lmod}(x_{t-1}^y))$  denotes the contrast and intensity intersection similarity between blobs  $x_t^w$  and  $x_{t-1}^y$ ,  $\text{Dif}(s(x_t^w), s(x_{t-1}^y))$  denotes the state difference between blobs  $x_t^w$  and  $x_{t-1}^y$  and  $\text{Dif}(P(x_t^w), P(x_{t-1}^y))$  is the covariance difference between blobs  $x_t^w$  and  $x_{t-1}^y$ . A blob sequence is detected as



a candidate abnormal sequence if it does not follow the normal pattern. Then FP-growth is applied on the abnormal sequences to find the abnormal activities in the associated blobs.

## B. Rain Streaks Removal-Enhanced Object Detection and Tracking-Spatio-Temporal Object Mining

The EODT-STOM method is more effective human activity detection in video surveillance system at night time. Under rainy conditions, the impact of rain streaks on video is often undesirable. In addition to a subjective degradation, the effects of rain can also severely affect the performance of video surveillance systems. So an effective rain streaks removal method is required for efficient video surveillance system.

So RSR-EODT-STOM method is proposed to remove rain streaks in the video frames. It is helpful to improve the accuracy of human activity prediction at the rainy time. For removing rain streaks, deep network architecture is used which removes the rain streaks from the individual images in the video frames based on the CNN. The CNN gets input rainy image  $X$  and returns their corresponding de-rained image  $Y$ . A Residual Network (ResNet) is one of the CNN architectures used to clean image of input rainy image. The ResNet returns a de-rained image which is not more efficient.

In order to improve the network learning process, it is required to reduce the solution space by compressing the mapping range. A negative residual mapping (neg-mapping) is used for this purpose in which the residual of the rainy image  $Y - X$  has a significant range reduction in pixel values. So, the residual is introduced into the ResNet to learn the mapping. Thus the residuals are used as the output of the parameter layers. The ResNet structure with neg-mapping is used for better distinguishing of rain streaks from object details. This structure guarantees that the input information can be propagated through all parameter layers, which helps to train the network. A detail layer is used as the input to the parameter layers. To this end, the rainy image is modeled as,

$$X = X_{detail} + X_{base} \quad (14)$$

In Eq. (14),  $X_{detail}$  denotes the detail layer and the  $X_{base}$  denotes the base layer. The base layer can be obtained using low-pass filtering of  $X$  after which the detail layer  $X_{detail} = X - X_{base}$ . The detail layers contain only the rain streaks and the object structure. In which the inference of background is removed by subtracting the base layer from the image. If the solution space has shrunk then the CNN performance will be improved. So combine the detail layer  $X_{detail}$  with the neg-mapping  $Y - X$  as the input to the parameter layers of ResNet. Finally it returns a de-rained image with cleaner visual de-raining effect. The ResNet with neg-mapping is trained on multiple rainy images with a goal of minimizing the objective function which is given as follows

$$\mathcal{L} = \sum_{i=1}^N \|f(X_{i,detail}, W, b) + X_i - Y_i\|_F^2 \quad (15)$$

In Eq. (15),  $F$  is the Frobenius norm,  $N$  is the number of

training images,  $f(\cdot)$  is ResNet,  $W$  is the weight and  $b$  is the biases. For  $X_{detail}$ , guided filtering is used as a low pass filter to split  $X$  into base and detail layers.

Removing image indexing, the proposed basic network structure can be expressed as,

$$\begin{aligned} X_{detail}^0 &= X - X_{base}, \\ X_{detail}^1 &= \sigma(BN(W^1 * X_{detail}^0 + b^1)), \\ X_{detail}^{2l} &= \sigma(BN(W^{2l} * X_{detail}^{2l-1} + b^{2l})), \\ X_{detail}^{2l+1} &= \sigma(BN(W^{2l+1} * X_{detail}^{2l} + b^{2l+1})), \\ Y_{approx} &= BN(W^L * X_{detail}^{L-1} + b^L) + X \end{aligned} \quad (16)$$

In Eq. (16),  $l = 1, 2, \dots, \frac{J-2}{2}$  with  $J$  the total number of layers,  $*$  indicates the convolution operation,  $BN(\cdot)$  indicates batch normalization to alleviate internal covariate shift,  $\sigma(\cdot)$  is a Rectified Linear Unit (ReLU) for non-linearity. In the above network, all pooling operations are removed to preserve spatial information.

In the first layer of ResNet with neg-mapping, filters of size  $h \times size_1 \times size_1 \times a_1$  is used to generate  $a_1$  feature maps  $size$  denotes filter size and  $h$  denotes the number of image channels. For the second layer  $L-1$ , filters are  $a_1 \times size_2 \times size_2 \times a_2$ . For the last layer, filters of size  $a_2 \times size_3 \times size_3 \times h$  to estimate the negative residual. The de-rained image is obtained directly adding the estimated residual to the rainy image  $X$ . Then the de-rained image is processed by EODT-STOM method to detect the human abnormal activity in the video frames.

## IV. RESULT AND DISCUSSION

In this section, the efficiency of Modified Histogram Of Gradient based Object Detection and Tracking-Spatio-Temporal Frequent Object Mining (MHOGODT-STFOM), Enhanced Object Detection and Tracking-Spatio-Temporal Frequent Object Mining (EODT-STFOM) and Rain Streaks Removal-EODT-STFOM (RSR-EODT-STFOM) is analyzed by using MATLAB 2018a. The MHOGODT-STFOM, EODT-STFOM and RSR-EODT-STFOM methods are compared in terms of accuracy, information gain ratio and true positive rate. For the experimental purpose, videos are collected at day time, night time and rainy time.

### A. Accuracy

Accuracy is the proportion of true results of human activity prediction (true positive and true negative) among the total number of cases examined. Accuracy can be calculated as,

*Accuracy*

$$= \frac{\text{True Positive (TP)} + \text{True Negative (TN)}}{\text{TP} + \text{TN} + \text{False Positive (FP)} + \text{False Negative (FN)}}$$

where, if the class label is positive and the human abnormal activity prediction outcome is positive then it is TP.

If the class label is negative and the human abnormal activity prediction outcome is negative then it is TN.

If the class label is negative and the human abnormal activity prediction outcome is positive then it is FP.

If the class label is positive and the human abnormal activity prediction outcome is negative then it is FN.

Fig. 1, shows the comparison of accuracy between MHOG-STFOM, EODT-STFOM and RSR-EODT-STFOM methods for different videos. The different videos are taken in X-axis and the accuracy value is taken in Y-axis. The EODT-STFOM method has better accuracy while predicting the human activities in the night time videos. The RSR-EODT-STFOM method shows high accuracy while predicting the human activities in the rainy time videos and night and rainy time videos.

Even though the time complexity of EODT-STFOM and RSR-EODT-STFOM is high while predicting the human activities in the normal time videos, the accuracy of these methods are little much better than the MHOG-STFOM.

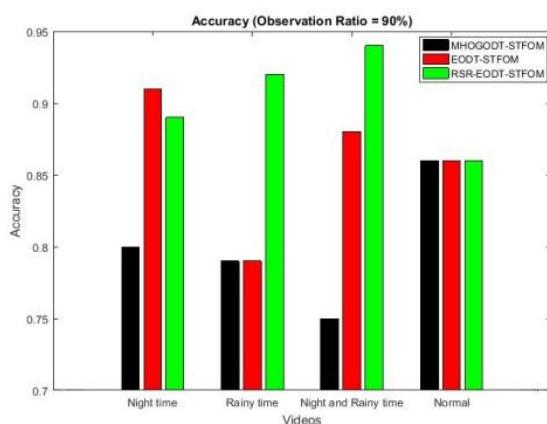


Fig. 1.Comparison of Accuracy

## B. Information Gain Ratio

Information gain ratio is defined as amount of information gain while predicting human activities in the videos.

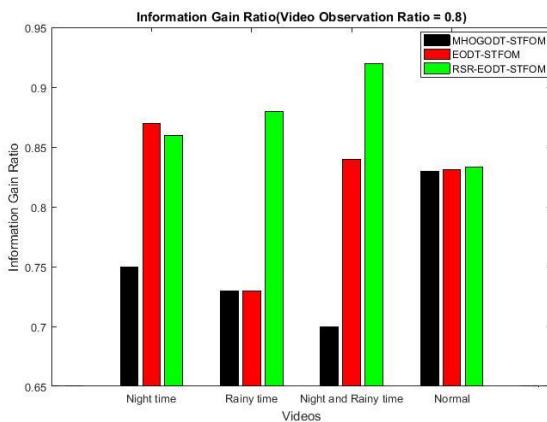


Fig. 2.Comparison of Information Gain Ratio

Fig. 2 shows the comparison of information gain ratio between MHOG-STFOM, EODT-STFOM and RSR-EODT-STFOM methods for different videos. The different videos are taken in X-axis and the information gain ratio value is taken in Y-axis. The EODT-STFOM method has better information gain ratio while predicting the human activities in the night time videos. The RSR-EODT-STFOM method shows high information gain ratio while predicting the human activities in the rainy time videos and night and rainy

time videos. Even though the time complexity of EODT-STFOM and RSR-EODT-STFOM is high while predicting the human activities in the normal time videos, the information gain ratio of these methods are little much better than the MHOG-STFOM.

## C. True Positive Rate

True Positive Rate is defined as the rate of human abnormal activity is predicted as human abnormal activity in videos.

Fig. 3 shows the comparison of true positive rate between MHOG-STFOM, EODT-STFOM and RSR-EODT-STFOM methods for different videos. The different videos are taken in X-axis and the true positive rate value is taken in Y-axis. The EODT-STFOM method has better true positive rate while predicting the human activities in the night time videos. The RSR-EODT-STFOM method shows high true positive rate while predicting the human activities in the rainy time videos and night and rainy time videos. Even though the time complexity of EODT-STFOM and RSR-EODT-STFOM is high while predicting the human activities in the normal time videos, the true positive rate of these methods are little much better than the MHOG-STFOM.

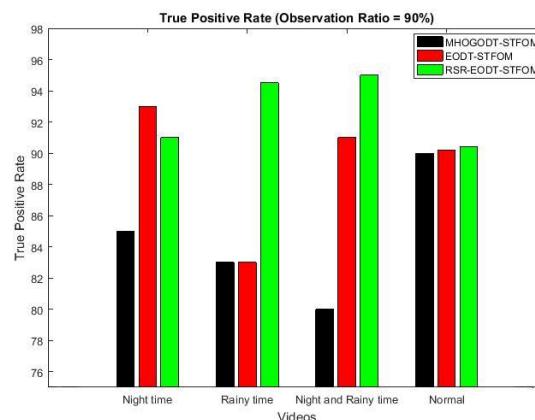


Fig. 3.Comparison of True Positive Rate

## V. CONCLUSION

In this paper, EODT-STFOM and RSR-EODT-STFOM are proposed for human activity prediction even at night time and rainy time. In EODT-STFOM method, MHOG, contrast and entropy information are used to detect the objects. Then the detected objects are tracked by using Kalman filter. Based on the object detection and object tracking, abnormal pattern sequences are detected and finally a FP-growth is applied to detect the infrequent activities which are considered as normal activities. In the RSR-EODT-STFOM method, a deep CNN architecture called ResNet with neg-mapping is used to remove the rain streaks in the video frames which enhance the visual effect of rainy time images. It returns de-rained images which are given as input to the EODT-STFOM for human activity prediction. The experimental results show that the proposed EODT-STFOM and RSR-EODT-STFOM methods are more effective in terms of accuracy, information gain ratio and true positive rate at night and rainy time.

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