1. INTRODUCTION

In the present era of big data, the presence of large volume of un-annotated data over the web has motivated the research for unsupervised data classification, recognition and segmentation. Owing to enhanced security mechanisms and deployment of surveillance cameras, the need for automated analysis of videos to detect abnormal and anomalous events has recently given rise to active research in computer vision and machine learning community in this field. [1] addresses the problem of analysing surveillance videos to identify unusual or anomalous events. The term “anomaly” is defined as the events which are not “usual” in the video i.e. after modelling the dominant behaviour in the video, the events which are not prevalent are being classified as anomalies.

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2. RELATED WORK

In [1], author had used topic based anomaly detection in surveillance videos, by using object based models, for foreground modeling and low-level feature description. In [1], Pathak et al. used foreground extraction method, ViBe proposed in [2]. In [5], author proposed Gaussian Mixture Model for foreground extraction.

2.1 MODELLING

Fixed number of topics: \( z_1, z_2, \ldots, z_k \). Each word in the vocabulary is attached with a single topic. Topics are hidden variables. Used for modelling the probability distribution. Computation:

- Marginalize over hidden variables
- Conditional independence assumption: \( p(w)z_1 \) and \( p(z_2)z \) are independent of each other.

\[ p(w) = \sum_z p(w,z_1)p(z_1) \]

- \( p(u) = \sum_{z_2} p(u,z_2)p(z_2) \]

2.2 DETECTION

Projection Model Algorithm

- Test document
- Topic vector
- m nearest training documents
- Check Frequency
- Eight spatial neighbours of word
- Word occurs more than \( f_{w, \theta} \)
times
- More than \( \frac{1}{f_{w, \theta}} \) neighbours have significant distribution

2.3 LOCALIZATION

Spatial Localization:

Every word has location information in it. Therefore we can directly localize the anomalous words in text document to their spatial locality.

Temporal Localization:

If we maintain a list of frame numbers corresponding to document-word pair, we can tag the frames with anomalous words.

Results

Comparison between ViBe foreground extraction and Gaussian Mixture Model foreground Extraction in traffic video dataset.

We performed experimentation on the Traffic junction dataset (i-Lids dataset: http://www.eecs.qmul.ac.uk/~andrea/avvs2007_d.html.) We kept the number of actions in the video to be 20, which served as the number of topics in the document. The document length was 1 = 4 to 1 = 10 seconds. Anomalous video clips were separated from the rest of the video clips for testing. From the remaining set, 75% of the clips were used for training and the remaining 25% of the clips were included in the test data along with the anomalous ones.

Conclusion

We can get better result if we improve the GMM foreground extraction methodology (by removing noise). The noise is resulting into lots of visual words which are not in the video, thus resulting in degraded result.

References