International Journal of Digital Literacy and Digital Competence
Volume 14 • Issue 1

Identification of Trajectory Anomalies on Video Surveillance Systems

Suman Mondal, Raja Narendra Lal Khan Women's College (Autonomous), Vidyasagar University, India*
Arindam Roy, Prabhat Kumar College, Contai, India
Sukumar Mondal, Raja Narendra Lal Khan Women's College (Autonomous), Vidyasagar University, India

ABSTRACT

Recently, CCTV surveillance applications have remarkably developed for public welfare. However, the investigation of different techniques for online implementation is always significantly restricted. Numerous implementations propose for detecting irregularities of moving objects in the videotape. Performance of fuzzy in trajectory's anomaly is one of the most robust detection procedures. In this paper, the authors propose a fuzzy implemented trajectory anomalies detection technique with the help of some parameters such as velocity, path deviation, and size of the moving objects. The critical aspect of the framework is a compact set of highly descriptive features extracted from a novel cell structure that helps us define support regions in a coarse-to-fine fashion. This paper also illustrates a small outline of different detection techniques. The authors also exhibit the outcome of experiments on the Queen Mary University of London junction dataset (QMUL).

KEYWORDS

Anomalies, Fuzzy, QMUL, Trajectory

INTRODUCTION

Anomaly detection is one of the most difficult problems in computer vision, mostly because it is difficult to extract a particular feature that connects to a particular occurrence. Instead of merely encoding spatial information on a picture, video also encodes motion information. However, the process of extracting more information necessitates large resources. Video analysis using two modalities provides significantly more information to detect a specific activity. Designing an information extraction approach that can efficiently and quickly represent information from videos is crucial.

Several studies have tried to use handcrafted features to categorise anomalies in videos. Edge Oriented Histogram (EOH) and Multi-layer Histogram of Optical Flow (MHOF) are two suggested techniques for detecting anomalies that represent appearances and motion, respectively (Cong, Yuan, & Tang, 2013). A different approach makes use of the shift in the temporal pattern by computing Markovian differences from the local pattern while the time scale is modelled globally (Dogra, Ahmed,

DOI: 10.4018/IJDLDC.330587 *Corresponding Author

& Bhaskar, 2016). With the use of the Gaussian Mixture Model (GMM), which uses mean shift to calculate location, speed, and direction, it is possible to identify vehicles in video and determine whether or not an accident will occur (Hui, Yaohua, Lu, & Jiansheng, 2014).

A generic technique to detecting anomalies, in addition to identifying anomalies in a particular criminal activity, involves employing a spatio-temporal feature detector to extract local descriptors of a normal event and training a classifier to obtain the global representation of a normal event. Despite the high cost of computing required, iDT is usually recognised as the best hand-engineered approach (Tran, Wang, Torresani, Ray, Lecun, & Paluri, 2018). When trained on a dataset of typical movies, all of these algorithms will identify patterns with low probabilities as anomalies.

At present days, our real−world network requires an automatic surveillance system. It is impossible to go after and review every entity in a surveillance network from everywhere in the real-time world. Detecting and identifying isolated and unfamiliar events from surveillance areas is exceptionally required to protect our society from massive illegal activities. To reduce human resources and preserve our essential institution, we utterly require an automated detection of abnormality on a surveillance system from several dimensions. In the present life, abnormality detection is an integral part of different research fields of computer vision. This research integrates and employs distinct sectors like person activity detection, human identification, visual surveillance, object trailing, etc. The researchers in this domain have done the execution of different experiments (Chandola, Banerjee, Kumar, 2009). The explorers furnish the inspection of various propositions to innovative outlooks in the publication (Sodemann, Ross, & Borghetti, 2012). However, it is insufficient to convey the necessary circumstances and challenges in this area. A colossal view and understanding of the presence of a data bank are essential, and no such endeavors are built in the orientation relating to our expertise. Here, we propose an innovative approach to detect anomalies in the video to help automated visual surveillance search organization. This paper also affects the new investigators, scientists, explorers, and students to take part in cracking drawbacks in this domain.

In the present situation, to terminate criminal offenses or traffic violations, CCTV (Closed−Circuit Television) surveillance the system has made other desires in numerous surroundings such as different stations, airports, critical convergence, etc. Acceptable identification and estimation of unpredictable activities within an area of interest are integral to a video surveillance network. Prompt detection of these relatively rare events that enable proactive calculation involves constant analysis of all the directions.

In this study, we suggest a brand-new framework for detecting video anomalies that is appropriate for all types of uncertain situations. Our framework uses a new cell structure to extract motion information from the scene based on local activity like velocity, path deviation, and object size. As a result, there are much less characteristics to process throughout the training and testing phases, which speeds up calculation. Our framework's primary features are:

- Foreground occupancy and optical flow features can be found in the short set of features that was extracted. While features from optical flow are helpful to detect events connected with abrupt motion, such as panic or fighting, features from foreground occupancy are valuable to capture events associated with weak motion, such as loitering or the aberrant presence of items.
- In complex settings where anomalous occurrences may be caused by quick motion, weak motion, or a combination of the two, a novel inference model has been used to appropriately explain the activity. This is especially helpful for sequences portraying realistic events, such as robbery, automobile accidents, and other perilous scenarios.

We use a well-known existing dataset to test our framework. The evaluation findings demonstrate that our framework outperforms several methods and produces outcomes that are competitive with those of other methods. Our framework achieves frame processing times in both scenarios that are appropriate for computation of sequences with up to 30 frames a second (FPS).

The details of the paper have been arranged in a sequence. Section 1 discusses the literature survey on detecting an anomaly in the video. We focus on building an expert surveillance system for tracking uncommon behaviors of moving objects in section 2. Origin, destination, path, deviation, and velocity are taken as an inspection to analyze the situation. In section 3, we describe the dataset and empirical result. The conclusion and future scope of the research work are presented in section 4. In the last section, we extract the references.

LITERATURE SURVEY

Unpredictable occasions are typically tricky to human analysts due to the excessive amount of information overload, inattention, and fatigue. For these circumstances, a robotic or semi−automatic intelligent system requires inspecting anomalies in a realistic and random environment with a degree of fuzziness. The concept of fuzzy set theory was introduced by Zadeh, (1962 & 1965) [x0, x1] to sense the idea of grades in class membership. Consistent processing techniques have been illustrated in Kraiman, Arouh & Webb, (2002) and Chandola, Banerjee, Kumar (2009) video surveillance systems (Rhodes, Bomberger, Zandipour, & Stolzar, 2009). We can get solutions to the problem using some supervised and unsupervised methods, such as unsupervised techniques using low−level optical features like motion and texture (Chen, & Huang, 2011) with various environments (Popoola, & Wang 2012 and Song, Shao, Zhang, Shibasaki, Zhao, Cui, & Zha 2013), anomaly detection using training data (Cong, Yuan, & Liu, 2013 and García-Valls, Lopez, & Fernández-Villar, 2013), topic−based model (Albusac, Vallejo, Castro-Schez, Glez-Morcillo, & Jiménez 2014 and Li, Chang, Wang, Ni, Hong, & Yan, 2015) reply on the unusual situation (Xiao, Zhang, & Zha, 2015) and tracking moving objects (Walia, & Kapoor, 2016). Simultaneous advancement in multi−object tracking (Walia, & Kapoor, 2016) has presented development in moving object tracking in random and complex environments. Investigators have started concentrating more on detecting abnormality (Dogra, Ahmed, & Bhaskar, 2016) due to adequate tracking results.

More contemporary achievements have been obtained in surveillance areas, such as the Service−Oriented Architecture (SOA), the approach applied in unorthodox CCTV applications. Most of the modern research compositions have been enlarged to model and analyze specific activities in an arranged way by skilled understandings. Nevertheless, they are inadequate to convey learning new context of interest with the help of previous scene examinations. There is some need for powerful processing techniques like non-template-based that analyze massive monitoring and observed datasets. Normal and anomalous patterns have contradicted it during the experimental study of the research. Such viewpoints are typically referred to as abnormality, novelty, or outlier detection methods, helping that a large amount of archival data is used for learning to detect normal behavior.

On the other hand, the two primary kinds of anomaly detection techniques are accuracy-oriented techniques, which focus on increasing detection accuracy, and processing time-oriented techniques, which emphasize speeding up frame processing. The latter category seeks to improve performance online.

Over the past few decades, significant advancements have been made in the field of accuracy-oriented approaches. However, the fast frame processing times of these approaches are typically achieved at the sacrifice of performance. These methods are distinguished by using a variety of strategies to choose the spatio-temporal parts of the scene that will be modelled and examined initially. Dense scanning (Roshtkhari, & Levine, 2013 and Roshtkhari, & Levine, 2013), multi-scale scanning (Bertini, Bimbo, & Seidenari, 2012, Cong, Yuan, & Tang, 2013, and Hu, Zhang, & Davis, 2013), and convolution-based Spatio Temporal Interest Point (STIP) detection (Cheng, Chen, & Fang, 2015 and Cheng, Chen, & Fang, 2015) are a few examples of these methods. Although the number of spatio-temporal regions chosen for analysis may need a high number of features to be processed, these methodologies typically give enough data to capture the scene's dynamics and spatio-temporal compositions (Saligrama, & Chen, 2012, Bertini, Bimbo, & Seidenari, 2012, Roshtkhari,

& Levine, 2013, Hu, Zhang, & Davis, 2013, Cheng, Chen, & Fang, 2015, and Cheng, Chen, & Fang, 2015). The complexity of defining a scene's spatio-temporal compositions has undergone significant reduction (Roshtkhari, & Levine, 2013 and Cheng, Chen, & Fang, 2015), yet many of the suggested enhancements may still necessitate lengthy calculations (Roshtkhari, & Levine, 2013, Roshtkhari, & Levine, 2013, Cheng, Chen, & Fang, 2015). These accuracy-focused approaches' highly descriptive qualities that boost performance are a crucial component as well. Among these, it has been demonstrated that optical flow features can improve detection precision (Zhu, Liu, Wang, Li, & Lu, 2014 and Zhu, Wang, & Yu, 2016). For instance, the authors of (Walia, & Kapoor, 2016) suggest a potential totally unsupervised non-negative sparse coding strategy that makes use of histograms of optical flow (HOFs) to detect anomalies in crowded situations. As a matching problem, the authors of (Cong, Yuan, & Tang, 2013) use Multi-scale HOFs (MHOFs), which preserve temporal contextual information, to find anomalies in crowded situations. However, computing such descriptive features could take a while [Roshtkhari, & Levine, (2013), Roshtkhari, & Levine, (2013), Hu, Zhang, & Davis, 2013, Zhu, Liu, Wang, Li, & Lu, 2014, and Mousavi, Mohammadi, Perina, Chellali, & Murino, 2015). For instance, it has been demonstrated that local descriptors computed using dense scanning approaches boost performance, but at the cost of several repeated computations [Chandola, Banerjee, Kumar, 2009 and Mondal, Roy, & Mandal, 2021).

Recently, processing-time-oriented techniques have drawn attention in the field of video anomaly detection [Roshtkhari, & Levine, 2013, Lu, Shi, & Jia, 2013, Biswas, & Babu, 2013). These techniques typically speed up computation by using local low-complexity descriptors [Adam, Rivlin, Shimshoni, & Reinitz, 2008, Zhu, Liu, Wang, Li, & Lu, 2014, Cheng, Chen, & Fang, 2015, and Mousavi, Mohammadi, Perina, Chellali, & Murino, 2015) or by limiting the number of features that need to be processed each frame (Reddy, Sanderson, & Lovell, 2011, Lu, Shi, & Jia, 2013 and Biswas, & Babu, 2013]. For instance, despite using multi-scale scanning techniques, the work of Lu et al. (Zhu, Liu, Wang, Li, & Lu, 2014) and Biswas and Babu (Biswas, & Babu, 2013) is able to simulate a limited number of features. Additionally, processing-time-oriented approaches could make use of quickly computed yet underwhelmingly descriptive properties. For instance, the motion vectors of a video sequence are used as features in a histogram-binning approach by the authors in (Mousavi, Mohammadi, Perina, Chellali, & Murino, 2015). The major feature used by the authors in (Zhu, Liu, Wang, Li, & Lu, 2014) is local temporal gradients that were extracted in a multi-scale manner. Using cell-based algorithms to extract characteristics from fixed spatio-temporal regions is another typical strategy to shorten processing times [Reddy, Sanderson, & Lovell, 2011, Bertini, Bimbo, & Seidenari, 2012, Cong, Yuan, & Tang 2013, and Mousavi, Mohammadi, Perina, Chellali, & Murino, 2015]. Cell-based approaches can therefore be utilized to limit the amount of retrieved features without the need for STIPs or other saliency detecting methods (Bertini, Bimbo, & Seidenari, 2012).

It is clear that in video anomaly detection algorithms, there is a trade-off between detection accuracy and processing speed. The problem is then to effectively manage this trade-off by utilizing a minimal number of highly descriptive attributes in order to achieve competitive accuracy for online performance. By using a small number of highly descriptive optical flow variables like velocity, path deviation, and moving object size, our proposed system strikes a balance between these trade-offs. This is accomplished by creating a fresh cell structure on the scene, from which only features from cells deemed important to the investigation are extracted.

PROPOSED METHOD

Our proposed method is divided into two stages, the training stage and the testing stage. These two stages are explained in Figure 1 and Figure 2.

According to the diagram, the proposed method has started with segregating plotted visual images into a set of segments (Sultani, Chen, & Shah, 2018) depending on each trajectory. After dividing the picture, we can get several regions, as illustrated in Figure 3. We also have each trajectories size and image size. So, we have calculated a Δw and Δh in Equation 1. Δw and Δh help to determine the number of rows and columns in a region.

$$\Delta w = \text{imagewidth} / \text{trajectorysize}\ ,\ \Delta h = \text{imageheight} / \text{trajectorysize} \qquad (1)$$

Here we have explained the generating of a non-overlapping region in the image extracted from video in algorithm 1.

Our first objective is to find out the average velocity of each region. To find the average speed, we have chosen the maximum number of areas from all the trajectories because if we can divide the image into smaller spaces, we will not get almost the actual velocity of the object. Choosing the maximum number of regions from all trajectories is explained in algorithm 2.

Now, we take a trajectory one by one from the testing set and select the regions for all the trajectory points. After selecting the areas, we have calculated the Euclidian distance among the points for all regions explained in algorithm 3. When we get these distances, we can be easily computed the velocity(v) of all areas with the help of Frame Per Second (FPS) in Equation 2. Here, dist(p1,p2,p3, ..., pn) means the distance among the points p1,p2,p3, ..., pn. These points are pixel coordinate values for each region.

$$v = (\text{dist}(p1,p2,p3,\ldots\ldots\ldots\ldots,pn)) / FPS \qquad (2)$$

So, our first objective achieves after getting the velocity of all the selected regions by the trajectory. Afterward obtaining speed, we have determined the average speed of all courses for a particular area described in Figure 4. After that, we implemented average path deviation from the training set and made classes according to the fuzziness of the path deviation through all trajectories.

```
Algorithm 1: divide the non-overlapping region
Result: we have got non-overlapping region; /* This procedure has been worked for only train set */
read all trajectories from training set and extracted image from video;
get number of trajectories in the training data set;
get image with and height;
for i = 1 to number of trajectories in increasing order do
        get each trajectory size;
        Δw = imagewidth / (each trajectory size); /* Δw means each non-overlapping region width */
        Δh = imageheight / (each trajectory size); /* Δh means each non-overlapping region height */
        for j = 1 to height in increasing order of (Δh+1) do
                for j = 1 to width in increasing order of (Δw+1) do
                        assign 4 co-ordinates of each region have been added for each trajectory;
                        calculate the number of region for each trajectory;
                end
         end
         add all the segmented region into the output trajectory;
end
```

Figure 1. Training phase

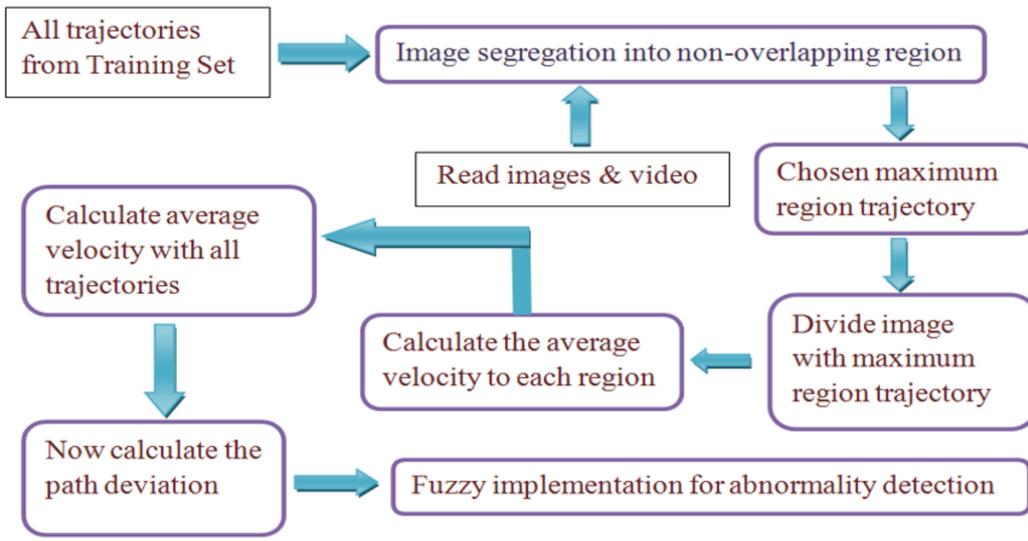


Figure 2. Testing phase

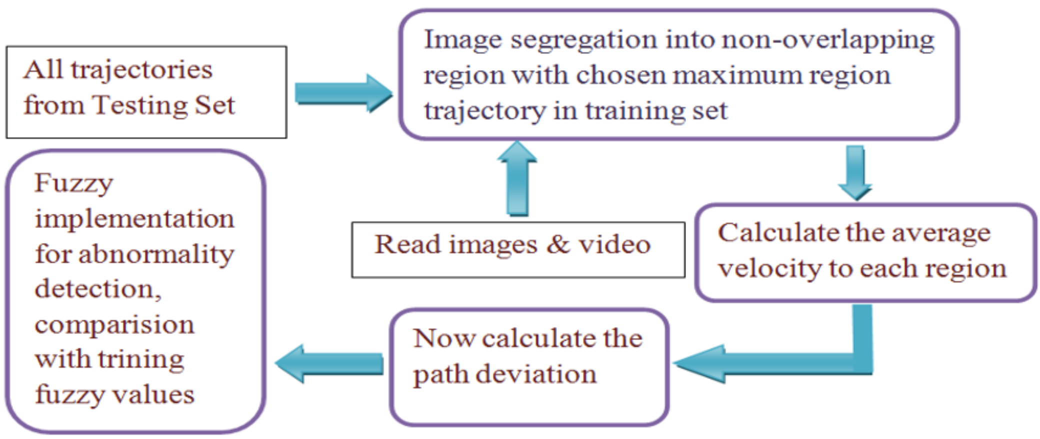
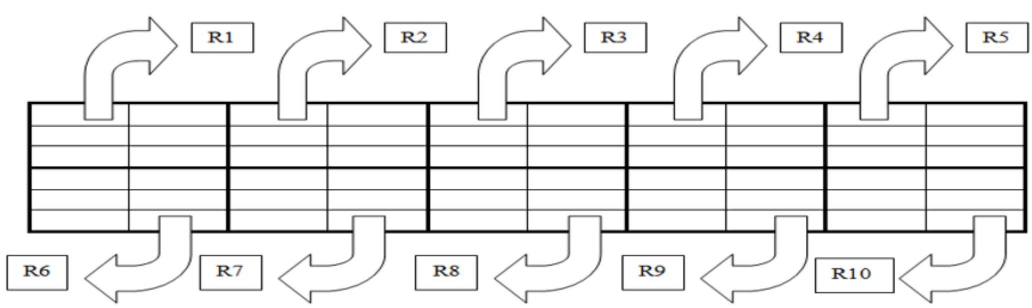


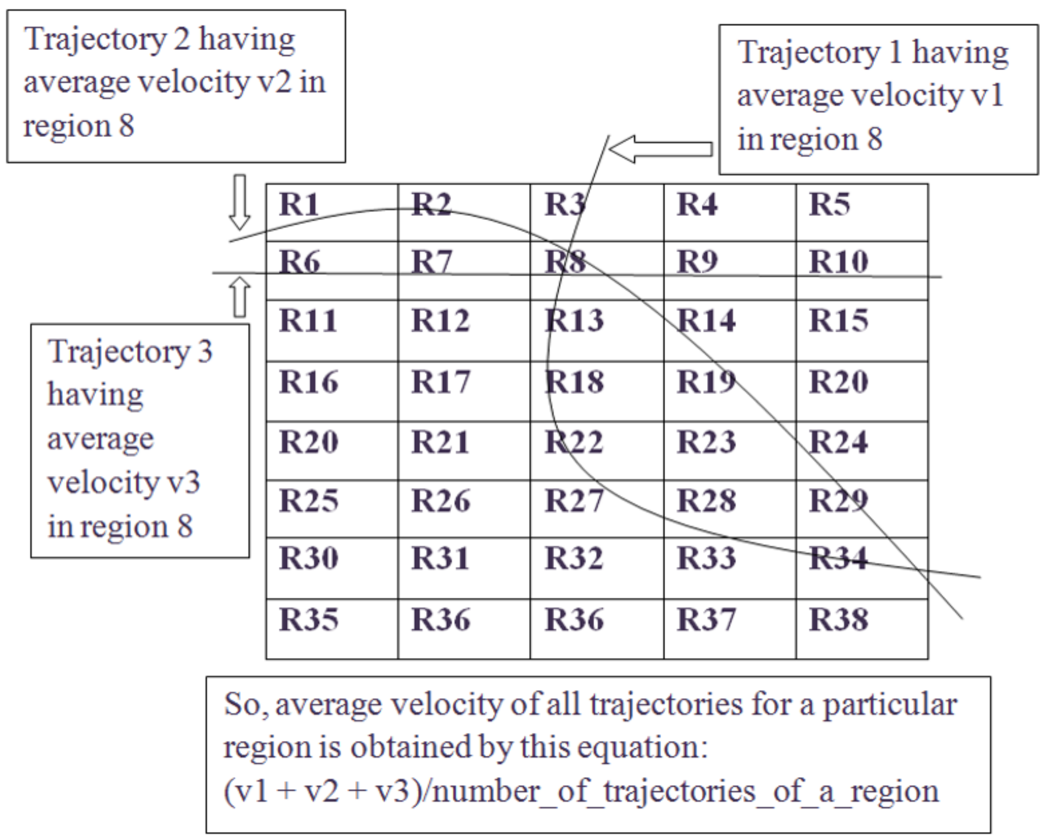
Figure 3. Divide images into some regions. Here 6 X 10 image size and each region has 2 columns and 3 rows, number of the region here is R1, R2, R3, ..., R10



```
Algorithm 2: choose the maximum number of the region
Result: we have chosen the maximum number of non-overlapping
regions of all trajectories; /* This procedure has been worked for
only train set */
read all trajectories from training set having non-overlapping
region;
for i = 1 to the number of trajectories in increasing order do
        get the number of the non-overlapping region for each
trajectory;
        if this is the maximum number of the region then
                choose the number of the region for future
usage;
       end
end
Algorithm 3: calculate Euclidian distance and velocity among all
non-overlapping regions
Result: we have got Euclidian distance and velocity among all non-
overlapping regions; /* This procedure has been worked for a train
set and test set data both */
read all trajectories having non-overlapping region;
using the maximum number of region, we have divided all the
trajectories;
calculate the number of trajectory points in each region and
also store their co-ordinate points;
for i = 1 to the number of trajectories in increasing order do
        get all the non-overlapping region;
        calculate Euclidian distance and velocity with the help
of frame per second;
        store them into the output trajectory database for the
next phase;
end
Algorithm 4: calculate fuzziness of path deviation for each
trajectory
Result: We have got fuzziness of all trajectories using path
deviation with the help of the class; /* This procedure has been
worked for a train set and test set data both */
read all trajectories from the dataset;
for i = 1 to the number of trajectories in increasing order do
        apply trapezoidal membership function on path deviation
and
        separates into three classes (low velocity, medium
velocity, and high velocity);
end
```

The implemented path deviation has also been taken from a training set and applied to testing for generating the classes in the test set. That fuzziness (explained in algorithm 4) have shown in Figure 5. Algorithm 5 illustrates the calculation of the size of the moving objects to take as a parameter in and testing set. The selection of moving objects is shown in Figure 6. We have also implemented fuzziness on the velocity (explained in algorithm 6) and assigned those velocities into two levels illustrated in Figure 7 and Equation 3 where avgv, highv, and lowv are average speed high−velocity low speed, respectively.

Figure 4. Explanation of obtaining the average velocity of all trajectories for a particular region



$$\mu = \frac{x - 12.5}{avgv - lowv}, 12.5 \leq x \leq 18 \qquad (3)$$

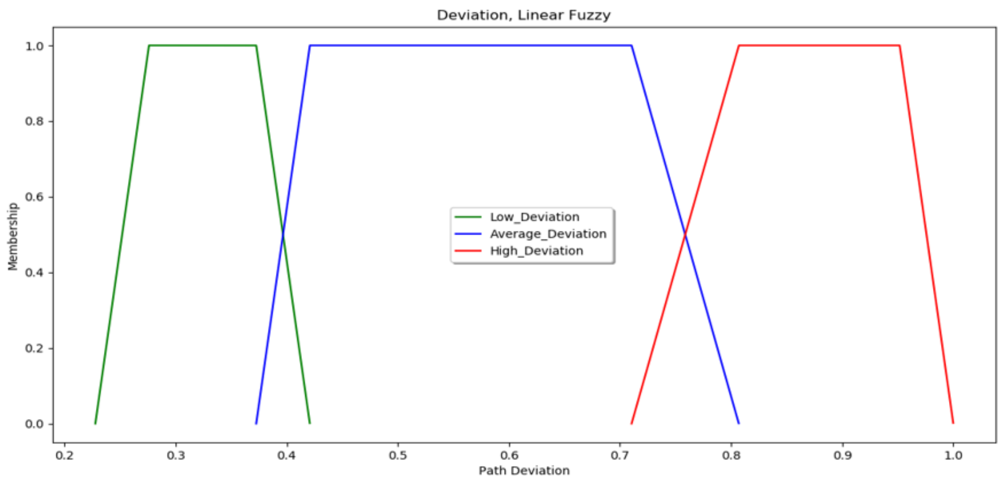
$$\mu = \frac{25 - x}{highv - avgv}, 18 \leq x \leq 25$$

Algorithm 5: calculate fuzziness of the Size of the moving objects
Result: We have got fuzziness of all objects using size; /* This procedure has been worked for a train set and test set data both */

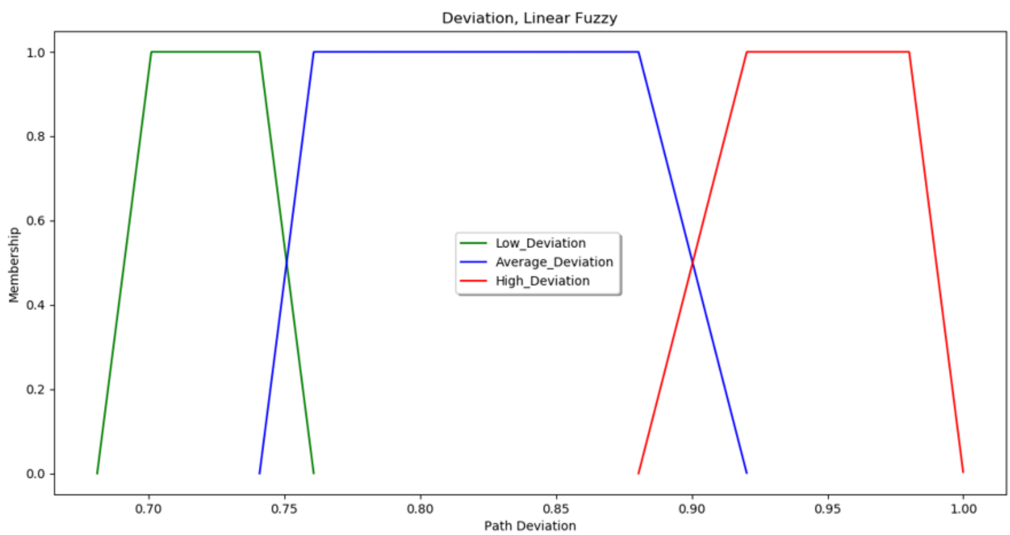
```
read all moving objects are involved from video surveillance;
for getting all the moving objects from the video do
        apply the Lukas-Kenedy algorithm for calculating the size of the all moving objects
end
```

Algorithm 6: calculate region-wise fuzziness of velocity for each trajectory and generate the heat map
Result: We have got fuzziness of all trajectories using velocity values with the help of the class; /* This procedure has been worked for a train set and test set data both */

Figure 5. After applying the trapezoidal member function on (a) training data and (b) testing data for path deviation



(a) Fuzziness of path deviation for training set



(b) Fuzziness of path deviation for the testing set

```
read all trajectories having non-overlapping region;
for i = 1 to the number of trajectory in increasing order do
        apply trapezoidal membership function on region-wise velocity values and
        separate with three classes (low velocity, medium velocity, and high velocity);
        also generates a region-wise heat map for understanding abnormalities ;
end
```

Figure 6. Size of some moving objects

After implementing Fuzziness, we can easily detect an abnormality of an object of a particular region with the help of the SVM (Support Vector Machine) (Lin, Lin, & Weng, 2007) classifier.

EXPERIMENTAL RESULTS

In this context, we have shown the results of the proposed detection technique of abnormality. Primarily, we have illustrated the data that is used for events. Then, we showed the outcomes.

DATASETS

In our experiments, we have used the Queen Mary University of London junction dataset (QMUL) (Long, Kapoor, 2015). This dataset is having 360 × 288 image resolution. It also has 50 minutes duration of video and 166 trajectories. We have taken 112 trajectories as training data, and the other has testing data. We have also shown the overall movement patterns of the dataset in Fig. 8.

Results

We have applied a trapezoidal fuzzy membership function on region-wise velocity values to draw a diagram for understanding the low, medium, and high velocity depicted in figure 9. The estimated values on the QMUL junction dataset for generating the graph are below.

Trapezoidal fuzzy membership functions have also been used on path deviation to understand the low, medium, and high velocity of moving objects in Figure 5, and estimated values are given below.

We have extracted seven regions of entry points of all trajectories and 4 clusters of exit points of all courses using the DBSCAN algorithm. The results are shown in Figure 10. We also generated a heat map to analyze the region−wise trajectory benchmark with different colors. With this, we can

Figure 7. Fuzzy Implementation on velocity. Here we have depicted low velocity, high velocity, and average velocity.

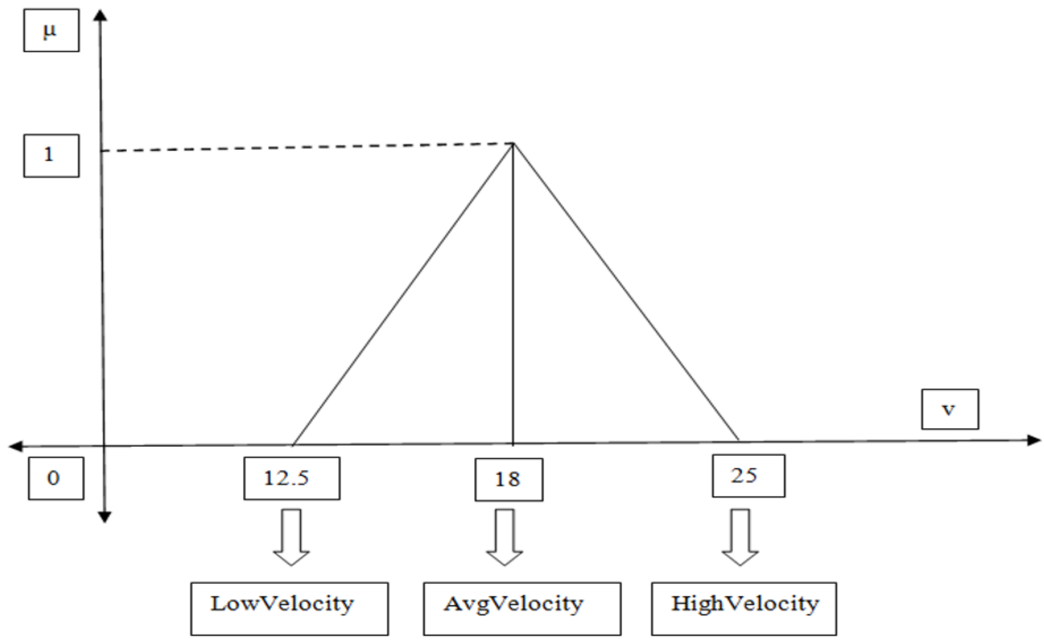


Figure 8. Fifty minutes cumulative sample of motion in QMUL junction video

be offered a clear perception of the movement of the objects in a video shown in 11. It has shown some colors like red indicating high−speed velocity, yellow indicating average speed velocity, white marking low momentum, etc.

Now, we are shown in figures 12 and 13 on video images where the actual trajectories are drawn concerning the regions. We have trained that region−wise trajectory velocity with Support Vector Machine (SVM) [Hsu, & Lin, 2002 and Lin, Lin, & Weng, 2007) to get a model through which we have tested other trajectories to detect the abnormalities. Here, region velocities and path deviation are features of the SVM. We have used radial basis function kernel and soft margin with no cross−validation. After testing, we have got 80.6994% abnormality among 473 region−velocities. We have also trained with path deviation with SVM getting 70.1493% accuracy on the testing set. We have combined the velocity, path deviation, and size. Then, we got 98.514% abnormality after adding all three parameters. Our method has outperformed both approaches [Loy, Xiang, Gong, 2008 and Mondal, Roy, & Mandal, 2021).

FUTURE SCOPE AND CONCLUSION

Understanding and analyzing random surveillance surroundings is an existing drawback worldwide. Therefore, it is essential to construct an eminent and competent artificial methodology to integrate with the consecutive changeable environment and combination of information. In this paper, we have proposed a detection technique for abnormalities from moving video objects. Here, we have only used the primary fuzzy method to detect the anomalies of moving objects using velocity, path deviation, and size of the moving things.

We also demonstrated as part of the evaluation that our framework is adaptable and can be customized to the properties of the sequences, if these are known a priori, in order to enhance performance. By utilizing this adaptability, our future work aims to improve the detection accuracy of our framework. Specifically, we will think about how to optimize our framework's parameters given a specific combination of environmental factors that were used to capture a sequence.

Our recent aim is to extend this method by collaborating with convolution neural networks or Long-Term Short-Term Memory (LSTM) which will show exact alarm activation for all regions of all trajectories.

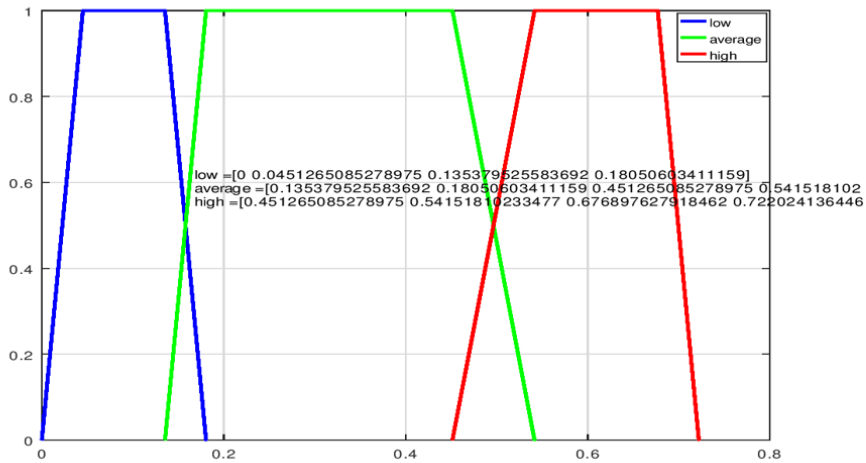
Table 1. Fuzzy implemented value of regions with respect to the region velocity

Dataset	Low Velocity	Medium Velocity	Max Velocity
Train Set	0.0000, 0.04513, 0.13538, 0.18051	0.13538, 0.18051, 0.45127, 0.54152	0.45127, 0.54152, 0.67690, 0.72202
Test Set	0.0000, 0.3485, 1.0456, 1.39426	1.0456, 1.39426, 3.4856, 4.18279	3.4856, 4.18279, 5.22849, 5.577060

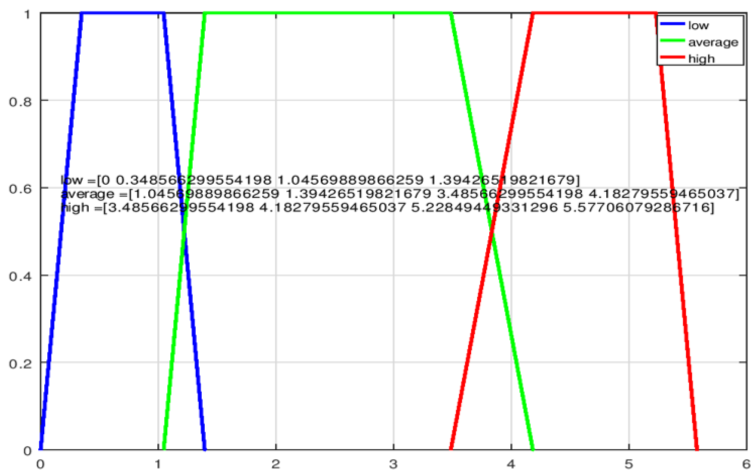
Table 2. Fuzzy implemented value of path deviation

Dataset	Low Velocity	Medium Velocity	Max Velocity
Train Set	0.22777, 0.27604, 0.37256, 0.42083	0.37256, 0.42083, 0.71041, 0.80694	0.71041, 0.80694, 0.95173, 1.00000
Test Set	0.68115, 0.70108, 0.74094, 0.76086	0.74094, 0.76086, 0.88043, 0.92028	0.88043, 0.92028, 0.98007, 1.00000

Figure 9. After applying trapezoidal member function on (a) training set and (b) testing set for velocity



(a) Fuzziness of velocity for training set



(b) Fuzziness of velocity for the testing set

Figure 10. (a) Extracted seven entry regions and (b) extracted four exit regions shown

(a) *(b)*

Figure 11. Heat map for (a) training set and (b) testing set

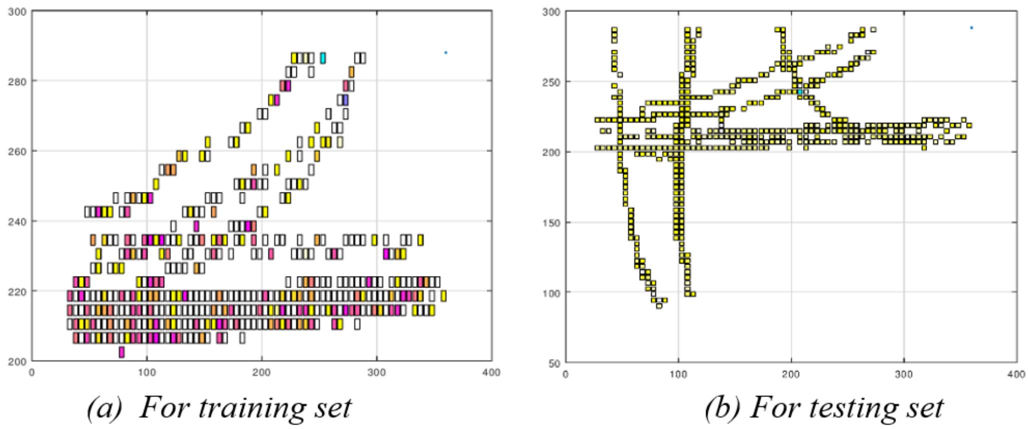


Figure 12. Trajectory on training image

Figure 13. Trajectory of testing image

CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

FUNDING AGENCY

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

REFERENCES

Adam, A., Rivlin, E., Shimshoni, I., & Reinitz, D. (2008). Robust real-time unusual event detection using multiple fixed-location monitors. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *30*(3), 555–560. doi:10.1109/TPAMI.2007.70825 PMID:18195449

Albusac, J., Vallejo, D., Castro-Schez, J. J., Glez-Morcillo, C., & Jiménez, L. (2014). Dynamic weighted aggregation for normality analysis in intelligent surveillance systems. *Expert Systems with Applications*, *41*(4), 2008–2022. doi:10.1016/j.eswa.2013.08.097

Bertini, M., Bimbo, A. D., & Seidenari, L. (2012). Multi-scale and real-time non-parametric approach for anomaly detection and localization. *Computer Vision and Image Understanding*, *116*(3), 320–329. doi:10.1016/j.cviu.2011.09.009

Biswas, S., & Babu, R. (2013). Real time anomaly detection in h.264 compressed videos. *National Conference on Computer Vision, Pattern Recognition, Image Processing and Graphics (NCVPRIPG),* 1 – 4. doi:10.1109/NCVPRIPG.2013.6776164

Chandola, V., Banerjee, A., Kumar, V. (2009). Anomaly detection: A survey. *ACM Computing Survey, 41*(3), 15:1–15:58.

Chen, D. Y., & Huang, P. C. (2011). Motion-based unusual event detection in human crowds. *Journal of Visual Communication and Image Representation*, *22*(2), 178–186. doi:10.1016/j.jvcir.2010.12.004

Cheng, K., Chen, Y., & Fang, W. (2015). Gaussian process regressionbased video anomaly detection and localization with hierarchical feature representation. *IEEE Transactions on Image Processing*, *24*(12), 5288–5301. doi:10.1109/TIP.2015.2479561 PMID:26394423

Cheng, K. W., Chen, Y. T., & Fang, W. H. (2015). Video anomaly detection and localization using hierarchical feature representation and gaussian process regression. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR),* 2909–2917. doi:10.1109/CVPR.2015.7298909

Cong, Y., Yuan, J., & Liu, J. (2013). Abnormal event detection in crowded scenes using sparse representation. *Pattern Recognition*, *46*(7), 1851–1864. doi:10.1016/j.patcog.2012.11.021

Cong, Y., Yuan, J., & Tang, Y. (2013). Video anomaly search in crowded scenes via spatio-temporal motion context. *IEEE Transactions on Information Forensics and Security*, *8*(10), 1590–1599. doi:10.1109/TIFS.2013.2272243

Dogra, D. P., Ahmed, A., & Bhaskar, H. (2016). Smart video summarization using mealy machine-based trajectory modeling for surveillance applications. *Multimedia Tools and Applications*, *75*(11), 6373–6401. doi:10.1007/s11042-015-2576-7

García-Valls, M., Lopez, I. R., & Fernández-Villar, L. (2013). iLAND: An enhanced middleware for real-time reconfiguration of service-oriented distributed real-time systems. *IEEE Transactions on Industrial Informatics*, *9*(1), 228–236. doi:10.1109/TII.2012.2198662

Hsu, C. W., & Lin, C. J. (2002). A comparison of methods for multiclass support vector machines. *IEEE Transactions on Neural Networks*, *13*(2), 415–425. doi:10.1109/72.991427 PMID:18244442

Hu, Y., Zhang, Y., & Davis, L. (2013). Unsupervised abnormal crowd activity detection using semiparametric scan statistic. *IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW),* 767–774. doi:10.1109/CVPRW.2013.115

Hui, Z., Yaohua, X., Lu, M., & Jiansheng, F. (2014). Vision-based realtime traffic accident detection. *11th World Congr. Intell. Control Autom*., 1035–1038.

Kraiman, J. B., Arouh, S. L., & Webb, M. L. (2002). Automated anomaly detection processor. *Proceedings of SPIE - The International Society for Optical Engineering, 4716*, 128–137. doi:10.1117/12.474940

Li, T., Chang, H., Wang, M., Ni, B., Hong, R., & Yan, S. (2015). Crowded scene analysis: A survey. *IEEE Transactions on Circuits and Systems for Video Technology*, *25*(3), 367–386. doi:10.1109/TCSVT.2014.2358029

Lin, H. T., Lin, C. J., & Weng, R. C. (2007). A note on platt's probabilistic outputs for support vector machines. *Machine Learning*, *68*(3), 71–74. doi:10.1007/s10994-007-5018-6

Long, C., & Kapoor, A. (2015). A joint gaussian process model for active visual recognition with expertise estimation in crowdsourcing. *International Journal of Computer Vision*, *116*(2), 136–160. doi:10.1007/s11263-015-0834-9 PMID:26924892

Loy, C. C., Xiang, T., & Gong, S. (2008). From local temporal correlation to global anomaly detection. *The 1st International Workshop on Machine Learning for Vision-based Motion Analysis - MLVMA*, 1–13.

Lu, C., Shi, J., & Jia, J. (2013). Abnormal event detection at 150 fps in matlab. *IEEE International Conference on Computer Vision (ICCV),* 2720–2727. doi:10.1109/ICCV.2013.338

Mondal, S., Roy, A., & Mandal, S. (2021). A supervised trajectory anomaly detection using velocity and path deviation. *Proceedings of International Conference on Frontiers in Computing and Systems*, 777–784. doi:10.1007/978-981-15-7834-2_72

Mousavi, H., Mohammadi, S., Perina, A., Chellali, R., & Murino, V. (2015). Analyzing tracklets for the detection of abnormal crowd behavior. *IEEE Winter Conference on Applications of Computer Vision (WACV),* 148–155. doi:10.1109/WACV.2015.27

Popoola, O. P., & Wang, K. (2012). Video-based abnormal human behavior recognition - a review. *IEEE Transactions on Systems, Man, and Cybernetics. Part C, Applications and Reviews*, *42*(Part C), 865–878. doi:10.1109/TSMCC.2011.2178594

Reddy, V., Sanderson, C., & Lovell, B. (2011). Improved anomaly detection in crowded scenes via cell-based analysis of foreground speed, size and texture. *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops (CVPRW),* 55 – 61. doi:10.1109/CVPRW.2011.5981799

Rhodes, B. J., Bomberger, N., Zandipour, M., & Stolzar, L. H. (2009). Anomaly detection and behavior prediction: Higher-level fusion based on computational neuroscientific principles. In *Sensor and Data Fusion In Tech*. I-Tech Education and Publishing. https://www.intechopen.com/chapters/6094

Roshtkhari, M., & Levine, M. D. (2013). Online dominant and anomalous behavior detection in videos. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR),* 2611–2618. doi:10.1109/CVPR.2013.337

Roshtkhari, M. J., & Levine, M. D. (2013). An on-line, real-time learning method for detecting anomalies in videos using spatiotemporal compositions. *Computer Vision and Image Understanding*, *117*(10), 1436–1452. doi:10.1016/j.cviu.2013.06.007

Saligrama, V., & Chen, Z. (2012). Video anomaly detection based on local statistical aggregates. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR),* 2112–2119. doi:10.1109/CVPR.2012.6247917

Sodemann, A., Ross, M., & Borghetti, B. (2012). A review of anomaly detection in automated surveillance. *IEEE Transactions on Systems, Man, and Cybernetics. Part C, Applications and Reviews*, *42*(6), 1257–1272. doi:10.1109/TSMCC.2012.2215319

Song, X., Shao, X., Zhang, Q., Shibasaki, R., Zhao, H., Cui, J., & Zha, H. (2013). A fully online and unsupervised system for large and high-density area surveillance: Tracking, semantic scene learning, and abnormality detection. *ACM Transactions on Intelligent Systems and Technology, 4*(2), 35:1–35:21.

Sultani, W., Chen, C., & Shah, M. (2018). Real-world anomaly detection in surveillance videos. *Clinical Orthopaedics and Related Research*, 6479–6488. https://arxiv.org/abs/1801.04264

Tran, D., Wang, H., Torresani, L., Ray, J., Lecun, Y., & Paluri, M. (2018). A Closer Look at Spatiotemporal Convolutions for Action Recognition. *Proceedings - IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 6450–6459. doi:10.1109/CVPR.2018.00675

Walia, G. S., & Kapoor, R. (2016). Recent advances on multi cue object tracking: A survey. *Artificial Intelligence Review*, *46*(1), 1–39. doi:10.1007/s10462-015-9454-6

Xiao, T., Zhang, C., & Zha, H. (2015). Learning to detect anomalies in surveillance video. *IEEE Signal Processing Letters*, *22*(9), 1477–1481. doi:10.1109/LSP.2015.2410031

Zadeh, L. A. (1962). From circuit theory to system theory. *Proceeding of Radio Engineering*, *50*, 856–865.

Zadeh, L. A. (1965). Fuzzy set, information, and control. Cambridge University Press

Zhu, X., Liu, J., Wang, J., Li, C., & Lu, H. (2014). Sparse representation for robust abnormality detection in crowded scenes. *Pattern Recognition*, *47*(5), 1791–1799. doi:10.1016/j.patcog.2013.11.018

Zhu, Z., Wang, J., & Yu, N. (2016). Anomaly detection via 3d-hof and fast double sparse representation. *IEEE International Conference on Image Processing (ICIP),* 286–290. doi:10.1109/ICIP.2016.7532364

Suman Mondal is an Assistant Professor at Yogoda Satsanga Palpara Mahavidyalaya. He is a research fellow at the Raja Narendra Lal Khan Women's College (Autonomous) Research Center. He earned both his B.Sc. and M.Tech. degree from the University of Calcutta. He also graduated from West Bengal University of Technology with a Master of Computer Application (MCA) degree. He has been a teacher for more than five years and worked in the industry for one year. He worked as a software developer for the company Azure Software Pvt. Ltd. prior to entering the teaching field. He is interested in computer vision for research. At Prabhat Kumar College in Contai, Dr.

Arindam Roy is an associate professor and the programme coordinator for the Bachelor of Computer Application (BCA). He is both a researcher and an academician. Vidyasagar University is where he earned his Ph.D. in mathematics. Additionally, he received his M.Sc. and B.Sc. in science from Vidyasagar University. He has been a teacher for more than 15 years. He has published in over 20 reputable journals. Under his direction, he finished two projects effectively. Soft computing optimization is his main field of study.

Sukumar Mondal is an Associate Professor and a coordinator of Research Cell at Raja Narendra Lal Khan Women's College (Autonomous). He also serves as the department's head of mathematics and the deputy examination controller. He is both a researcher and an academician. In 2003, he graduated with a Ph.D. in mathematics from Vidyasagar University. In 1992 and 1994, respectively, he completed his B.Sc. and M.Sc. degrees, for which Vidyasagar University gave him a Silver Medal. He has been a teacher for more than 20 years. He has published in over 45 reputed International journals. Under his direction, he has finished five projects effectively. Graph theory, fuzzy graph theory, and optimization techniques make up his research interests. He has produced four Ph. D. scholars.