
ISSN: 2321-2152
IJMECE
International Journal of modern electronics and communication engineering
E-Mail
editor.ijmece@gmail.com
editor@ijmece.com
www.ijmece.com

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 1, 2025

OBJECT DETECTION ALGORITHM FOR VIDEO SURVEILLANCE APPLICATIONS

Dr. V. MOUNIKA[1], V V LAKSHMI LALITHA RIMMALAPUDI[2], MUDRAGADA JAYA KRISHNA MANIDEEP[3], ADDEPALLI SRUTHI ANUSHA[4], GANJI UMA MAHESWAR[5], KAMMILA RAMA RAJU[6]

[1]Associate Professor, Dept. Of ECE, PRAGATI ENGINEERING COLLEGE

[23456]UG Students, Dept. Of ECE, PRAGATI ENGINEERING COLLEGE

ABSTRACT

Object detection is essential for video surveillance, enabling automated monitoring and real-time threat detection. This study implements various detection techniques such as face detection, skin detection, color detection, shape detection, and target detection to improve surveillance accuracy. The system is developed using MATLAB 2017b, leveraging its advanced image processing and machine learning tools. Challenges such as lighting variations, occlusions, and real-time processing constraints are addressed to enhance system efficiency. The proposed methodology demonstrates improved accuracy in security applications, traffic monitoring, and automated surveillance, with future integrations focusing on AI and edge computing.

INTRODUCTION

With the rapid advancement of digital image processing, video surveillance has become a crucial tool for security, traffic monitoring, and public safety. Image retrieval and object detection play a significant role in analyzing and interpreting surveillance data. Traditional methods often suffer from occlusions, poor lighting conditions, and high false alarm rates. This research proposes a robust object detection algorithm incorporating multiple techniques to enhance surveillance effectiveness.

LITERATURE SURVEY

Image retrieval and object detection have evolved through various methodologies. Conventional methods such as color histograms, texture-based segmentation, and contour analysis have been widely used. Recent advancements include machine learning-based classifiers, deep learning approaches such as YOLO and Faster R-CNN, and feature extraction techniques using Gabor filters and wavelet transforms. The literature highlights the necessity for adaptive algorithms to mitigate real-world surveillance challenges.

PROPOSED SYSTEM

The proposed system integrates multiple detection techniques, utilizing MATLAB's image processing toolbox. The workflow includes:

1. **Preprocessing:** Image enhancement and noise reduction.
2. **Feature Extraction:** Shape, color, texture, and motion features are extracted.
3. **Classification:** Supervised learning models categorize objects.

4. **Tracking and Recognition**: Real-time object tracking ensures robust detection.

The system employs YOLO for high-speed detection and Faster R-CNN for precision-based applications. Data augmentation techniques improve accuracy under varying environmental conditions.

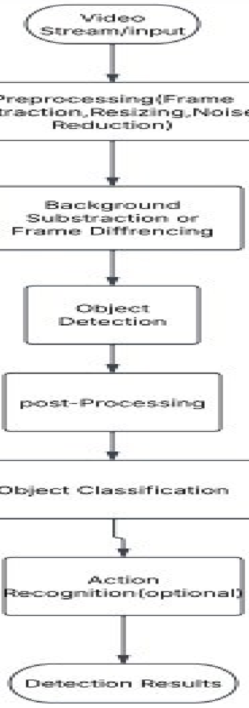

Figure.1 Flow Chart

SIMULATION RESULTS

we introduce the implementation details of our proposed model and analyse the effects of the modules in the network. We refer to our tracker as GDT (Gated fusion Deformable object Tracker) and we compare GDT with state-of-the-art trackers in the benchmark datasets. To validate the effectiveness of each module, we separately train the following three models: network without the two modules (Baseline), network with the deformable convolution module only (Baseline+Deform), and the complete network (Baseline+Deform+Gate). We compare the performance of these models on the OTB-2013 dataset. In Fig. 6(left), we evaluate the overall tracking performance by the success rate metric on the entire dataset. In Fig. 6(right), we measure the tracking performance on the videos containing the deformation attribute.

Below figures shows the user interface that was developed using GUI interface and the outputs that we get after selecting each button. The buttons present are Browse, Frame Separation, Object Detection and Final Object Detection.

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 1, 2025

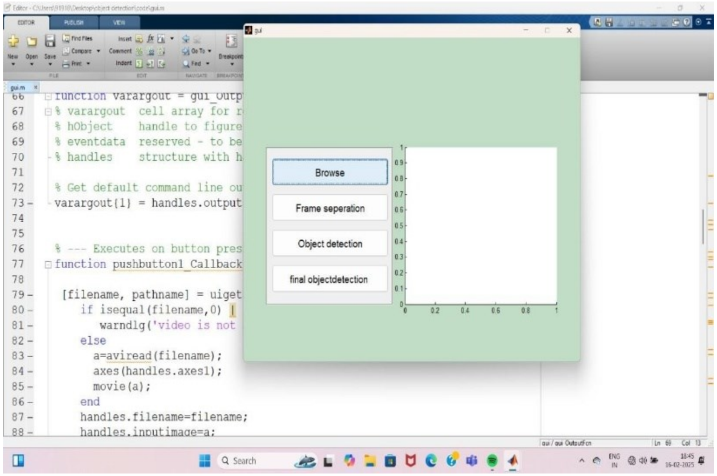

Figure.2 Browse for image

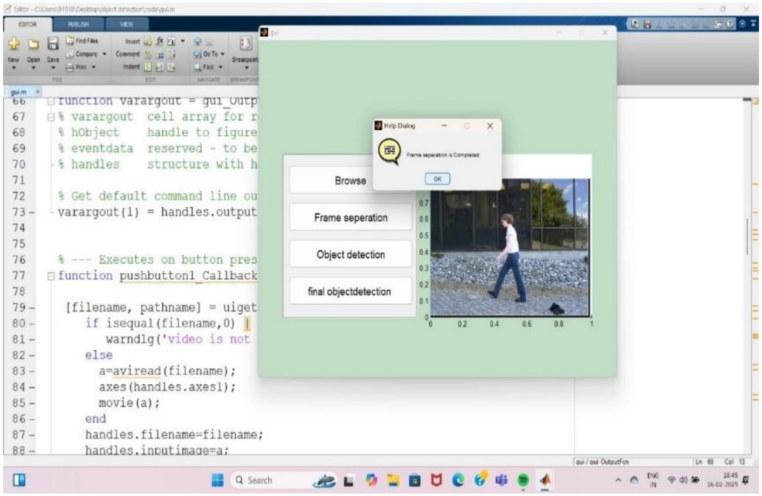

Figure.3 Frame Separation

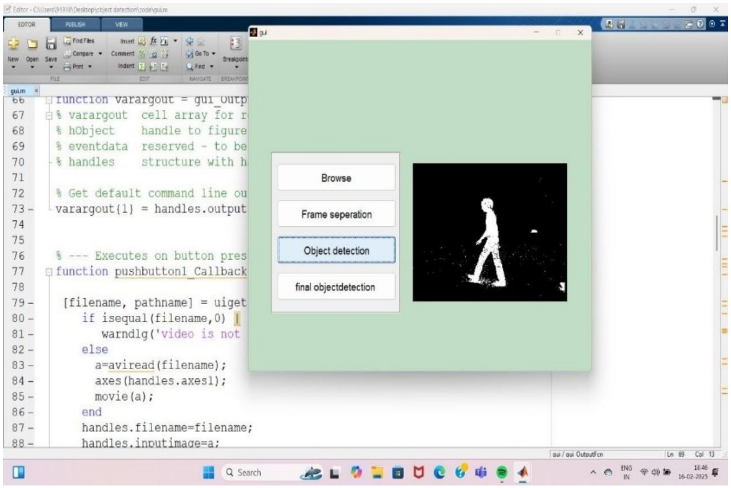

Figure.4 Object detection

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 1, 2025

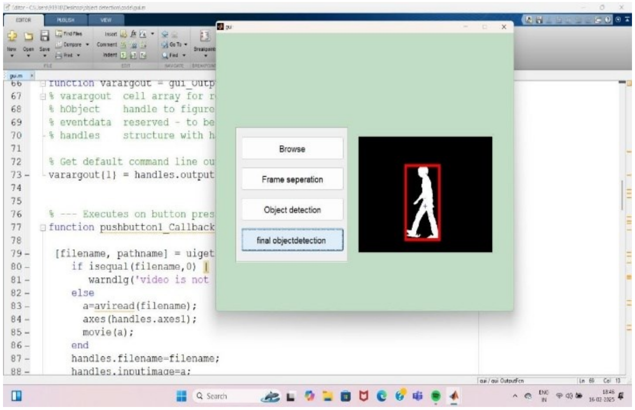

Figure.5 Final Object detection

ADVANTAGES

- **Enhanced Security:** Real-time threat detection for improved surveillance.
- **Automated Monitoring:** Reduces manual supervision efforts.
- **Scalability:** Suitable for large-scale deployments such as smart cities.
- **AI Integration:** Future enhancements with deep learning models.

APPLICATIONS

- **Traffic Monitoring:** Identifies vehicles, violations, and congestion.
- **Public Security:** Detects suspicious activities in crowded areas.
- **Industrial Safety:** Ensures compliance with safety regulations.

CONCLUSION

We have proposed a deformable convolution layer to model target appearance variations in the CNN-based tracking-by detection framework. We aim to capture target appearance variations via deformable convolution and supplement its normal convolution features through the online learned gating module. The gating module controls how the deformable convolutional features and the normal features are fused. Experimental results show that the proposed tracker performs favourably against the state-of-the-art methods. There are still limitations in our proposed model. Our deformable convolution slightly degrades the robustness of the model, since its deformation estimation may fail in some extreme situations, including long-term occlusion, fast and large deformation, or significant illumination variation. For the future work, we would like to improve the robustness of the deformable convolution by enhancing the features extraction stage of our framework. This can be accomplished by collecting more data or adopting a data augmentation technique (e.g., image warping) to independently train the deformable convolution module. In addition, the online learned gating module may not be adequately adaptive to difficult videos. To alleviate this problem, we aim to improve the gating module in the offline training stage. Moreover, in the future, we will consider to generalize our approach to different sources of image data, e.g., RGB-D data and medical images.

FUTURE SCOPE

Object detection in video surveillance is continuously evolving with advancements in artificial intelligence (AI), deep learning, and edge computing. The future holds promising developments that will significantly enhance the accuracy, efficiency, and scalability of surveillance systems.

Traditional object detection methods rely on predefined feature extraction techniques, which may struggle in complex environments. The integration of AI and deep learning models, such as Convolutional Neural Networks (CNNs) and Transformer-based architectures, will enable more precise detection, reducing false alarms caused by lighting changes, occlusions, and background noise. These models will also be capable of recognizing complex behaviors, such as suspicious activities or abnormal movements, allowing proactive security measures.

References

1. Z. Kalal, K. Mikolajczyk, and J. Matas, “Tracking learning detection,” TPAMI.
2. H. Grabner, M. Grabner, and H. Bischof, “Real-time tracking via on-line boosting.” in BMVC, 2006.
3. B. Babenko, M.-H. Yang, and S. Belongie, “Visual tracking with online multiple instance learning,” in CVPR, 2009.
4. S. Hare, S. Golodetz, A. Saffari, V. Vineet, M.-M. Cheng, S. L. Hicks, and P.H. Torr, “Struck: Structured output tracking with kernels,” TPAMI.
5. S. Hong, T. You, S. Kwak, and B. Han, “Online tracking by learning discriminative saliency map with convolutional neural network,” in ICML, 2015.
6. L. Zhang, J. Varadarajan, P. N. Suganthan, N. Ahuja, and P. Moulin, “Robust visual tracking using oblique random forests,” in CVPR, 2017.
7. H. Nam and B. Han, “Learning multi-domain convolutional neural networks for visual tracking,” in CVPR, 2016.
8. G. Ning, Z. Zhang, C. Huang, X. Ren, H. Wang, C. Cai, and Z. He, “Spatially supervised recurrent convolutional neural networks for visual object tracking,” in IEEE International Symposium on Circuits and Systems, 2017, pp. 1–4.
9. Y. Song, C. Ma, X. Wu, B. L. Gong, Lijun, W. Zuo, C. Shen, R. W. H. Lau, and M.-H. Yang, “Vital: Visual tracking via adversarial learning,” in CVPR, 2018.
10. S. Pu, Y. Song, C. Ma, H. Zhang, and M.-H. Yang, “Deep attentive tracking via reciprocative learning,” in NIPS, 2018.
11. B. Han, J. Sim, and H. Adam, “Branchout: Regularization for online ensemble tracking with convolutional neural networks,” in ICCV, 2017.
12. D. S. Bolme, J. R. Beveridge, B. A. Draper, and Y. M. Lui, “Visual object tracking using adaptive correlation filters,” in CVPR, 2010.
13. J. F. Henriques, R. Caseiro, P. Martins, and J. Batista, “High-speed tracking with kernelized correlation filters,” TPAMI, 2015.
14. M. Danelljan, G. Hager, F. Khan, and M. Felsberg, “Accurate scale ¨ estimation for robust visual tracking,” in BMVC, 2014. [15] C. Ma, X. Yang, C. Zhang, and M.-H. Yang, “Long-term correlation

tracking," in CVPR, 2015. M. Danelljan,G. Bhat, F. S. Khan, and M. Felsberg, "Eco: efficient convolution operators for tracking," in CVPR, 2017.

15. M. Danelljan, A. Robinson, F. S. Khan, and M. Felsberg, "Beyond correlation filters: Learning continuous convolution operators for visual tracking," in ECCV, 2016.
16. M. Danelljan, G. Hager, F. Shahbaz Khan, and M. Felsberg, "Learning spatially regularized correlation filters for visual tracking," in ICCV, 2015.
17. H. K. Galoogahi, T. Sim, and S. Lucey, "Correlation filters with limited boundaries," in CVPR, 2015.
18. C. Ma, J.-B. Huang, X. Yang, and M.-H. Yang, "Robust visual tracking via hierarchical convolutional features," in TPAMI, 2018.
19. Y. Qi, S. Zhang, L. Qin, H. Yao, Q. Huang, J. Lim, and M.-H. Yang, "Hedged deep tracking," in CVPR, 2016.
20. T. Zhang, C. Xu, and M.-H. Yang, "Multi-task correlation particle filter for robust object tracking," in CVPR, 2017.
21. H. Kiani Galoogahi, A. Fagg, and S. Lucey, "Learning backgroundaware correlation filters for visual tracking," in CVPR, 2017.
22. C. Sun, D. Wang, H. Lu, and M.-H. Yang, "Learning spatial-aware regressions for visual tracking," in CVPR, 2018.
23. L. Wang, W. Ouyang, X. Wang, and H. Lu, "Visual tracking with fully convolutional networks," in ICCV, 2015.