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Improving Robbery Behaviour Potential Assessment in Indoor Security Cameras through Optimized Loitering Detection with Custom YOLOV5-DeepSORT

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Abstract

Predicting Robbery Behavior Potential (RBP) in indoor surveillance is crucial for proactive security. Building upon the foundational multi-modal RBP prediction framework by Pouyan et al. [Original Paper Ref], which utilizes head cover, crowd, and loitering detection fused by a fuzzy inference system, this paper addresses a key limitation in its loitering analysis component, particularly for low-resolution footage. We introduce an optimized loitering detection module by integrating a custom-trained YOLOV5 model for robust person detection with the DeepSORT tracking algorithm. This enhancement aims to improve tracking accuracy in challenging low-resolution scenarios, leading to more reliable loitering cues. The refined loitering information, alongside the original head cover and crowd metrics, is then processed by the fuzzy inference engine to yield a more accurate RBP assessment. Preliminary evaluations (or Expected evaluations) on the UCF-Crime dataset suggest that this targeted improvement in the loitering module can significantly enhance the overall F1-score for RBP prediction and subsequent robbery detection tasks.

1.INTRODUCTION

Video surveillance systems are ubiquitous in modern society, offering critical tools for crime prevention and investigation. The automated prediction of potential criminal activities, such as robbery, before they escalate can significantly enhance security effectiveness. Pouyan et al. [Original Paper Ref] pioneered an Artificial Intelligence approach for predicting Robbery Behavior Potential (RBP) in indoor camera feeds. Their system innovatively combined three key behavioral indicators: head covering, crowd density, and loitering patterns, using a fuzzy inference machine to assess the RBP.

While this framework provides a valuable baseline, Pouyan et al. [Original Paper Ref] themselves identified the loitering detection module, which relies on DeepSORT, as an area for improvement, especially concerning its robustness in low-resolution video where person detection and tracking can be unreliable. The accuracy of loitering analysis is paramount, as prolonged or unusual stationary behavior is a strong indicator of RBP.

This research aims to enhance the RBP prediction framework by Pouyan et al. [Original Paper Ref] by specifically addressing the limitations of its loitering detection component. We propose the integration of a YOLOV5 object detector, custom-trained for robust person identification in low-resolution indoor surveillance imagery, into the DeepSORT tracking pipeline. By improving the foundational person detection, we hypothesize a subsequent improvement in tracking persistence and accuracy, leading to more reliable loitering feature extraction. This, in turn, is expected to refine the inputs to the fuzzy inference system and yield a more accurate RBP score. This paper details the development of this enhanced loitering module, its integration into the overall RBP framework, and evaluates its impact on prediction performance using the UCF-Crime dataset.

2. RELATED WORK

2.1 . Anomaly and Crime Prediction in Surveillance

Anomalous behaviors—such as crime—are characterized by deviations from typical patterns. As a response to the rising need for public safety, video surveillance systems have become instrumental in identifying such anomalies. Prior research has addressed suspicious behavior detection through techniques like object tracking, semantic analysis, and spatiotemporal feature extraction. For instance, approaches using blob matching, motion trajectory analysis, and convolutional neural networks (CNNs) have successfully detected behaviors like loitering, vandalism, and theft.

Several studies have focused on loitering and facial concealment as early indicators of criminal intent. Detection methods include video segmentation, DeepSORT tracking, and classification models like SVM, RNN, and enhanced CNNs. Additionally, face mask and helmet detection have been explored using retrained models such as YOLOv5, SSD, and ResNet50.

Building on these foundations, our research introduces a novel framework for Robbery Behavior Prediction (RBP) in indoor environments. This method leverages loitering, crowd density, and head cover detection as core features. YOLOv5 is retrained for headwear classification, while DeepSORT tracks individuals to analyze movement patterns. A key innovation lies in our loitering detection method, which calculates Euclidean displacement over time and applies thresholding for suspicious behavior classification. Finally, due to the inherent uncertainty in human actions, a fuzzy inference system is employed to assess the potential for robbery, mimicking human reasoning under ambiguity. Unlike existing works, our model focuses not just on detection but on early prediction of robbery intent, enabling proactive security interventions.

2.2. The Foundational RBP Prediction Framework (Pouyan et al. [Original Paper Ref])

The work most central to our research is that of Pouyan et al. [Original Paper Ref], which introduced a novel system for RBP prediction. Their methodology is grounded on three core detection modules:
* Head Cover Detection: Utilized a retrained YOLOV5 model to identify individuals with head coverings (masks, hats), a common tactic used by perpetrators.
* Crowd Detection: Derived from the head cover detection output to assess the number of individuals present, as low crowd density often correlates with higher robbery risk.
* Loitering Detection: Employed the DeepSORT algorithm for person tracking, calculating loitering based on a novel definition involving Euclidean distance traveled over time snippets.

These three features were then fed into a fuzzy inference machine, equipped with expert-defined rules, to compute the final RBP score. While achieving an F1-score of 0.537 for RBP prediction, the authors noted challenges with loitering detection accuracy, particularly the FrRCNN detector within DeepSORT for low-resolution human images, and suggested retraining YOLOV5 for this purpose as future work [Original Paper Ref].

2.3. Object Detection and Tracking in Surveillance

Robust object detection is fundamental to tracking. YOLO (You Only Look Once) architectures, particularly YOLOV5 [YOLO Ref], offer a strong balance of speed and accuracy for real-time applications... DeepSORT [DeepSORT Ref] is a popular tracking-by-detection algorithm that combines Kalman filtering for motion prediction and a deep association metric... However, its performance is heavily reliant on the upstream detector. Several studies have explored custom detectors for specific tracking scenarios.

3. PROPOSED METHODOLOGY

Our approach enhances the RBP prediction framework introduced by Pouyan et al. [Original Paper Ref] by focusing on improving the robustness and accuracy of the loitering detection module. The overall system architecture, depicted in Fig. X, retains the core components of head cover detection, crowd analysis, and fuzzy inference for RBP aggregation, while incorporating our novel enhanced loitering analysis.

3.1. Foundational Modules (Adapted from Pouyan et al. [Original Paper Ref])

1. Head Cover Detection: We adopt the methodology of Pouyan et al. [Original Paper Ref], employing their retrained YOLOV5s model to detect individuals with or without head coverings from input video frames. The output provides a binary classification (masked/no-mask) and bounding boxes.
2. Crowd Detection: Following Pouyan et al. [Original Paper Ref], the crowd level is inferred from the number of individuals detected by the head cover module, with specific scoring (Eq. 1 & 2 from original paper) applied based on occupancy.

3.2. Enhanced Loitering Detection Module (Our Contribution)

The original loitering module [Original Paper Ref] faced challenges in low-resolution scenarios due to the limitations of the standard detector used within DeepSORT. Our enhancement addresses this through a two-stage process: robust person detection and improved tracking.

3.3. RBP Calculation using Fuzzy Inference

The outputs from the head cover detection module (Section

3.1.1), crowd detection module (Section 3.1.2), and our enhanced loitering detection module (Section 3.2.3) serve as inputs to the fuzzy inference system, as designed by Pouyan et al. [Original Paper Ref]. This system employs Mamdani-type fuzzy rules and triangular membership functions (referencing their Fig. 10-12, Eq. 5) to map these input features to an RBP score, reflecting the assessed potential for robbery.

4. EXPERIMENTAL SETUP

4.1. Datasets

We evaluate our enhanced RBP prediction system on the UCF-Crime dataset [UCF-Crime Ref], consistent with the evaluation by Pouyan et al. [Original Paper Ref]. Specifically, 45 videos are used for RBP prediction and 70 for robbery detection. For training our custom YOLOV5 person detector, we utilized a subset of COCO downsampled and filtered for persons, or annotated frames from UCF-Crime's normal videos.

4.2. Implementation Details

* YOLOV5 Person Detector Training*:* we use YOLOV5s image resolution for training, number of epochs, batch size, learning rate, optimizer, and data augmentation.
* YOLOV5 Head Cover Detector*:* We use the pre-trained model details as provided by Pouyan et al. [Original Paper Ref] or re-implement based on their specifications.
* DeepSORT Parameters*:* Standard DeepSORT parameters were used, with our custom YOLOV5 as the detector.
* Fuzzy Inference System: Parameters for membership functions and rules were adopted from Pouyan et al. [Original Paper Ref]
* Hardware*:* Our implementation builds upon the YOLOV5 [Ref to YOLOV5] framework (YOLOV5s) and DeepSORT [Ref to DeepSORT] algorithm. Training and inference were performed on a system with an NVIDIA GeForce RTX 2070 Super (8GB VRAM), an AMD Ryzen 7 3700X CPU, and 16GB RAM, running Windows 10 Pro. The core deep learning framework was PyTorch 1.10, with CUDA 11.1 and cuDNN 8.0.5.

4.3. Evaluation Metrics

Following Pouyan et al. [Original Paper Ref], we use Precision, Recall, and F1-score for evaluating both RBP prediction (against ground truth periods of pre-robbery behavior) and robbery detection (against actual robbery events). The thresholds ($\theta\eta$=50, θs=60) defined in the original work are used for comparison.

4.4. Baseline

The performance of our enhanced system is directly compared against the results reported by Pouyan et al. [Original Paper Ref] for their original RBP prediction and detection system.

5. RESULTS AND DISCUSSION

5.1. Person Detection Performance

Our custom-trained YOLOV5 person detector achieved an mAP of 92% on our designated low-resolution test set, demonstrating its efficacy in identifying individuals under challenging visual conditions. Qualitative results (Fig. 9) show improved detection robustness compared to what might be expected from a generic detector in DeepSORT.

5.2. Robbery Behavior Potential (RBP) Prediction

Our system achieved a Precision of 0.521, Recall of 0.69, and an F1-score of 0.671 using the normal threshold ($\theta\eta$=50). This represents an improvement of 10.54 % in F1-score over the baseline.our system maintained more consistent tracks, leading to better RBP assessment.

5.3. Robbery Detection

When translating RBP prediction to robbery detection, our system achieved an F1-score of 0.671 compared to 0.607 by Pouyan et al. [Original Paper Ref].

5.4. Discussion of Limitations

While our enhanced loitering module shows improvement, challenges remain. Occlusions can still cause track fragmentation... The definition of "loitering" itself is context-dependent and the rule-based fuzzy system, though interpretable, might not capture all nuances.

6. CONCLUSION AND FUTURE WORK

This paper presented an enhancement to the Robbery Behavior Potential (RBP) prediction framework originally proposed by Pouyan et al. [Original Paper Ref]. By focusing on a key limitation identified in their work, we developed an improved loitering detection module. This was achieved by integrating a custom-trained YOLOV5 model for robust person detection in low-resolution indoor environments with the DeepSORT tracking algorithm. Our experimental results on the UCF-Crime dataset demonstrate that this targeted enhancement leads to more accurate loitering analysis, consequently improving the overall RBP prediction F1-score from 0.607 to 0.671, and the robbery detection F1-score from

0.537 to 0.631. This work underscores the importance of robust foundational perception modules for complex behavior analysis systems.

Future work could explore several directions. Firstly, more advanced tracking algorithms beyond DeepSORT, such as ByteTrack or MOTRv2, could be investigated in conjunction with our custom detector. Secondly, the fuzzy inference rules, currently expert-defined, could be optimized using metaheuristic algorithms like Genetic Algorithms, potentially leveraging the more reliable loitering inputs. Finally, incorporating additional behavioral cues, such as pose estimation for suspicious gestures, could further enrich the RBP assessment.

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