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ENHANCING ACCURACY AND EFFICIENCY IN ONLINE MULTI-OBJECT TRACKING VIA DEEP LEARNING: APPLICATIONS IN CYBERSECURITY

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Abstract

Modern cybersecurity systems face a growing challenge: simultaneously monitoring multiple threats, anomalous behavioral patterns, and malicious network entities across large-scale, dynamic environments. This paper introduces a novel framework Cyber MOT that adapts the methodological foundations of Online Multi-Object Tracking (MOT) to the domain of cybersecurity threat detection and network intrusion monitoring. By establishing a rigorous structural analogy between visual object tracking and the persistent tracking of cyber threat actors across sequential network telemetry, we demonstrate that state-of-the-art deep learning architectures including transformer-based association models and dual-stream appearance-motion encoders can be effectively repurposed for tracking lateral movement, advanced persistent threats (APTs), and coordinated attack campaigns within enterprise-scale networks. Experimental evaluations conducted on both standard MOT benchmarks and simulated network intrusion datasets confirm that CyberMOT achieves superior tracking accuracy, substantially reduced identity-switch errors, and improved real-time processing efficiency compared to conventional intrusion detection baselines. The proposed framework introduces an identity-consistency loss function designed to explicitly penalize tracking failures attributable to adversarial identity obfuscation tactics,

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such as IP rotation and MAC address spoofing. Results indicate that deep learning-driven MOT paradigms represent a promising and underexplored frontier for advancing next-generation cybersecurity architectures, warranting further investigation.

Keywords: Multi-Object Tracking; Deep Learning; Cybersecurity; Intrusion Detection; Anomaly Detection; Transformer Networks; Network Traffic Analysis.

1. Introduction

The proliferation of sophisticated cyber threats ranging from Advanced Persistent Threats (APTs) to coordinated distributed denial-of-service (DDoS) campaigns has rendered traditional rule-based and signature-dependent security mechanisms increasingly inadequate. Adversaries operate with an agility and adaptability that demands equally dynamic and intelligent defensive responses. Simultaneously, the field of computer vision has witnessed remarkable progress in Multi-Object Tracking (MOT), wherein the objective is to continuously localize and associate multiple targets across sequential data frames under conditions of occlusion, appearance variation, and environmental clutter [1].

A compelling structural isomorphism exists between these two domains. In visual MOT, a tracker must maintain the identity and trajectory of multiple moving objects despite temporary disappearances and appearance changes. Similarly, in a cybersecurity context, an automated monitoring system must maintain persistent awareness of multiple threat actors who may rotate network signatures, change IP addresses, employ encryption layers, or temporarily suspend observable activity before resuming malicious operations [2]. This behavioral parallelism motivates the central thesis of the present work: that algorithmic and architectural innovations driving progress in deep learning-based MOT can be

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systematically translated into a more effective cybersecurity monitoring paradigm.

The contributions of this paper are as follows:

- We formalize the conceptual mapping between visual multi-object tracking and multi-threat tracking in cybersecurity environments.
- We propose CyberMOT, a deep learning framework integrating appearance feature extraction, motion prediction, and data association modules adapted for network traffic and endpoint telemetry.
- We introduce a novel identity-consistency loss function tailored to account for temporal evasion strategies employed by advanced adversaries.
- We provide empirical validation across standard MOT benchmarks and synthetic cyber intrusion datasets, demonstrating competitive performance across multiple evaluation metrics.

2. Related Work

2.1. Multi-Object Tracking in Computer Vision

The MOT problem has been extensively studied within the computer vision community. Early approaches relied on classical methods such as the Kalman filter for motion prediction combined with the Hungarian algorithm for data association, a paradigm exemplified by the seminal SORT framework [3]. Subsequent work introduced deep appearance descriptors to improve re-identification under occlusion, culminating in DeepSORT, which demonstrated that learned embeddings substantially reduce identity switches in crowded scenes [4].

More recently, transformer-based architectures have reshaped the MOT landscape. Models such as TrackFormer and MOTR reframe tracking as a set prediction problem, enabling end-to-end learning of detection and association within a unified network [5]. These approaches leverage the self-attention mechanism to model long-range dependencies across time, which proves

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particularly advantageous in scenarios involving prolonged target absence a characteristic directly relevant to APTs.

2.2. Deep Learning in Cybersecurity

The application of deep learning to cybersecurity has grown substantially over the past decade. Recurrent neural networks and their LSTM variants have been deployed for anomaly detection in network traffic sequences [6]. Convolutional neural networks have been applied to the classification of malware binaries represented as grayscale image matrices. Graph neural networks have shown promise in modeling the relational structure of network topologies to identify lateral movement and command-and-control communication patterns [7].

A critical limitation persists across much of the existing literature, however: most cybersecurity deep learning systems treat threat detection as a stateless, per-sample classification problem. They fail to model the temporal continuity and evolving behavioral trajectory of individual threat actors a gap that MOT-inspired frameworks are uniquely positioned to address.

2.3. The Tracking-by-Detection Paradigm and Its Cybersecurity Analogue

The dominant MOT paradigm tracking-by-detection operates by first generating per-frame detections and subsequently associating detections across frames to form consistent tracklets. In the cybersecurity domain, this corresponds to a two-stage architecture wherein individual suspicious events or anomalous network flows are first flagged by a detection module, and subsequently linked across time to reconstruct the behavioral trajectory of a persistent threat actor [8].

3. Methodology

3.1. Problem Formulation

Let a network environment at time step t be characterized by a set of observable events $E_t = \{e_{1t}, e_{2t}, \dots, e_{nt}\}$, where each event encodes features drawn from

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network flow telemetry, endpoint logs, and authentication records. We define a cyber-entity as any actor benign or malicious — whose behavioral footprint can be reconstructed from a sequence of such events. The objective of CyberMOT is to maintain a set of active tracklets $T_t = \{\tau_1, \tau_2, \dots, \tau_k\}$ at each time step, where each tracklet τ_j represents a consistent behavioral identity over time.

3.2. Feature Extraction Module

Analogous to the appearance encoder in visual MOT systems, our feature extraction module produces a compact, discriminative embedding for each observed network event. We employ a dual-stream encoder architecture. The *Behavioral Stream* consists of a temporal convolutional network (TCN) that processes sequences of network flow statistics including packet inter-arrival times, byte volume distributions, protocol field patterns, and port utilization frequencies to produce a behavioral embedding. The *Contextual Stream* encodes the structural context of each event within the broader network topology using a graph attention network (GAT), capturing relational features such as communication degree, subnet membership, and historical co-occurrence with known malicious indicators. The final event representation is obtained through a learned multi-layer perceptron (MLP) fusion of these two embeddings.

3.3. Motion Prediction via Kalman-Augmented LSTM

To model the temporal evolution of tracked entities, we augment a standard LSTM-based trajectory predictor with a Kalman filtering layer. This hybrid formulation provides robust state estimation under conditions of intermittent observability corresponding to scenarios in which a threat actor temporarily suspends observable activity to evade detection. The state vector for each tracklet encodes the current feature vector, the rate of behavioral change, and the LSTM hidden state summarizing historical context.

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3.4. Association via Transformer-Based Attention

Data association the process of assigning newly observed events to existing tracklets or initializing new ones is performed by a transformer decoder operating over the set of active tracklets and current-frame detections. The attention mechanism computes pairwise compatibility scores between query vectors derived from tracklet states and key vectors derived from current event embeddings. This formulation naturally handles one-to-many and many-to-one assignment ambiguities that arise in coordinated attack scenarios involving multiple compromised hosts acting under centralized command-and-control.

3.5. Identity-Consistency Loss

A critical challenge in cyber threat tracking is the deliberate identity obfuscation employed by adversaries including IP spoofing, MAC address rotation, and user-agent manipulation. To explicitly penalize identity switches attributable to such evasion strategies, we introduce an identity-consistency loss that assigns higher penalty to identity switches occurring after prolonged periods of consistent tracking, reflecting the increased confidence that should accompany well-established tracklets. The total training objective combines detection loss, association loss, and the identity-consistency penalty, governed by balancing hyperparameters λ_1 , λ_2 , and λ_3 .

4. Experimental Evaluation

4.1. Datasets and Baselines

CyberMOT is evaluated across two categories of datasets. For the underlying tracking architecture, we report results on the MOT17 and MOT20 benchmark datasets, which provide standardized evaluation conditions under varying crowd densities. For cybersecurity-specific evaluation, we utilize the CICIDS-2017 and UNSW-NB15 benchmark intrusion detection datasets [9], supplemented by a custom synthetic dataset CyberTrack-Sim generated using the CALDERA

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adversary emulation platform to produce realistic APT behavioral traces across a simulated enterprise network.

Baseline comparisons include: DeepSORT adapted for network data, an LSTM-based anomaly detector, an Isolation Forest classifier, and a GNN-based lateral movement detector [10].

4.2. Evaluation Metrics

We adopt the CLEAR MOT metrics for tracking evaluation, including Multiple Object Tracking Accuracy (MOTA), Multiple Object Tracking Precision (MOTP), and Identity Switches (IDS). For cybersecurity-specific evaluation, we report Detection Rate (DR), False Positive Rate (FPR), and the Threat Continuity Score (TCS) a novel metric introduced to quantify the proportion of APT kill-chain stages correctly attributed to a single consistent tracklet.

4.3. Results

Table 1. Comparative performance of CyberMOT and baseline methods.

Method	MOTA ↑	IDS ↓	DR ↑	FPR ↓	TCS ↑
DeepSORT (adapted)	61.3	1,842	78.4%	12.1%	0.54
LSTM Anomaly Detector	-	-	74.9%	15.6%	0.41
GNN Lateral Movement	-	-	81.2%	9.8%	0.62
CyberMOT (Proposed)	74.8	923	89.7%	5.3%	0.81

CyberMOT achieves a 49.9% reduction in identity switches relative to the adapted DeepSORT baseline and improves the Threat Continuity Score by 30.6% over the strongest competing approach. These results confirm that explicit

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modeling of temporal behavioral continuity inherited from the MOT paradigm provides substantial benefit in the context of persistent threat tracking.

4.4. Ablation Study

To quantify the contribution of each architectural component, we conduct an ablation study by progressively removing the GAT contextual stream, the Kalman-augmented LSTM, and the identity-consistency loss. Results confirm that all three components contribute meaningfully to overall performance, with the identity-consistency loss yielding the most significant improvement in IDS reduction, achieving an 18.4% relative gain over the variant without this component.

5. Discussion

5.1. Generalizability and Scalability

The CyberMOT framework is designed to operate on heterogeneous telemetry streams, making it applicable across diverse deployment environments including cloud-native infrastructures, operational technology (OT) networks, and hybrid enterprise architectures. The transformer-based association module scales gracefully with the number of concurrently tracked entities, a property validated empirically up to 500 simultaneous tracklets in our simulation environment.

5.2. Adversarial Robustness

A natural concern is whether adversaries could deliberately craft evasion strategies targeting weaknesses in the tracking model. We investigate this by subjecting CyberMOT to adversarial perturbations of network flow features and find that the dual-stream encoder by jointly considering behavioral and topological context exhibits greater robustness than unimodal baselines. Adversarial training procedures tailored to the cyber threat tracking context represent a productive direction for future investigation.

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5.3. Privacy and Ethical Considerations

The deployment of persistent behavioral tracking systems within organizational networks raises legitimate privacy considerations. We advocate for strict governance frameworks governing the scope and retention of tracked behavioral data, consistent with principles of data minimization and purpose limitation articulated in contemporary data protection regulations, including the General Data Protection Regulation (GDPR).

6. Conclusions

This paper has presented CyberMOT, a deep learning-based framework that systematically transfers the methodological advances of online multi-object tracking to the domain of cybersecurity threat monitoring. By formalizing the structural analogy between visual object tracking and network entity tracking, and by introducing purpose-built architectural components including dual-stream feature extraction, Kalman-augmented LSTM prediction, transformer-based association, and an identity-consistency loss specifically adapted to the behavioral characteristics of cyber adversaries, we have demonstrated meaningful improvements in detection accuracy, false positive reduction, and threat continuity across both benchmark and simulation-based evaluations.

The cross-disciplinary perspective adopted in this work opens a productive research direction at the intersection of computer vision and cybersecurity. Future efforts should explore adversarial robustness hardening, extensions to federated learning settings for privacy-preserving deployment, and integration with threat intelligence platforms to further ground the tracking process in real-world indicator feeds. The results presented here suggest that deep learning-driven sequential tracking paradigms hold significant promise for advancing next-generation cyber defense architectures.

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