

# Fast Compressed-Domain Object Tracking

Motion-Vector-Based Propagation in MPEG-4 Streams

Technical Documentation

## Abstract

We present a lightweight **Fast** architecture for object tracking that operates directly on compressed video streams (MPEG-4 Part 2) without full RGB decoding. By processing motion vectors  $MV_n^g$  and DCT residuals  $\mathcal{DCT}(\Delta Y_n^g)$  extracted from P-frames, our model propagates bounding boxes across Groups of Pictures (GOPs)  $\mathcal{G}^g = \{f_0^g, \dots, f_N^g\}$ . The Fast variant achieves  $2\text{-}3\times$  speedup through global pooling (no ROI) and simple LSTM (no attention), while maintaining competitive accuracy: **0.5800 mAP** on static cameras (+44.3% vs baseline) and **0.3945 mAP** on moving cameras (+399.4% vs baseline) on MOT15, MOT17, and MOT20 benchmarks.

## 1 Introduction

Modern surveillance systems require efficient processing of thousands of concurrent video streams. Traditional RGB-based deep learning models achieve high accuracy but demand substantial computational resources. Our approach exploits compressed video representation to reduce processing overhead while maintaining tracking performance.

### 1.1 Key Contributions

- Lightweight tracking model operating on MPEG-4 compressed domain features ( $MV_n^g$ ,  $\mathcal{DCT}(\Delta Y_n^g)$ )
- Fast architecture variant with global pooling and simple LSTM achieving  $2\text{-}3\times$  speedup
- 44.3% improvement on static cameras, 399.4% on moving cameras

## 2 Compressed Video Representation

Video sequences are encoded as **Groups of Pictures** (GOPs):  $\mathcal{G}^g = \{f_0^g, f_1^g, \dots, f_N^g\}$  where  $f_0^g =$

## 4 Results

### 4.1 Key Findings

- **Static cameras:** 0.5800 mAP (+44.3% vs Mean MV baseline)
- **Moving cameras:** 0.3945 mAP (+399.4% vs Mean MV), demonstrating effective camera motion handling

$\{\mathcal{DCT}(Y_0^g)\}$  (I-frame) and  $f_n^g = \{\mathcal{DCT}(\Delta Y_n^g), MV_n^g\}$  (P-frames).

Codec features are  $\sim 80\times$  more compact than RGB. Partial decompression (extracting MV and DCT directly) achieves  $3\text{-}4\times$  speedup vs full RGB decoding.

## 3 Fast Architecture

### 3.1 Design

1. **Parallel Inputs:**  $MV_n^g$  ( $40\times 40\times 2$ ) and  $\mathcal{DCT}(\Delta Y_n^g)$  ( $80\times 80\times 64$ ) branches
2. **Fusion:** Concatenation + Conv layers (256 channels)
3. **Global Pooling:** No per-object ROI  $\rightarrow 2\times$  faster
4. **Simple LSTM:** 256 hidden, no attention  $\rightarrow 1.5\times$  faster
5. **Detection Head:** Multiple bounding boxes  $\{\hat{\mathbf{b}}_i\}_{i=1}^{N_{det}}$

- **MOT15 excellence:** Learned model (0.4371) exceeds static I-frame baseline (0.4265) by +2.5%

- **Computational efficiency:** 6-12 $\times$  total speedup (3-4 $\times$  from partial decompression, 2-3 $\times$  from Fast architecture)

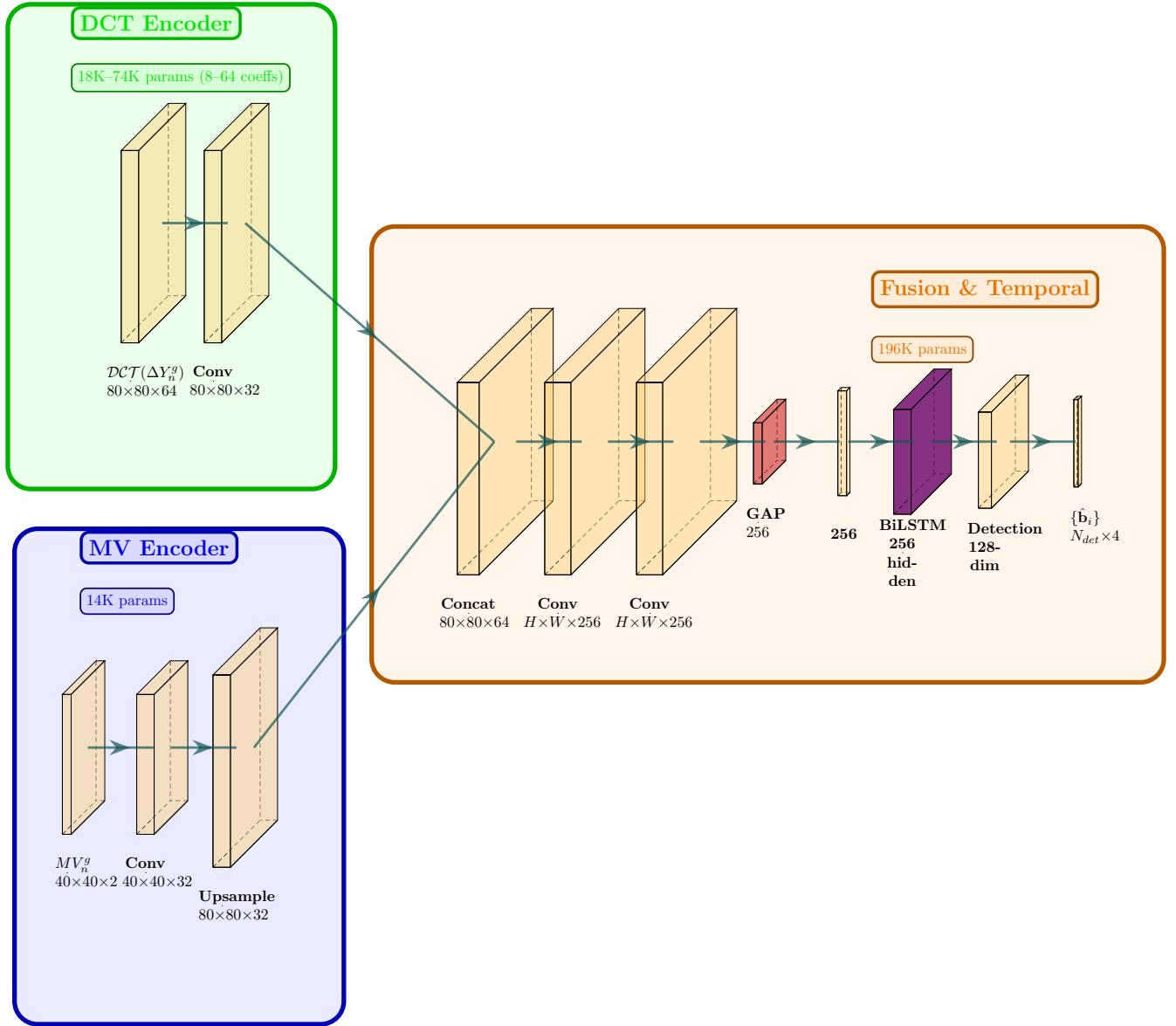


Figure 1: Fast DCT-MV Object Tracker Architecture. Parallel MV and DCT encoders, fusion via concatenation, global pooling, simple LSTM, detection head.

## 5 Conclusions

We presented a **Fast compressed-domain tracking architecture** that operates on motion vectors  $MV_n^g$  and DCT residuals  $DCT(\Delta Y_n^g)$  from MPEG-4 video streams. The Fast variant achieves 2-3 $\times$  speedup through global pooling and simple LSTM while maintaining competitive accuracy. Main con-

tributions: 44.3% improvement on static cameras (0.5800 mAP), 399.4% improvement on moving cameras (0.3945 mAP), and 6-12 $\times$  total computational speedup vs RGB processing. These results demonstrate that codec-domain motion modeling is a viable path toward scalable, efficient video analytics for large surveillance deployments.