Object Tracking using Statistic-based Feature Fusion Technique

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Object Tracking using Statistic-based Feature Fusion Technique

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Introduction

Goal
Automatically track objects in wide area motion imagery (WAMI).

Constraints/Challenges
Very low resolution, presence of noise, illumination variation, occlusions, complex object motion, and complex object shapes.

Proposed Innovation
To better combine features of the DRIFT algorithm through fusion based on past frame effectiveness.

Fusion of Likelihood maps
• Each feature histogram is classified using Earth Mover’s Distance
• A likelihood map is created for each feature for the search area
• Weights selected from previous frame performance
• Fusion based on variance ratio between target and background:

\[ w_i = \frac{VR(L_i, p, q)}{\sum_{i=1}^{N} VR(L_i, p, q)} \]

\[ VR(L_i, p, q) = \frac{\text{var}(L_i, (p + q)/2)}{[\text{var}(L_i, p) + \text{var}(L_i, q)]} \]

where object pixels, p, and background pixels, q

DRIFT Algorithm

Feature Extraction Method
1. Intensity image extracted from video frames
2. Four directional Kirsch kernels used to filter images
3. Gaussian ringlet masks used to create feature histograms for each Kirsch filtered image and the intensity image
4. Histograms from Kirsch filtered images concatenated to retain rotation invariance
5. All Histograms concatenated to create feature descriptor

Feature Likelihood Maps

Search Area

Fused Likelihood Map

Tracking process

Object center selection (initial frame)

Next frame

Search area selection

Feature extraction

Center point selection

Kalman tracker updated

Kalman Tracker
Kalman tracker based on state equations of position and velocity to estimate position if an object is not detected.

Results

• Results for constant weighting and variance ratio based weighting are compared
• 8 WAMI sequences were used for evaluations

Spatial Robustness – Evaluated using different initial bounds

Center Error Threshold
Overlap Threshold

Temporal Robustness – Evaluated using different starting frames

Precision Plot
Success Plot

Center Error Threshold
Overlap Threshold

Frame Detection Accuracy

Center Location Error

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<th>DRIFT variable</th>
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Center Location Error

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