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Overview

We investigated important tracking algorithms including KD-Tree along with Kalman Filter and Scale-Invariant Feature Transform (SIFT) throughout the third week of study. Our study looked at these techniques to determine their ability in handling problems that appeared in our dataset such as partial occlusions and different object sizes and fragmented tracking data. We used VIRE dataset alongside our prior analysis to gain deeper understanding about object tracking across diverse environmental settings.

1. KD-Tree for Nearest Neighbor Search:

K-Dimensional Tree (KD-Tree) functions as a data structure to execute rapid searches for nearest neighbors. The data structure efficiently arranges multidimensional spatial data to become one of the most frequently used technologies in object tracking which links tracklets between frames.

Application in Object Tracking:

The tracking system identifies optimal frame-to-frame object connections through its closest match functionality.

The method lowers the difficulty of identifying tracklet connections within extensive datasets.

Totally improved multi-object tracking (MOT) performance through its ability to recover candidates quickly.

Challenges:

High-dimensional spaces produce performance reduction because of the curse of dimensionality.

The system detects modifications of moving objects which generates potential errors in the system.

2. Kalman Filter for Motion-Based Prediction:

The Kalman Filter operates as a repeated algorithm that produces state estimations of dynamic systems based on uncertain measurement data. The system finds extensive usage in object tracking because it enables reliable prediction of upcoming positions.

Application in Object Tracking:

It foretells object paths by completing the trajectory for situations where the detection gets lost because of blockage.

Time-based tracking of object positions becomes smoother because detection noise receives refinement throughout the tracking period.

Linear tracking functions best with this filter while the Extended or Unscented Kalman Filter extends functionality to non-linear tracking needs.

Challenges:

The algorithm makes use of Gaussian noise assumptions even when the real-world scenarios do not match this model.

Trajectory estimation accuracy suffers from sudden changes in motion because of such conditions.

3. Feature-Based Object Recognition depends on the Scale-Invariant Feature Transform (SIFT) detection method:

The Scale-Invariant Feature Transform algorithm detects image features which overcome problems caused by scaling and rotation together with illumination changes.

Application in Object Tracking:

The system tracks objects through the utilization of distinctive feature descriptors.

Partial visibility does not pose problems because this method recognizes partially visible objects.

The approach enables the separation of objects that have identical appearances through individual feature analysis.

Challenges:

The process remains too complex to allow real-time implementation.

Extreme object deformations together with blurring conditions result in failures when performing feature matching.

4. Exploration of the VIRE Dataset:

The VIRE dataset enables researchers to study object tracking methods specifically for complex and diversified environments. The dataset contains various video sequences which were recorded under distinctive lighting situations and from different angles with multiple object densities.

Key Features:

The collection provides several genuine video sequences that subject tracking robustness tests across urban environments along with indoors.

The dataset provides three distinct challenges to testers including object blockage as well as altered object size and image warping effects.

The benchmark tracks objects throughout each video frame to evaluate tracking system performances.

Relevance to Our Project:

The evaluation platform serves to verify the performance of KD-Tree, Kalman Filter, and SIFT for data processing on material which diverges from VisDrone.

Our tracklet merging technique benefits from this broader framework because it ensures better robustness in evaluation results.

The evaluation process revealed new tracking obstacles which include working with objects in conditions of poor illumination and fast image distortions.

Conclusion and Next Steps

Technical examination of these algorithms alongside research of the VIRE dataset led to the identification of potential tracklet merging enhancement methods. Their mixed application helps strengthen tracking robustness because each algorithm delivers unique performance over weaknesses. Our group has arranged to implement these plans throughout the following weeks.

The tracking system will integrate these examined methods.

An assessment of their performance needs to be conducted on both VisDrone and VIRE datasets.

Tweaking algorithm parameters should lead to enhanced tracking efficiency as well as precise tracking results.

Our investigation serves as a platform for building an advanced offline tracklet merging method to restore thorough connected paths from broken tracklets.