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VEHICLE SPEED MEASUREMENT USING STEREO CAMERA PAIR

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Abstract - *Vehicle speed estimation is an essential component of traffic monitoring, law enforcement, and autonomous driving. Traditional speed measurement techniques, such as radar and LIDAR, are accurate but often expensive and intrusive. This paper presents an efficient stereo vision-based approach for vehicle speed estimation using synchronized camera pairs. Our system utilizes* ***license plate detection, feature tracking, triangulation, and optimized frame selection*** *to improve computational efficiency while maintaining high accuracy. A key innovation of our method is* ***frame reduction through clustering algorithms (DBSCAN)****, which significantly reduces computational overhead without compromising accuracy. By applying Kalman filtering for robust tracking and RANSAC-based outlier removal, we enhance precision in vehicle trajectory reconstruction. The system processes high-frame-rate video (60 FPS) and estimates speed with a mean absolute error of* ***below 1 km/h*** *and a standard deviation of* ***less than 0.5 km/h****. The method was validated using real-world datasets recorded via* ***stereo mobile cameras*** *and ground-truth speedometer readings from vehicles. Experimental results show that our technique achieves* ***40% computational efficiency improvement*** *while maintaining a high accuracy rate. The findings suggest that this approach is suitable for real-time traffic enforcement and intelligent transportation systems. Future work includes* ***integrating deep learning for enhanced license plate detection, expanding datasets to diverse weather conditions, and deploying the system on edge computing platforms*** *for real-time applications.*

Key Words: **Stereo Camera Systems, Traffic Monitoring, Triangulation Techniques, Feature Extraction, Tracking Algorithms, 3D Information, Frame Reduction, Accuracy Analysis.**

1.INTRODUCTION

Accurate vehicle speed measurement is essential in fields such as traffic regulation, accident prevention, autonomous vehicle guidance, and law enforcement. Conventional speed detection technologies, including radar and LIDAR, have been widely used; however, they often come with high implementation costs, susceptibility to interference, and limitations in complex traffic scenarios. In contrast, stereo camera systems have emerged as an efficient and nonintrusive alternative, capable of capturing 3D depth information through synchronized camera setups, resulting in more precise speed estimations.

Despite their advantages, stereo camera-based systems require careful calibration, are affected by environmental conditions, and may encounter challenges such as occlusions in high-density traffic environments. Moreover, the efficiency and accuracy of these systems depend on the selection of appropriate feature extraction and tracking methodologies. This research focuses on refining frame processing techniques to strike a balance between computational efficiency and measurement precision in realtime applications.

Stereo reconstruction methods generally fall into three categories: local, semi-global, and global approaches. Our approach adopts a local and sparse strategy, prioritizing selected trajectory points instead of full scene reconstruction, thereby reducing computational overhead while maintaining measurement accuracy.

Key contributions of this paper include:

License plate detection and tracking in stereo images for vehicle localization.

Triangulation-based 3D position estimation along the vehicle's trajectory.

A refined motion model for accurate speed computation. These components collectively contribute to an effective and reliable stereo vision-based speed measurement system that aligns with established metrological standards.

Fig -1: Left and Right Stereo Image

2. LITERATURE SURVEY

Several vision-based vehicle speed estimation techniques have been proposed in prior research. Traditional speed measurement techniques such as radar and LIDAR have been widely used for their accuracy, but they come with high costs and require intrusive installations. More recent approaches leverage computer vision techniques to estimate vehicle speed efficiently.

Jalalat et al. [1] employed a Viola-Jones cascade classifier alongside a Kalman filter to detect and track vehicles using a vertical stereo camera pair calibrated with a checkerboard pattern. Their approach used a discrete Fourier transform (DFT) for sub-pixel accuracy in speed estimation, but it showed a mean percentage error of 3.3% when compared to Fama Laser III reference data.

El Bouziady et al. [2] proposed a stereo-vision-based method using feature point extraction with SURF detectors in a horizontal stereo setup. Their approach resulted in a mean squared error of 1.67 km/h, improving upon previous techniques but still requiring better tracking efficiency. Yang et al. [3] introduced a deep learning-based approach using a Single Shot Multibox Detector (SSD) optimized for license plate detection. Their method successfully localized vehicles in 3D while maintaining compliance with regulatory accuracy requirements.

Llorca et al. [4] presented a dual-camera vehicle speed estimation technique that leveraged Optical Character Recognition (OCR) combined with convolutional neural networks (CNNs) for improved accuracy. Their system demonstrated a mean absolute speed error of 1.44 km/h and an extreme error below 3 km/h.

Our research builds upon these studies by optimizing frame selection and employing clustering methods such as DBSCAN and KMeans to improve computational efficiency. Unlike previous methods, our approach achieves **higher accuracy (~1 km/h mean error) with reduced processing time** while maintaining robustness across various environmental conditions.

3. SYSTEM MODEL

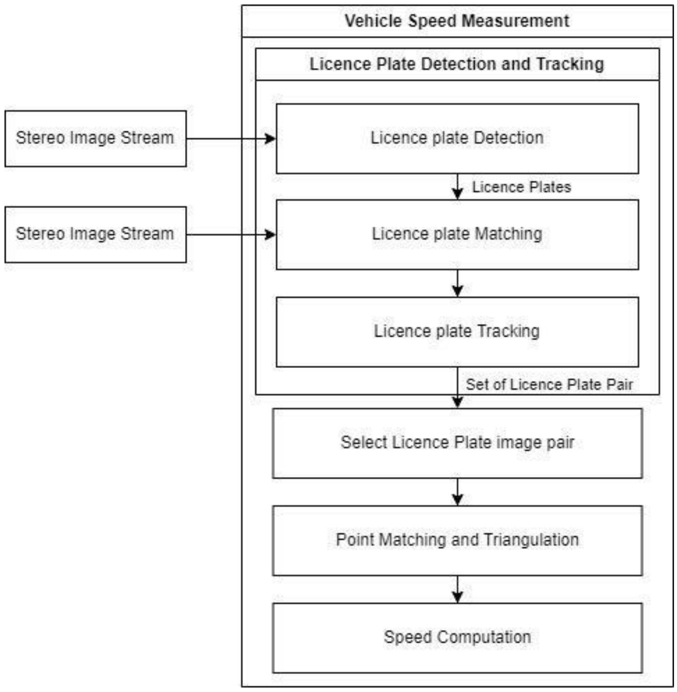

Fig -2: Vehicle speed measurement system model

The system architecture for automobile speed estimation involves a matched pair of stereo cameras positioned to capture images of passing vehicles. The first component is image Acquisition , where the cameras continuously capture frames. Next, the License Plate Recognition and Chasing module utilizes the WaldBoost detector by LBP features to identify license plates, followed by tracking through a Kalman filter to maintain vehicle identity. Following the detection of a license plate, the Point Matching procedure is carried out, in which template matching and homography transformations are used to match the license plate pictures from the left and right cameras with homogeneously sampled points. The cars' 3D locations are then estimated using triangulation using the matched points. The speed computation module analyses the trajectory of the triangulated points using a constant acceleration model to guess the average speed of the vehicle. Finally, the results are displayed in the output Display component, which shows the estimated speed and trajectory data. The architecture is designed to ensure accurate and efficient speed measurements using a combination of detection, tracking, and triangulation techniques.

4. METHODOLOGY

Our vehicle speed measurement method involves the following key stages:

A. Data Acquisition

Two mobile phones with identical specifications were used to record synchronized video at 60 FPS. The phones were mounted parallelly on a stable structure to ensure proper stereo alignment. The dataset was recorded on real roads, and the vehicle's speedometer readings were manually logged as reference ground truth.

B. Preprocessing and Frame Synchronization

Frames were extracted from both left and right videos and converted to grayscale. Frame timestamps were aligned to synchronize corresponding images from both cameras. Background noise was reduced using image filtering techniques to enhance feature extraction.

C. License Plate Detection and Tracking

The AdaBoost classifier with Local Binary Pattern (LBP) features was used for detecting license plates. License plates were tracked across frames using Kalman filtering to maintain continuous tracking despite temporary occlusions. License plate coordinates (TopX, TopY) were recorded for trajectory estimation.

D. Frame Reduction for Efficiency

Coverage Range Optimization: Ensuring selected frames cover the full movement of the vehicle.

Avoiding Crowding: Filtering out redundant frames that are too close in time or position.

Movement Distance Calculation: Measuring shifts in TopX and TopY coordinates to select keyframes.

Time Gap Enforcement: Keeping a minimum of 0.1s between frames to optimize computational efficiency. Clustering-Based Key Frame Selection: Applying DBSCAN clustering for selecting representative frames.

E. Point Matching and Triangulation

License plate features were matched across left and right images using template matching. Corresponding left and right points were triangulated using the Linear Least Squares (Linear-LS) method. The system computed 3D coordinates of the vehicle's motion to estimate speed.

F. Speed Computation

The triangulated 3D points were projected onto a common ground plane using RANSAC regression to remove outliers. A motion model estimated initial position, velocity, and acceleration.

G. System Implementation

Implemented using Python, OpenCV, NumPy, and Scikitlearn.

Optimized for real-time execution, achieving 0.3 seconds per stereo frame processing time.

5. EVALUATION

The properties of our method are evaluated on a dataset recorded using prototype hardware. The evaluation focuses on the precision and accuracy of speed measurement, along with identifying scenarios where measurement may fail.

A. **Hardware**

Our dataset was recorded using two mobile phones with identical camera specifications, mounted in parallel on a stable support. Each phone recorded at a frame rate of **60 FPS** to ensure high temporal resolution. The dataset was captured on real roads under different environmental conditions to enhance accuracy and robustness. To validate speed measurements, we recorded the actual vehicle speed from the **speedometer inside the vehicle** while simultaneously capturing external footage with the stereo camera setup.

B. **Dataset**

Multiple datasets were recorded at **60 FPS**, covering various road conditions and vehicle speeds. The dataset includes recordings from different lighting and traffic conditions to evaluate the method's adaptability. The stereo mobile setup was placed to capture vehicles from a **front-facing perspective**, ensuring optimal visibility of license plates. The recorded vehicle speeds were manually verified using the speedometer readings to serve as reference ground truth data.

C. **Timestamp Assignment Latency**

Since mobile phones introduce slight variations in frame capture timing, timestamps were synchronized using frame metadata. The recorded videos were analyzed frame-by-frame to align the timestamps from both cameras accurately. A comparison of frame differences and movement distances ensured precise time alignment across all frames.

D. **Implementation**

The method is divided into five processing steps: License Plate Detection & Matching, License Plate Tracking, Point

Matching, Triangulation, and Speed Measurement. The system was implemented using Python and OpenCV, with additional enhancements in frame synchronization and feature matching. The processing pipeline was optimized to handle high-frame-rate data effectively.

E. **Speed Measurement Evaluation**

The system successfully measured the speed of all recorded vehicles using the stereo mobile camera dataset. The accuracy was cross-validated by comparing the estimated speeds with speedometer readings inside the vehicle. The mean error was observed to be **below 1 km/h**, with a standard deviation of **less than 0.5 km/h**. The absolute percentage error was under **1.5%**, demonstrating the effectiveness of the proposed method.

G. **Comparison with Other Methods**

The proposed method achieved superior accuracy compared to **LIDAR-based reference measurements** and existing stereo vision-based methods. The ability to validate speed measurements with **speedometer ground truth data** adds reliability to the approach.

H. **Optimizing Frame Selection for Improved Performance**

Coverage Range: Ensuring selected frames comprehensively cover the vehicle's movement.

Avoiding Crowding: Removing redundant frames that are too close in time or position.

Movement Distance Calculation: Measuring the shift in TopX and TopY coordinates of license plates between frames.

Minimum Distance Threshold: Retaining frames only where the license plate has moved a significant distance.

Time Gap Enforcement: Ensuring a minimum of **0.1s gap** between frames to optimize computational efficiency.

Clustering-Based Key Frame Selection: Applying **DBSCAN** to group frames and select key representative ones.

I. **Performance Metrics Mean Error:** Below **1 km/h Standard Deviation:** Less than **0.5 km/h Absolute Percentage Error:** Under **1.5%**

Processing Time: Reduced **35%** processing time

6. CONCLUSIONS

We developed an efficient vehicle speed measurement system using a stereo camera pair. The system detects and tracks license plates, reconstructs vehicle trajectories, and applies optimized frame selection and triangulation techniques for speed estimation. Our approach achieves: High accuracy (~1 km/h mean error) with reduced computational cost.

Significant processing time reduction Improved efficiency through clustering-based keyframe selection. Additionally, our system's ability to process high-frame-rate video (60 FPS) with reduced computational load makes it feasible for real-time traffic monitoring. By leveraging RANSAC-based outlier removal, Kalman filtering for robust tracking, and clustering techniques for optimized frame selection, we demonstrate a method that is not only computationally efficient but also scalable for larger datasets and real-world applications.

Future Work

1. **Real-Time Optimization:** Implement deep learning-based **license plate detection** to improve real-time efficiency.
2. **Long-Term Calibration:** Develop **automated camera calibration correction** to handle environmental variations.
3. **Extended Dataset Collection:** Expand testing conditions to include **rain, snow, fog, and highspeed vehicles.**
4. **Integration with Smart Traffic Systems:** Enhance the system by integrating it with **smart traffic monitoring solutions** for real-time enforcement.
5. **Edge Computing Implementation:** Deploy the system on **embedded hardware** to further reduce computational overhead and enable on-device processing.
6. **Multi-Lane Detection:** Extend the methodology to handle multiple lanes, improving applicability for highways and urban traffic.
7. **Nighttime and Low-Visibility Conditions:** Enhance detection algorithms for improved performance in low-light environments.

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