**CMPE259 -HWK3**

**Literature Survey on Various Research Papers using various Self Driving Algorithms**

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# Key Points

* The proposed threat detection system tackles a critical challenge in autonomous driving - perceiving the environment and identifying potential hazards in real-time. This enables the vehicle to plan safe, collision-free paths.
* YOLO object detection provides key perceptual inputs for autonomous navigation. Training it on large, diverse datasets can improve generalization to novel objects. Choice of network architecture and training methodology also impacts accuracy.
* Multi-modal sensor fusion (cameras, lidar, radar) can complement vision-based techniques like YOLO to boost object detection accuracy in varied conditions. This provides redundancy for safety-critical systems.
* Lane detection gives important spatial cues to focus computation on relevant regions. More advanced techniques can build rich drivable space maps handling unmarked roads.
* Distance estimation is a vital capability for path planning and manoeuvres. Stereo vision, lidar and radar offer more robust spatial awareness than monocular vision. Sensor uncertainty modelling also improves safety.
* Safety assessment via heuristics like the two-second rule provides an initial autonomous decision-making capability. But reinforcement learning based approaches can give more optimized policies for complex scenarios.
* Broadly, the paper provides a strong foundation for object detection and threat analysis modules in an autonomous vehicle stack. But realizing truly safe self-driving cars will require extensive real-world testing, fail-safe designs and interpretable decision making.
* The YOLO model achieves 93% accuracy on object detection.
* The overall system achieves 82.65% accuracy on threat detection tested on a car crash dataset.

## Strengths

* Uses real-time video data from dashcams for threat detection, making it more practical.
* Combines multiple computer vision techniques like YOLO, lane detection, depth estimation for robust threat assessment.
* Achieves low latency threat detection suitable for autonomous vehicles.
* Quantitatively evaluates system accuracy on a dataset of real car crash videos.

## Weaknesses

* Only evaluates on dashcam videos from a single car, may not generalize to diverse real-world conditions.
* Accuracy of 82.65% may be insufficient for reliable threat detection in safety-critical autonomous vehicles.
* Does not consider obstructions coming from sides or behind the vehicle.
* Assumes lane markings are present, may not work well in absence of clear markings.
* Uses a fixed region of interest, adaptive region selection could improve accuracy.

## Key Aspects

* Real-time computer vision for vehicular threat detection
* Object detection using YOLO
* Distance estimation using regression
* Lane detection for defining region of interest
* Two-second rule for safety assessment
* Evaluated on real car crash videos

**In summary, the paper demonstrates a real-time threat detection system using computer vision techniques, with quantitative evaluation. Key limitations are lack of diverse test conditions and insufficient accuracy for reliable real-world use. Future work on adaptive region of interest selection and incorporating side/rear cameras could help address these limitations.**

Additional

**These are some interesting enhancements happening in this field:**

**Additional Enhancement Suggestions:**

1. **Motion Planning Integration:**
   * Utilize the proposed threat detection pipeline for early identification of potential collisions, feeding into the motion planning module to adjust speed and plan evasive maneuvers.
2. **Model Training:**
   * Train the YOLO model on a more extensive and diverse dataset, encompassing objects commonly encountered by self-driving cars, to enhance generalizability.
3. **Multi-Camera Integration:**
   * Incorporate additional cameras (side, rear, 360-degree) to achieve comprehensive object detection and threat analysis. Fuse data from multiple cameras to enhance robustness.
4. **Adaptive Region Selection:**
   * Develop an adaptive algorithm for region selection, dynamically prioritizing areas based on factors like speed, road conditions, and maneuver patterns. This ensures focused computation on the most relevant regions.
5. **Depth Sensing Modalities:**
   * For distance estimation, consider using stereo cameras or alternative depth-sensing modalities like lidar, moving beyond monocular vision for improved distance accuracy.
6. **Drivable Space Detection:**
   * Instead of focusing solely on lane markings, implement lane detection to mark the drivable space. This enables safe maneuvering even in the absence of well-defined lanes.
7. **Semantic Segmentation:**
   * Explore semantic segmentation in addition to object detection to identify non-vehicle obstacles such as people, animals, and debris for a more comprehensive threat analysis.
8. **Diverse Dataset Evaluation:**
   * Evaluate the system on a diverse dataset that covers various weather, lighting, and traffic conditions to enhance generalizability and real-world applicability.
9. **High Accuracy Threshold:**
   * Set a high accuracy threshold (99% or higher) as a prerequisite before allowing the system to control the vehicle, emphasizing the critical importance of safety.
10. **Continuous Model Updating:**
    * Implement continuous online model updates using the latest data from the vehicle's sensors to ensure adaptability to changing conditions and sustained system performance.

**Overall Perspective:**

In essence, the proposed threat detection pipeline can be significantly enhanced by incorporating larger datasets, additional sensors, adaptive algorithms, and rigorous real-world testing. These improvements are crucial for developing reliable and safe self-driving car systems, emphasizing the integration of cutting-edge technology and a commitment to stringent safety standards.