

Tuan Tran Nguyen

# A Reliability-Aware Fusion Concept Toward Robust Ego-Lane Estimation Incorporating Multiple Sources

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# List of Acronyms

**ACC** Adaptive Cruise Control

**ADAS** Advanced Driver Assistance System

**ANN** Artificial Neural Network

**AP** Autonomy Percentage

**AV** Availability

**AVG** Average Fusion

**BE** Baseline

**BN** Bayesian Network

**CART** Classification and Regression Tree

**CH** Center Hypothesis

**CNN** Convolutional Neural Network

**DDD** Driver Drowsiness Detection

**DGPS** Differential Global Positioning System

**DNN** Deep Neural Network

**DST** Dempster–Shafer theory

**DT** Decision Tree

**FCH** First Center Hypothesis

**FEX** Feature Extraction

**FLH** First Left Hypothesis

**FN** False Negative

**FP** False Positive

**FRH** First Right Hypothesis

**FS** F-Score

**FSL** Feature Selection

**GCS** Grid Coordinate System

**GPS** Global Positioning System

**JDL** Joint Directors of Laboratories

**kNN** k-Nearest Neighbors

**KPI** Key Performance Indicator

**LDW** Lane Departure Warning

**LH** Left Hypothesis

**Lidar** Light Detection and Ranging

**LKA** Lane Keeping Assist

**LM** Left Marking

**MA** Maximum Availability

**MED** Median Selection

**MIN** Minimum Selection

**MP** Mapping reliabilities to UTM

**NB** Naive Bayes

**NN** Neural Network

**OEM** Original Equipment Manufacturer

**OP** Overlapping Percentage

**PR** Precision

**Radar** Radio Detection and Ranging

**RAN** Random Selection

**RE** Recall

**ReLU** Rectified Linear Unit

**RF** Random Forests

**RH** Right Hypothesis

**RM** Right Marking

**SAE** SAE International

**SCH** Second Center Hypothesis  
**SGD** Stochastic Gradient Descent  
**SLH** Second Left Hypothesis  
**SRH** Second Right Hypothesis  
**SVM** Support Vector Machine  
  
**TCH** Third Center Hypothesis  
**TJP** Traffic Jam Pilot  
**TLH** Third Left Hypothesis  
**TLU** Threshold Logic Unit  
**TN** True Negative  
**TP** True Positive  
**TRH** Third Right Hypothesis  
  
**UTM** Universal Transverse Mercator  
  
**VCS** Vehicle Coordinate System  
**VH** Vehicle Hypothesis  
  
**WBF** Weight-Based Fusion  
**WIF** Winners Fusion  
**WTA** Winner-Takes-All

# Abstract

The foundation of autonomous driving is a perception system, which can provide sufficient results in all relevant situations. In this context, the road estimation task is an indispensable part, which entails many challenges due to the variety of environmental conditions. To cope with the challenges of this task, the information from multiple sources has to be combined such as optically detected lane markings, the preceding vehicle, occupancy grid. This requirement results from the fact that all sensors have their specific advantages and drawbacks regarding the current environment. For example, the visibility of lane markings can affect the performance of the marking detector. Accordingly, the premise, which is assumed by many works, that all information sources and sensors respectively are uniformly reliable and the following application of an average fusion of all sources are inappropriate to produce sufficient results continually.

Hence, this thesis introduces a new and innovative fusion framework for lane estimation, which incorporates reliabilities of the sources so that the fusion considers only the most reliable sources. Therefore, at first, we extend the commonly known JDL fusion model to integrate the reliability aspect at multiple levels, where reliability represents higher-level uncertainty. Secondly, we define a novel source-independent metric to evaluate the reliability of all information sources within the context of road estimation. Thereby, this measure compares the predicted road course with the manually driven trajectory regarding the angle deviation. Thirdly, a data-driven reliability estimation approach is introduced, where the reliability of each source is separately learned and estimated by a classifier. By that, the set of data for the training consists of the relevant information from sensors' measurements, consensus, and contextual information as well as the past performance of the corresponding hypothesis. Eventually, the reliability-based fusion clusters the hypotheses and then selects the most reliable group. Consequently, only the hypotheses belonging to the chosen group contribute to the final estimation, and the unreliable sources are omitted from the fusion. This supports the system to solve conflict situations among the sources in an appropriate way.

By performing a thorough evaluation using real-world data recordings, our reliability-based fusion approach can improve the overall availability of automated driving. Besides, our reliability-aware framework can be generalized to combine high-level data from multiple sources with varying performances, where the reliability estimation is easily adaptable to new sensors and scenarios.

# Zusammenfassung

Die Schlüsselanforderung des vollautomatisierten Fahrens ist ein System zur Umfeldwahrnehmung, das alle möglichen Szenarien abdecken kann. Dabei ist die Fahrbahnschätzung ein wichtiger Bestandteil, welcher aufgrund verschiedener Umweltbedingungen viele Herausforderungen mit sich bringt. Um diese Herausforderungen zu bewältigen, müssen die Informationen aus unterschiedlichen Sensorquellen, z. B. kamerabasierte Markierungserkennung, vorausfahrendes Fahrzeug, Belegungsgitter, etc., miteinander kombiniert werden. Abhängig vom Einsatzszenario hat jede Quelle ihre spezifischen Vor- und Nachteile, beispielsweise können die Sichtbarkeit und das Vorhandensein von Markierungen die Performanz des Markierungsdetektors beeinflussen. Daher sind die Annahmen bestehender Ansätze, dass alle Quellen immer gleich zuverlässig sind, und der Einsatz einer Mittelwertbildung zur Kombination der Quellen ungeeignet ist, um permanent robuste Ergebnisse zu liefern.

Deshalb stellt diese Arbeit ein neues Fusionsframework für die Fahrbahnschätzung vor, welches die Zuverlässigkeit der Sensoren mit einbezieht. Das Ziel besteht darin, nur die zuverlässigsten Quellen für die Fusion zu berücksichtigen. Zu diesem Zweck wird als Erstes das JDL-Fusionsmodell erweitert, um den Zuverlässigkeitsaspekt als höhere Unsicherheit zu integrieren. Zweitens wird eine neue sensorunabhängige Metrik zur Zuverlässigkeitsbewertung der Quellen präsentiert, die den geschätzten Straßenverlauf mit der manuell gefahrenen Trajektorie im Hinblick auf die Winkelabweichung vergleicht. Drittens präsentiert diese Arbeit einen datengetriebenen Ansatz für die Zuverlässigkeitsschätzung, bei dem die Zuverlässigkeit jeder Quelle anhand eines Klassifikationsmodells separat gelernt und präzisiert wird. Dabei bestehen die Trainingsdaten aus den relevanten Merkmalen von Sensormessungen, der Konsens- und Kontextinformation sowie aus der bisherigen Performanz der entsprechenden Hypothese. Auf Basis der Dempster-Shafer-Evidenztheorie gruppiert die zuverlässigkeitsbasierte Fusion die verfügbaren Hypothesen. Danach werden nur Elemente der zuverlässigsten Gruppe zur endgültigen Fusion beitragen und die restlichen Hypothesen sind ausgeschlossen. Dies ermöglicht dem System, Konfliktsituationen zwischen den Quellen besser zu lösen.

Eine ausführliche Evaluierung mit realen Messdaten zeigt, dass der zuverlässigkeitsbasierte Fusionsansatz die Gesamtverfügbarkeit des automatisierten Fahrens steigert. Ferner kann dieser Ansatz auf die Probleme angewendet werden, bei denen Daten auf hohen Abstraktionsebenen aus mehreren Quellen mit unterschiedlicher Performanz zu kombinieren sind. Außerdem bietet dieser Ansatz die Möglichkeit, die Zuverlässigkeitsschätzung mit geringer Komplexität an neue Sensoren und Szenarien anzupassen.