Evidential deep neural networks: application in semantic analysis for autonomous vehicles

PhD Thesis Defence, February 10, 2026

Presented by
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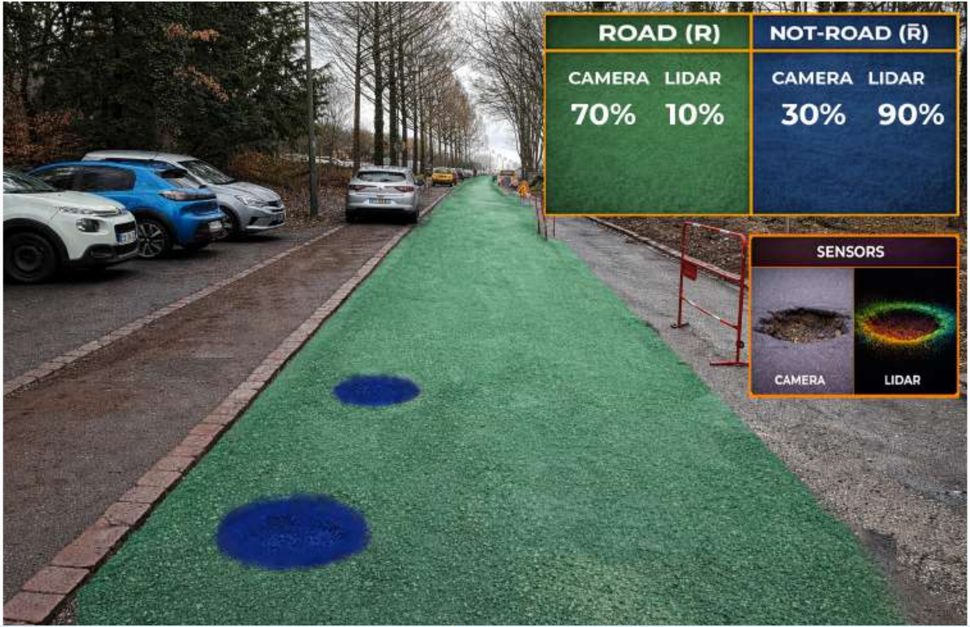
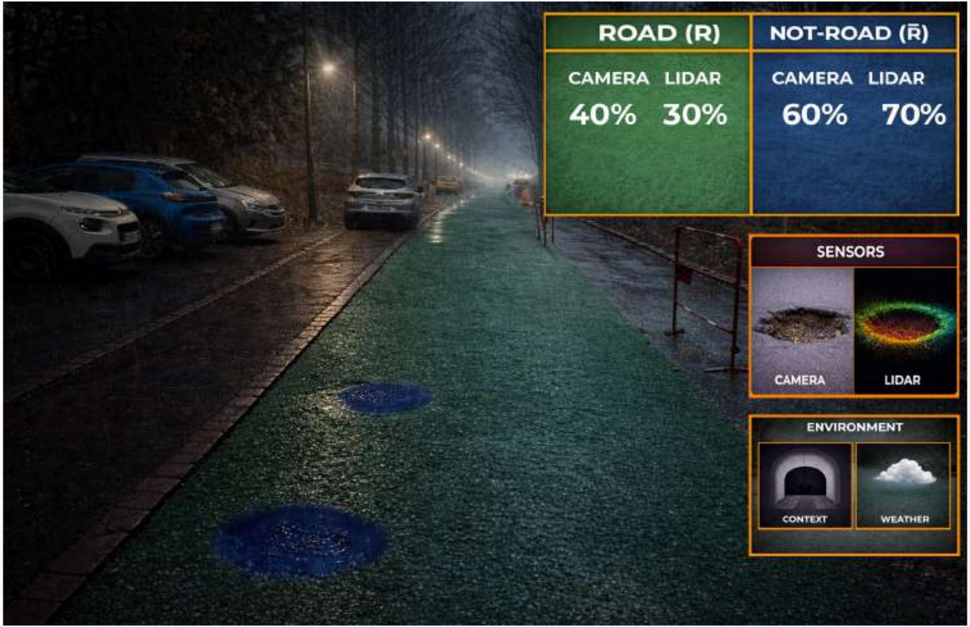
Thesis director: **Jean-Philippe LAUFFENBURGER**

Daily driving scene

What decision now?



What decision now?



Thesis research project - EviDeep (ANR)

anr®

EviDEEP

Evidential theory

Combining evidence

Ambiguous data

Handling conflict

Jean Dezert (ONERA)

Deep neural networks

Semantic analysis for AVs

Multi-modal features

Probabilistic models

MIAM and MSD (IRIMAS)

Evidential deep neural networks: application in semantic analysis for AVs

ONERA

IRIMAS UNIVERSITÉ HAUTE-ALSACE

Presentation outline

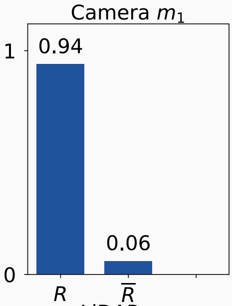
Evidential background

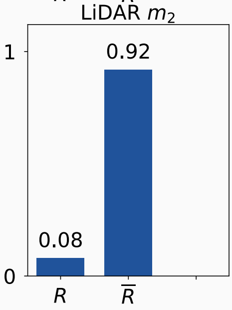
Evidential deep neural networks for autonomous vehicles

Evidential fusion of deep neural networks for multi-class segmentation

Future challenges

Combining evidence





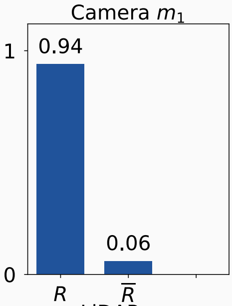
FoD (frame of discernment)
$\Theta = \{\theta_1, \ldots, \theta_n\}$, mutually exclusive
Example: $\Theta = \{R, \overline{R}\}$ (road / not-road)

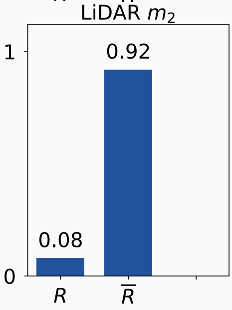
m : mass function

R : Road
$\overline{R}$: Not-Road

evidence (BBA)

Combining evidence





FoD (frame of discernment)
$\Theta = \{\theta_1, \ldots, \theta_n\}$, mutually exclusive
Example: $\Theta = \{R, \bar{R}\}$ (road / not-road)

Mass function | evidence

also known as BBA (belief basic assignment) [Shafer, 1976]
$\sum_{A \subseteq \Theta} m(A) = 1, \quad A \in \{R, \bar{R}, \Theta\}$
Example: $m(R)$, $m(\bar{R})$, $m(\Theta)$

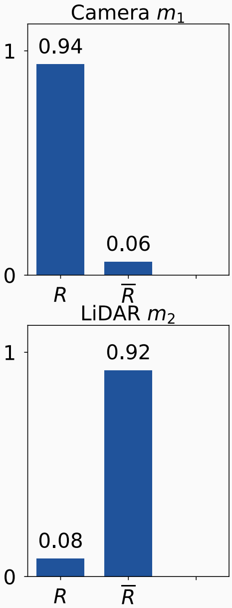
$m(\Theta) = 1 \rightarrow$ **vacuous (total ignorance)**

m : mass function

R : Road
$\bar{R}$: Not-Road

evidence (BBA)

Combining evidence: belief theory basics



Discounting $\rightarrow$ reliability α [Shafer, 1976]

$$m'(R) = \alpha\, m(R)$$
$$m'(\bar{R}) = \alpha\, m(\bar{R})$$
$$m'(\Theta) = 1 - \alpha\big(1 - m(\Theta)\big)$$

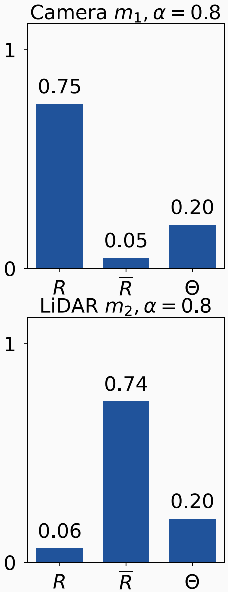
m : mass function

R : Road

$\overline{R}$: Not-Road

evidence (BBA)

Combining evidence: belief theory basics



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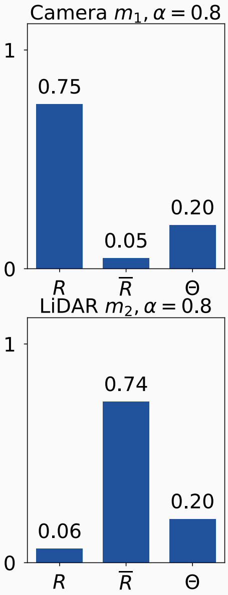
evidence (BBA)

Combining evidence: conjunctive rule



Conjunctive rule $\rightarrow$ (keeps K) [Shafer, 1976]

$$m_{\cap}(R) = m_1(R)m_2(R) + m_1(R)m_2(\Theta) + m_1(\Theta)m_2(R)$$

$$m_{\cap}(\bar{R}) = m_1(\bar{R})m_2(\bar{R}) + m_1(\bar{R})m_2(\Theta) + m_1(\Theta)m_2(\bar{R})$$

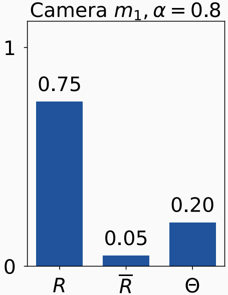
$$m_{\cap}(\emptyset) = m_1(R)m_2(\bar{R}) + m_1(\bar{R})m_2(R) \quad \textbf{(K)}.$$

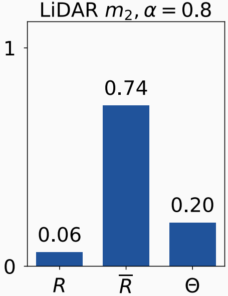
m : mass function
α : discounting

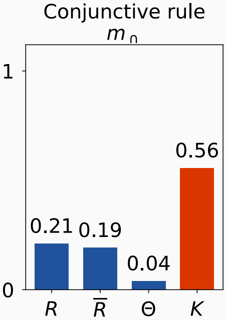
R : Road
$\overline{R}$: Not-Road
Θ : Ignorance

evidence (BBA)

Combining evidence: conjunctive rule







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m : mass function
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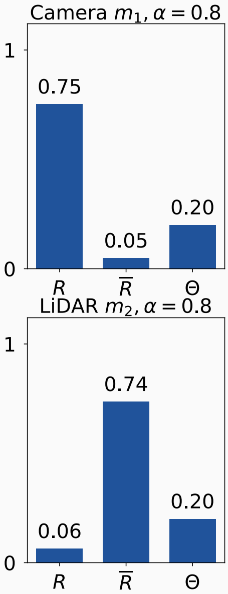
evidence (BBA)
conflict K

Combining evidence: DS rule



DS rule $\rightarrow$ normalize conflict [Shafer, 1976]

$$m_{\mathrm{DS}}(A) = \frac{m_{\cap}(A)}{1-K}, \qquad A \in \{R, \bar{R}, \Theta\}.$$

(**conflict** K is removed, remaining masses are renormalized)

m : mass function
α : discounting

R : Road
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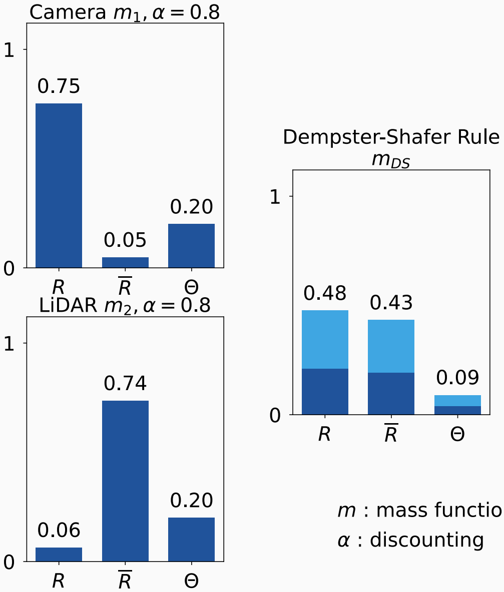
Θ : Ignorance

evidence (BBA)

Combining evidence: DS rule



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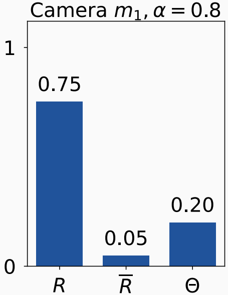
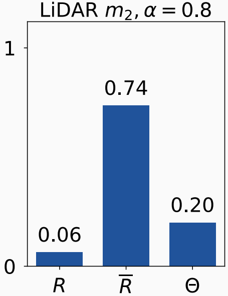
evidence (BBA)
conflict K
redistributed/ norm.

Combining evidence: PCR6$^+$ rule





PCR6$^+$ $\rightarrow$ redistributes conflict [T. Dezert et al., 2021]

$$m^{\mathrm{PCR6}^+}_{1,2,\dots,S}(A) = m^{\cap}_{1,2,\dots,S}(A) + \sum_{j \in \{1,\dots,\mathcal{F}\} \mid A \in \mathbf{X}_j \wedge \pi_j(\emptyset)} \left[\left(\kappa_j(A) \sum_{i \in \{1,\dots,S\} \mid X_{j_i} = A} m_i(X_{j_i}) \right) \cdot \frac{\pi_j(\emptyset)}{\sum_{X \in \mathbf{X}_j} \left(\kappa_j(X) \sum_{i \in \{1,\dots,S\} \mid X_{j_i} = X} m_i(X_{j_i}) \right)} \right].$$

m : mass function
α : discounting

R : Road
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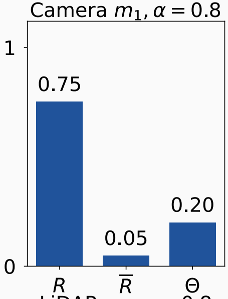
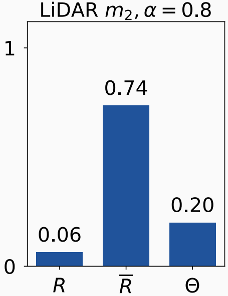
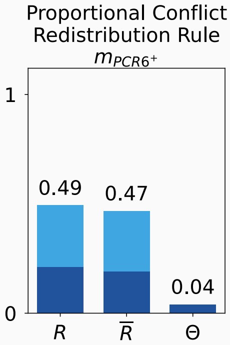
Θ : Ignorance

evidence (BBA)

Combining evidence: PCR6$^+$ rule







PCR6$^+$ $\rightarrow$ redistribute conflict [T. Dezert et al., 2021]

$m_{\text{PCR6}^+}(A) = m_{\cap}(X) + \Delta_A(K), \qquad A \in \{R, \bar{R}, \Theta\},$

where $\Delta_A(K)$ redistributes conflict proportionally to supports

$\kappa_j(A)$: proportional weight

$\pi_j(\emptyset)$: partial conflict

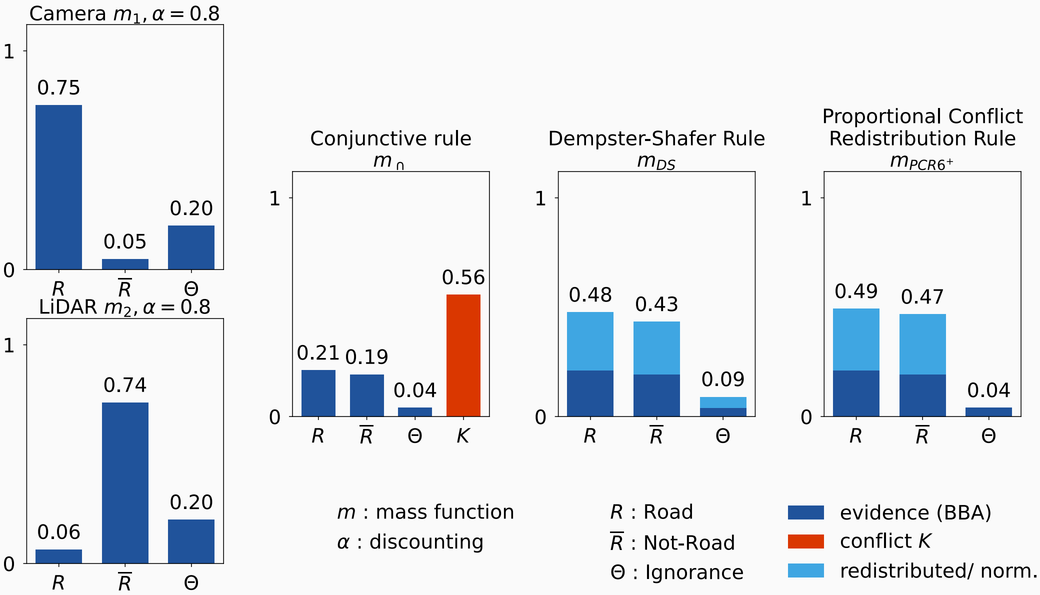
$\mathbf{X}_j$: conflicting elements

m : mass function
α : discounting

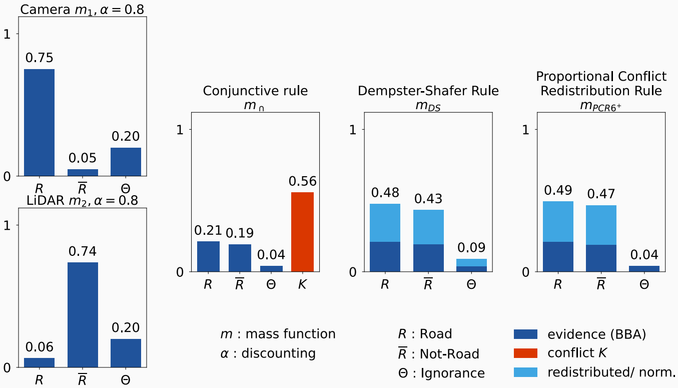
R : Road
$\overline{R}$: Not-Road
Θ : Ignorance

evidence (BBA)
conflict K
redistributed

Combining evidence: fusion rules



Combining evidence: fusion rules



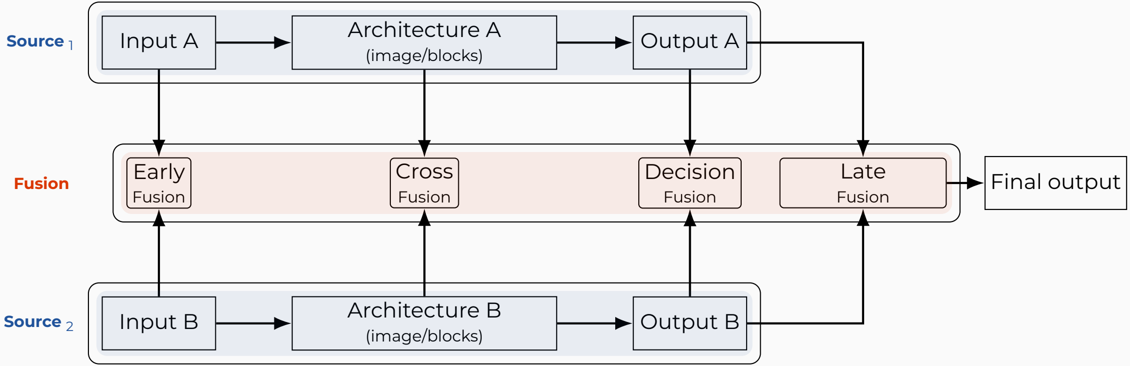
DS rule

+simple +associative +neural to vacous BBA
–sensitive –dictatorial
–cancels all K

PCR6+

+proportional redist. +robust
+non-dictatorial +neutral to vacous BBA
–quasi-associative –complex

How to plug this evidence combination with deep neural networks?



Existing literature: Evidential deep neural networks

2000 · 2019 · 2020 · 2021 · 2022 · 2023 · 2024 · 2025

[Denœux, 2000]

+ Introduced **D2P** with NNs
+ **Evidential** classification

Theoretical

[Capellier et al., 2019]

+ Application in **AVs**
+ **Evidential lidar detection**

– Mono-sensor setup
– Multi-layer perceptron

[Tong et al., 2021]

+ **D2P**
+ **Evidential segmentation**

– Pet segmentation
– Mono-sensor

[Huang et al., 2022]

+ **Evidential segmentation**
+ **D2P**-based outputs

– Medical imaging
– Limited multi-sensor context

[Geletu et al., 2022]

+ **Cross-fusion** multi-sensor
+ **Road detection**

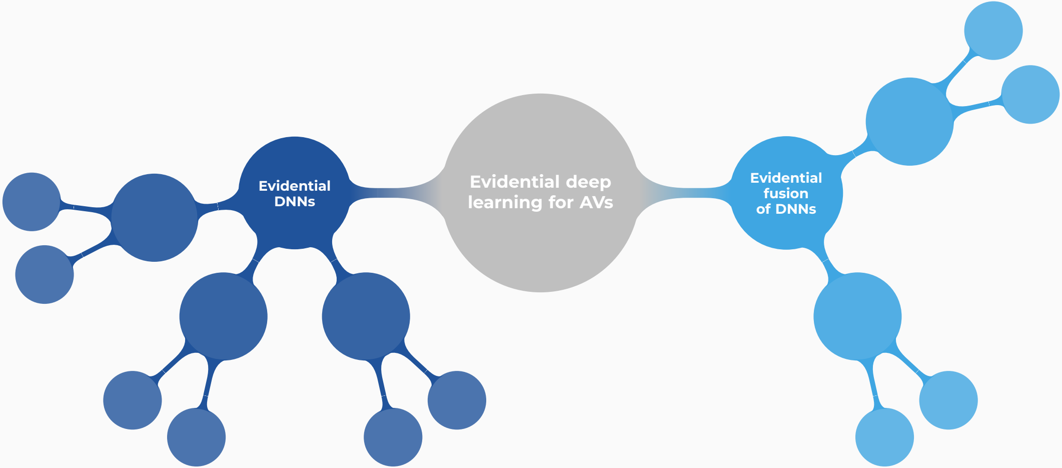
– Evidential reasoning

[Deregnaucourt et al., 2025]

+ **Evidential late fusion**
+ Focus in **AVs**

– D2P

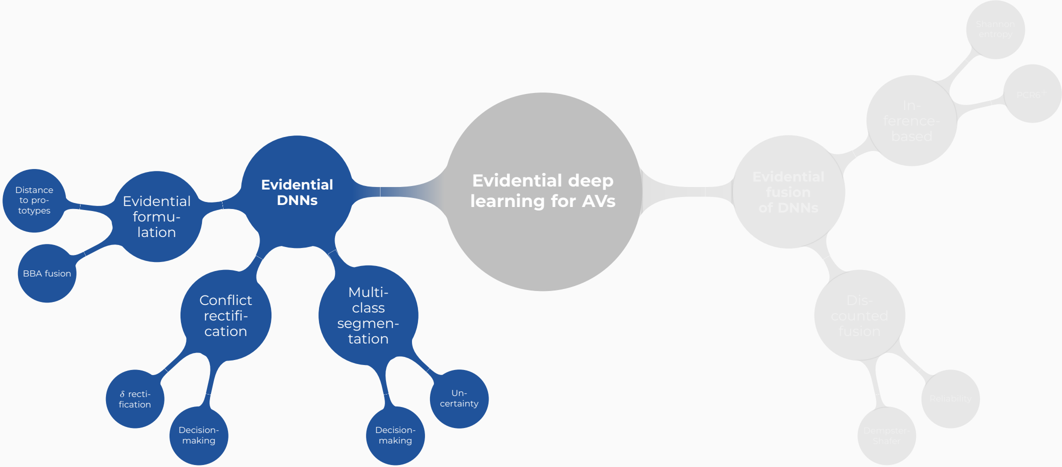
Thesis main research directions



Two research directions

- **Evidential deep neural networks for autonomous vehicles**
- **Evidential fusion of deep neural networks for multi-class segmentation**

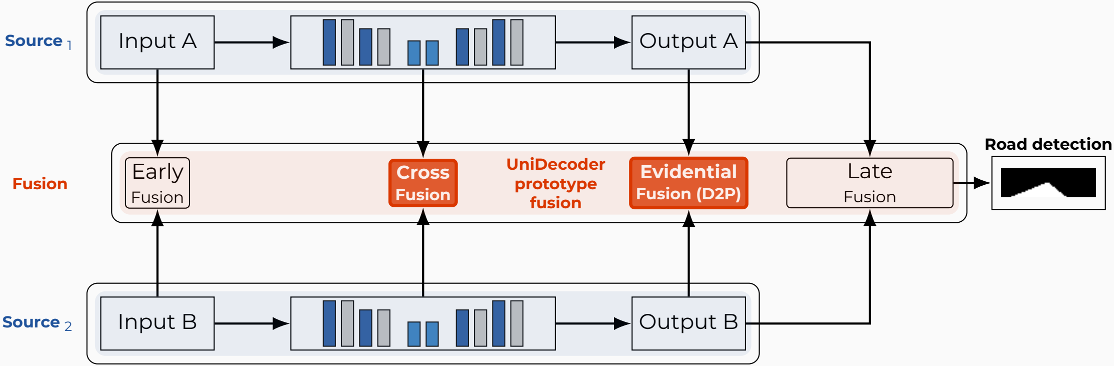
Evidential deep neural networks for autonomous vehicles



First research directions

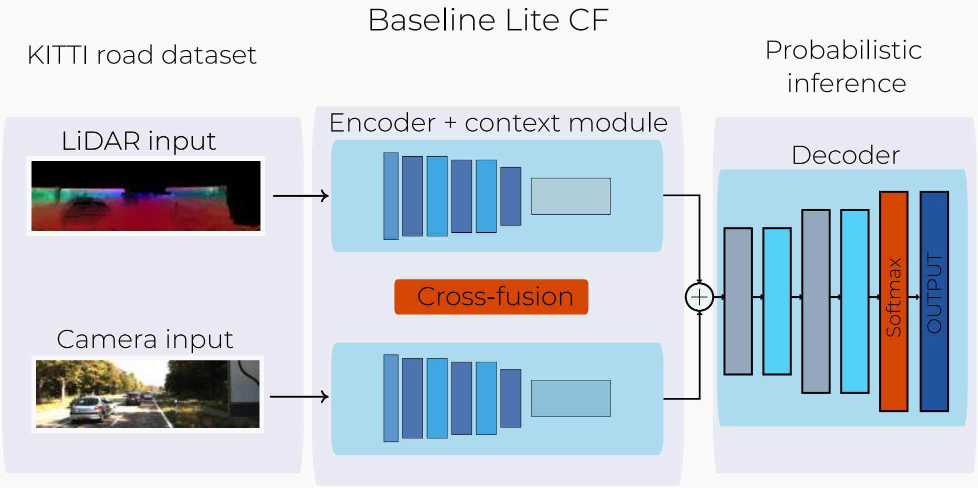
- **LiDAR-camera fusion based on evidential formalism**
- **Conflict management in distance to prototypes and decision-making**
- **Extension to multi-class segmentation: uncertainty and quality indicators**

EDNN: where is fusion happening?



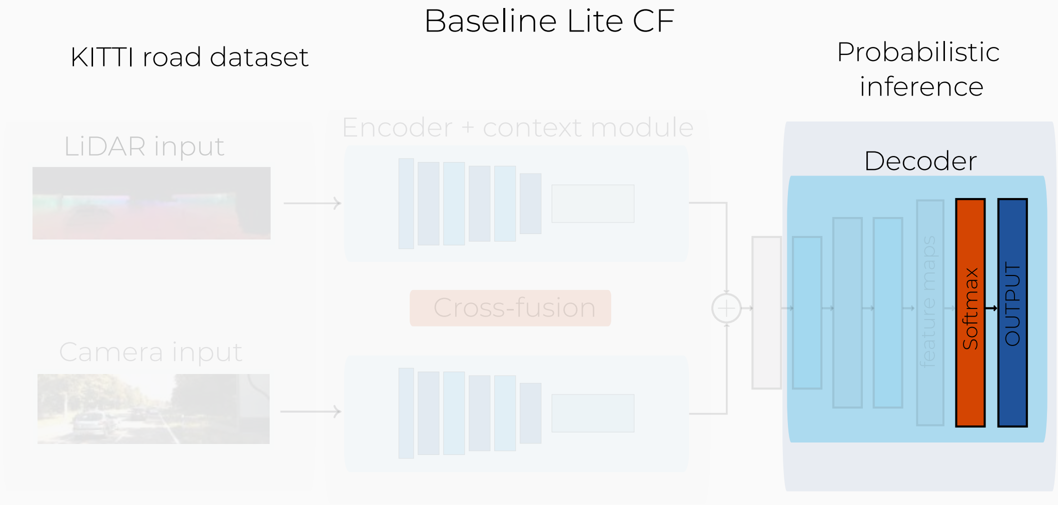
Road detection $\rightarrow$ KITTI road dataset, 2 classes: **Road:** $\bar{R}$, **Not-Road:** $(\bar{R})$

Baseline architecture: Lite-CF



Architecture Lite CF with unified decoder [Geletu et al., 2022].

Baseline architecture: Lite-CF



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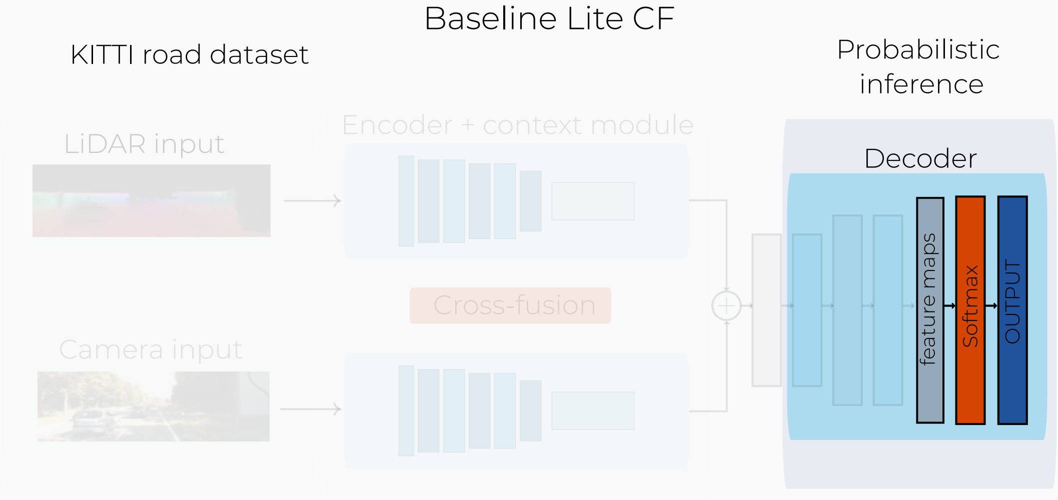

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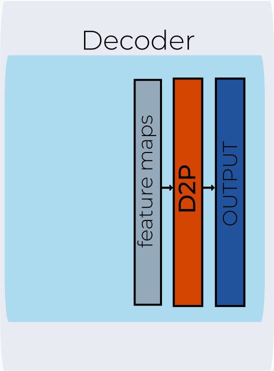
Baseline architecture: Lite-CF

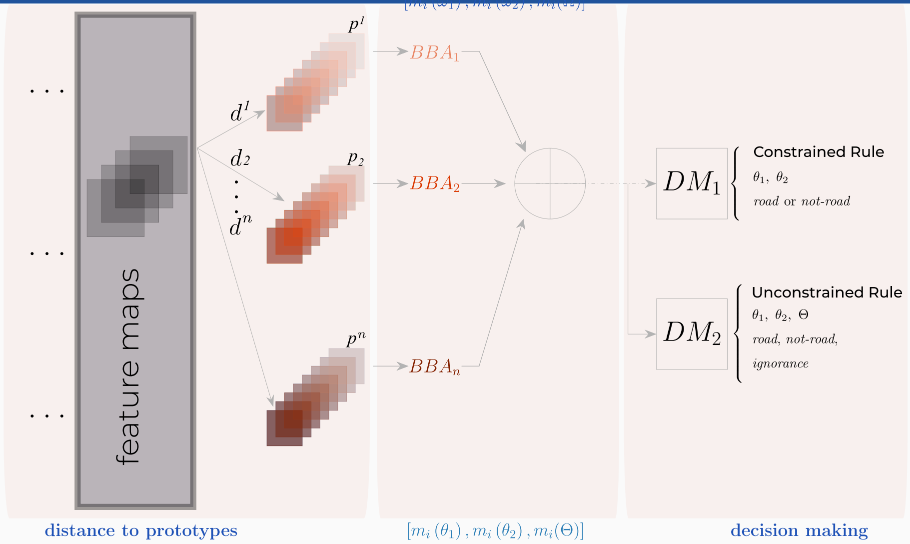
Evidential Lite CF

KITTI road dataset

Evidential formulation



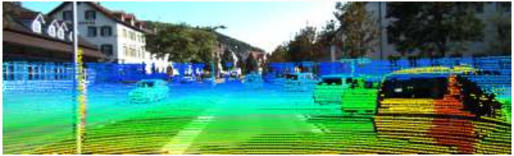
Evidential formulation: distance to prototypes (D2P)



DM$_1$ (decisions in Θ): $\hat{A} = \arg\max_{A\in\{\theta_1,\theta_2\}} m_{DS}(A)$ $(\theta_1$ or $\theta_2) \rightarrow$ *Lite-CF-Evi1*

DM$_2$ (decisions in 2^Θ): $\hat{A} = \arg\min_{A\in\{\theta_1,\theta_2,\Theta\}} d_{(\cdot)}(m_{DS}, m_A)$ (includes Θ) $\rightarrow$ *Lite-CF-Evi2*

Prediction example with evidential formulation

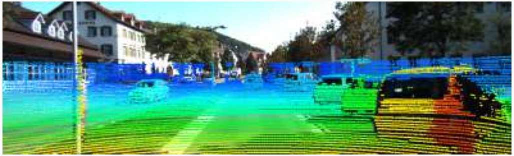


(a) Projection LiDAR

(b) Camera image

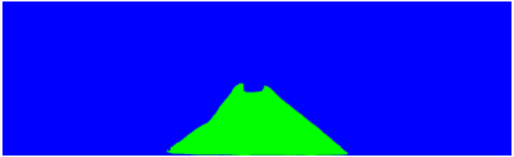
(c) Ground truth

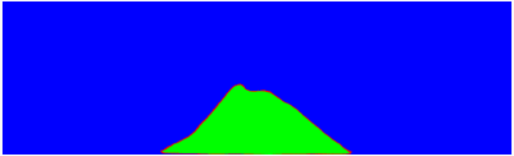
Prediction example with evidential formulation


(a) Projection LiDAR


(b) Camera image


(c) Ground truth


(d) Prediction DM_1


(e) Prediction DM_2

Prediction example with evidential formulation - zoomed detail

(a) Projection LiDAR

(b) Camera image

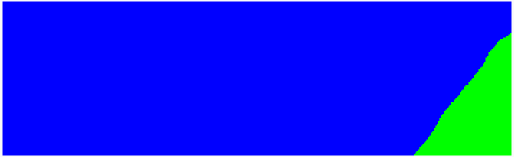
(c) Ground truth

Prediction example with evidential formulation - zoomed detail

(a) Projection LiDAR

(b) Camera image

(c) Ground truth



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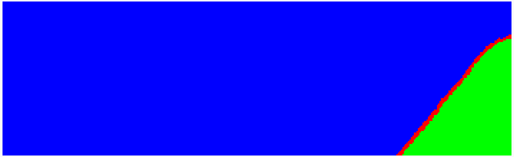
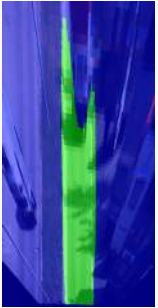


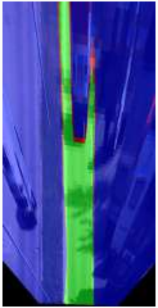
(e) Prediction DM_2

Road detection results

(a) LiDAR and camera perspective view



(b) BEV Probabilistic: Lite-CF Baseline



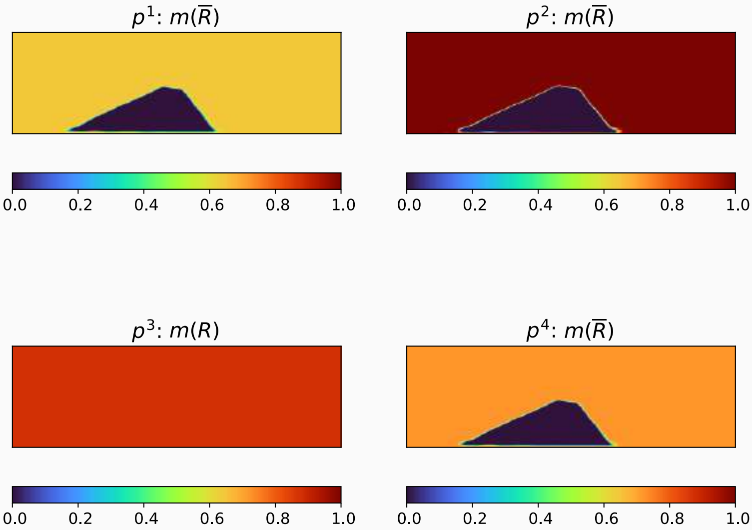
(c) BEV Evidential Baseline DM_2

Model Arch.	# Params	MaxF	PRE	REC	ER	FPS
Baseline	2,737,213	95.50 ± 0.52	95.57 ± 0.69	95.45 ± 0.74	1.61 ± 0.21	**35**
DM_1	**2,737,066**	$\mathbf{96.91 \pm 0.36}$	$\mathbf{96.74 \pm 0.56}$	$\mathbf{97.09 \pm 0.71}$	1.11 ± 0.14	33
DM_2	**2,737,066**	–	–	–	$\mathbf{0.81 \pm 0.13}$	29

✔ Proposed **evidential** formulation (DS Rule) **improves MaxF** and **decreases** the **error rate**.

Publication: **M. N. Geletu*, D-V. Giurgi*** et al., et al., *Evidential Deep-Learning-Based Multi-Modal Environment Perception for IVs*, **IV 2023** | IEEE IV 2023

Conflict management: prototypes visualizations

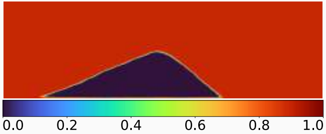


- **Three prototypes** with **reliable evidence**
  → $\bar{R}$ assigned, where not-road is expected
- **The evidence of** p^3 **contradicts** the others
  → $\bar{R}$ labelled everywhere.

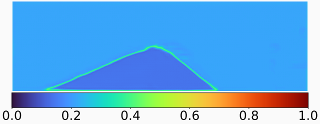
Publication: **D-V. Giurgi** *et al.*, *Conflict Management in a Distance to Prototype-Based Evidential Neural Network*, **IJAR 2025**

Conflict: before and after rectification

(a) Camera image



(b) Conflict between prototypes



(c) After rectification $\delta = 1$

Pixel	**DM$_2$ decision** (d_{BI})	**Conflict** K	
		Before rect.	**After rect.**
1 (Not-road)	Not-road	**0.89**	**0.20**
2 (Road)	Road	**0**	**0.17**

Step 1: Distance

$d^i = \|x - p^i\|$

→

Step 2: Construct BBAs

$m^i(\{\theta_j\}) = \alpha^i u^i_j \phi^i(d^i)$

$\phi^i(d^i) = \exp(-\gamma^i (d^i)^2), \; \gamma^i = (\eta^i)^2 + \boldsymbol{\delta}$

→

Step 3: BBA Fusion

DS: $(m_1 \oplus m_2)(A)$

Conflict rectification: road detection results

Rectification impact (4 prototypes, 10-fold CV)

Metric	MaxF	Precision	Recall	ER (%)
Before ($\delta = 0$)	96.92 ± 0.40	96.68 ± 0.46	97.17 ± 0.67	1.11 ± 0.16
After ($\delta = 1$)	**97.15 ± 0.32**	**96.93 ± 0.21**	**97.38 ± 0.62**	**1.03 ± 0.14**

Conflict rectification with δ:
- **improves road detection performance**
- **less vacuous** and **less conflicting** prototypes $\rightarrow$ **more informative**
- **ignorance representation**

Publication: D-V. Giurgi *et al.*, *Conflict Management in a Distance to Prototype-Based Evidential Neural Network*, **IJAR 2025**

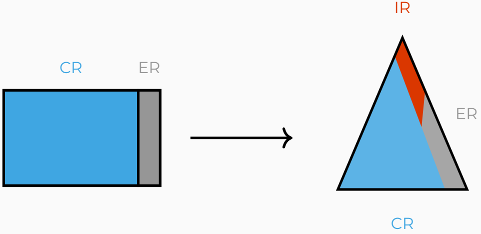
Conflict management: decision-making metrics

Need to quantify and express the ignorance class.

Extended confusion matrix

GT \ DM	$\bar{R}$	R	⊖
$\bar{R}$	TN	FP	IN
R	FN	TP	IP

Illustrative example (CR, ER, IR)



$$CR = \frac{(TP+TN)\times 100}{\text{total}}; \quad ER = \frac{(FP+FN)\times 100}{\text{total}}; \quad IR = \frac{(IP+IN)\times 100}{\text{total}}$$

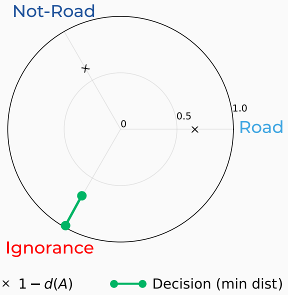
where $CR + ER + IR = 100\%$

Conflict management: decision-making example

Illustrative example: Road, Not-Road, Ignorance $(R, \bar{R}, \Theta) \rightarrow m_{DS} = [0.47, 0.43, 0.09]$

Belief-interval distance [J. Dezert et al., 2016]

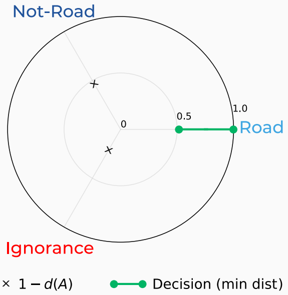
d_{BI} = [0.33, 0.37, **0.32**]



→ decide **Ignorance**

Jousselme's distance [Jousselme et al., 2001]

d_J = [**0.48**, 0.52, 0.78]

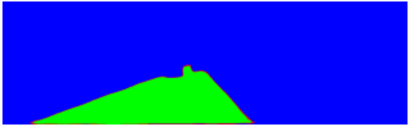


→ decide **Road**

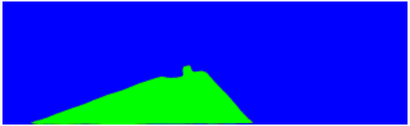
Results with distance based methods

(a) Camera image

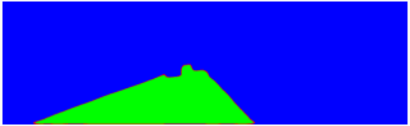
(b) Ground truth mask



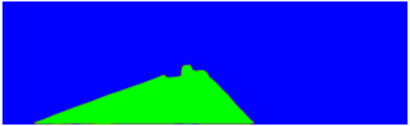
(c) Belief-interval d_{BI}, $\delta = 0$



(d) Jousselme, d_J, $\delta = 0$



(e) Belief-interval, $\delta = 1$



(f) Jousselme, d_J, $\delta = 1$

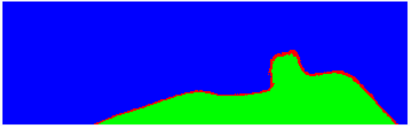
✔ **Before**: Ignorance at boundaries $\Rightarrow$ **After**: Increased IR, improved alignment

D.-V. Giurgi *et al.*, *Conflict Management in a Distance to Prototype-Based Evidential Neural Network*, **IJAR 2025**

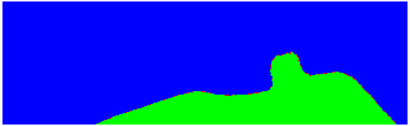
Results with distance based methods - zoomed detail

(a) Camera image

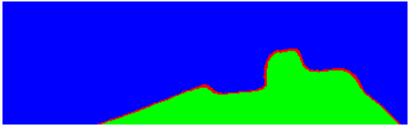
(b) Ground truth mask



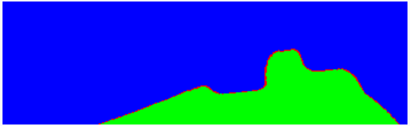
(c) Belief-interval d_{BI}, $\delta = 0$



(d) Jousselme, d_J, $\delta = 0$



(e) Belief-interval, $\delta = 1$

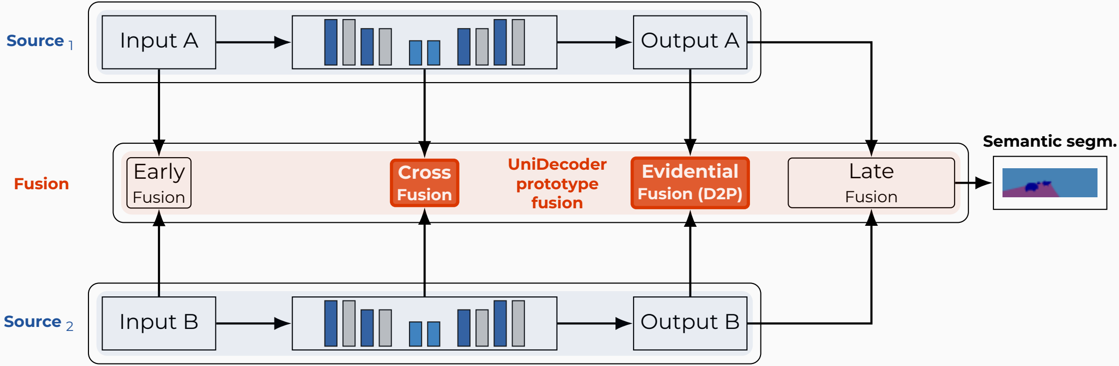


(f) Jousselme, d_J, $\delta = 1$

✔ **Before**: Ignorance at boundaries $\Rightarrow$ **After**: Increased IR, improved alignment

D.-V. Giurgi *et al.*, *Conflict Management in a Distance to Prototype-Based Evidential Neural Network*, **IJAR 2025**

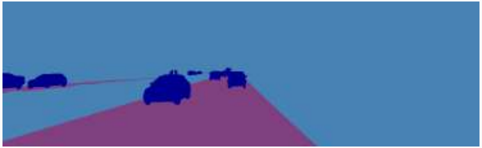
Extension to multi-class segmentation



Semantic segmentation with 3 classes (scalability), $\rightarrow$ KITTI semantic:

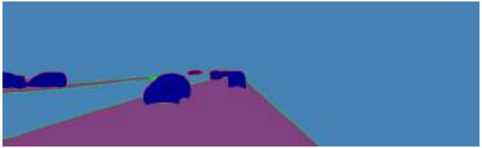
- (R, V, B) (**Road, Vehicle, Background**)
- (R, V, B, Θ) - total ignorance
- $(R, V, B, R \cup V, R \cup B, V \cup B)$ - partial ignorance

Multi-class segmentation with ignorance - zoomed detail



(a) Ground truth mask

(b) Total ignorance (belief-interval)



(c) Partial ignorance (belief-interval)

Ignorance distribution

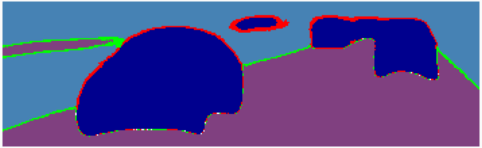
Total ignorance: **939 pixels (0.20%)**

Partial ignorance: **3,406 pixels (0.73%)**

Multi-class segmentation with ignorance - zoomed detail

(a) Ground truth mask

(b) Total ignorance (belief-interval)



(c) Partial ignorance (belief-interval)

Ignorance distribution

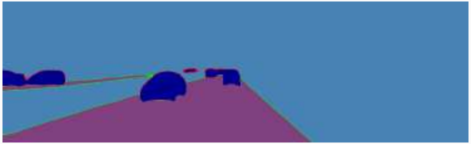
Total ignorance: **939 pixels (0.20%)**

Partial ignorance: **3,406 pixels (0.73%)**

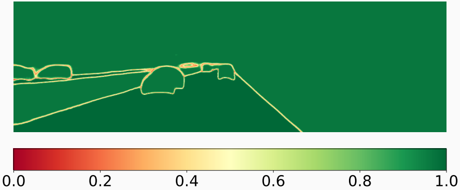
Multi-class segmentation results - quality indicator

IoU metric, probabilistic vs evidential

Model	Mean IoU	Road	Vehicle	Background
Lite-CF (Prob.)	0.9238	0.9271	0.8712	0.9732
Lite-CF-Evil	**0.9271**	**0.9316**	**0.8745**	**0.9751**



(a) Prediction with partial ignorance



(b) Quality indicator $q_{(.)}$ per pixel

The **quality indicator** shows that **confidence** in decisions is **weaker at boundaries**

Publication: D-V. Giurgi *et al.*, *Decision Based on Belief Interval for Multi-class Obstacle Perception of Self-driving Cars*, **DSmT, Vol.5, 2023.**

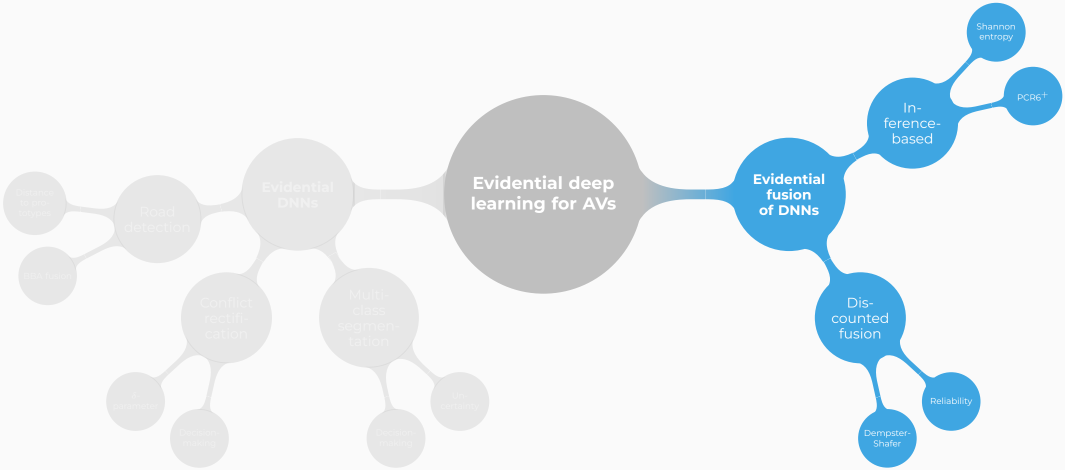
Conclusions on evidential deep neural networks

Evidential deep neural networks for AV: road detection

- **Uncertainty** representation (**D2P**)
- **Improved** road **detection**
- **Reliable prototype evidence** due to conflict management
- Scalable for segmentation tasks, **extension to multi-class**
- **Decision-making** to explicit ignorance handling

D-V. Giurgi et al., *Conflict Management in a Distance to Prototype-Based Evidential Neural Network*, **IJAR 2025**
M. N. Geletu*, D-V. Giurgi* et al., *Conflict Management in a Distance to Prototype-Based Evidential Deep Learning*, **BELIEF 2024**
D-V. Giurgi et al., *Decision Based on Belief Interval for Multi-class Obstacle Perception of Self-driving Cars*, **DSmT, Vol.5, 2023.**
M. N. Geletu*, D-V. Giurgi*, et al., *Evidential Deep-Learning-Based Multi-Modal Environment Perception for IVs*, **IV 2023**

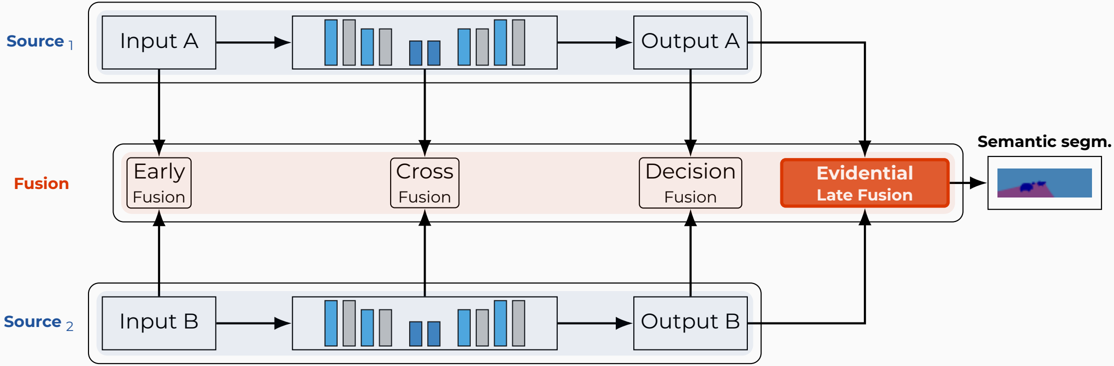
Evidential fusion of DNNs for multi-class segmentation



Second main research direction

- **Inference-based late fusion: PCR6^{+} and Shannon entropy weighting**
- **Evidential late fusion: DS rule and SPOTIS (SPOTIS - table preference ordering towards ideal solution) $\rightarrow$ reliability discounting**

Evidential late fusion of DNNs

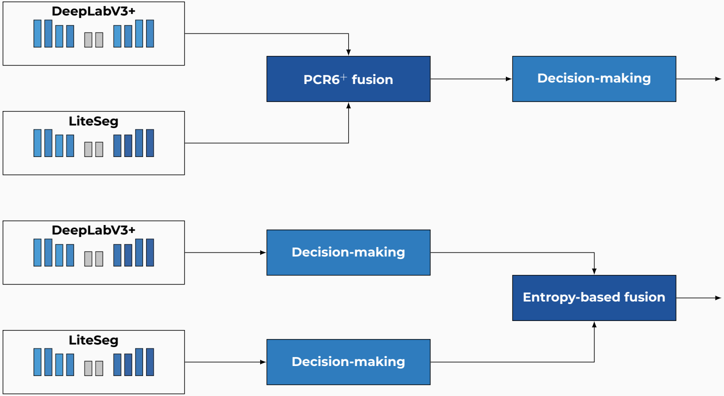


Semantic segmentation:

→ Two DNNs: **DeepLabV3+** and **LiteSeg**;
→ KITTI semantic, 3 cls.: **Road (R), Vehicle (V), Background (B)**.

Architecture for the two approaches : PCR6$^+$ and Shannon entropy

Two evidential late-fusion strategies for DeepLabV3+ and LiteSeg



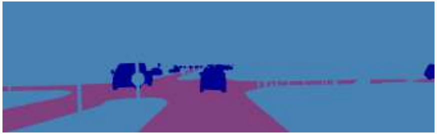
Motivation:

- PCR6$^+$ **redistributes** conflicting evidence proportionally to the sources involved in each conflict;
- Entropy fusion **weights** model outputs according to their uncertainty. [D-V. Giurgi et al., 2024].

Publication: D-V. Giurgi et al., *Fusion of Semantic Segmentation Models for Vehicle Perception Tasks*, **FUSION 2024** |

Inference-based fusion results: worst case

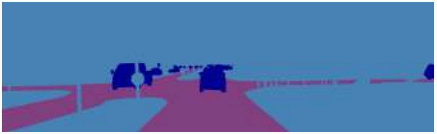
(a) Camera



(b) Ground truth

Inference-based fusion results: worst case

(a) Camera



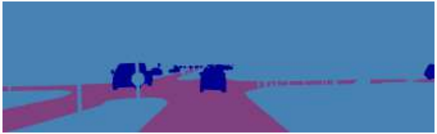
(b) Ground truth

(c) LiteSeg

(d) DeepLabV3+

Inference-based fusion results: worst case


(a) Camera


(b) Ground truth


(c) LiteSeg


(d) DeepLabV3+


(e) Shannon fusion


(f) PCR6$^+$ fusion

Inference-based fusion results: worst case - zoomed detail

(a) Camera

(b) Ground truth

Inference-based fusion results: worst case - zoomed detail

(a) Camera

(b) Ground truth

(c) LiteSeg

(d) DeepLabV3+

Inference-based fusion results: worst case - zoomed detail

(a) Camera

(b) Ground truth

(c) LiteSeg

(d) DeepLabV3+

(e) Shannon fusion

(f) PCR6$^+$ fusion

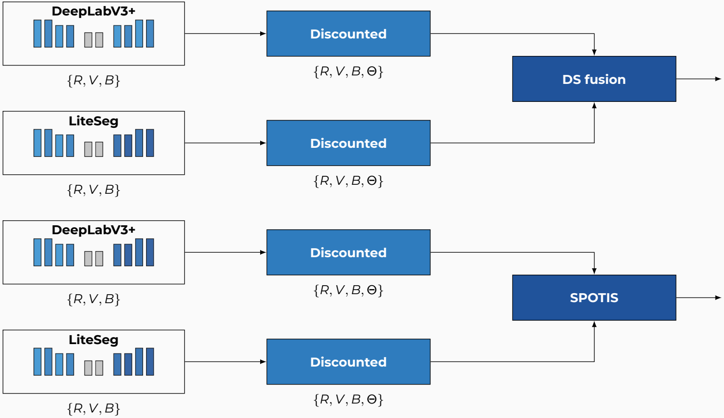
Quantitative results

Model	Road	Vehicle	Background	Mean IoU
LiteSeg	0.9547 ± 0.0140	0.9126 ± 0.0227	0.9815 ± 0.0077	0.9496
DeepLabV3+	0.9500 ± 0.0154	0.8959 ± 0.0188	0.9794 ± 0.0085	0.9418
Fusion via Shannon entropy	**0.9581 ± 0.0148**	0.9136 ± 0.0192	0.9825 ± 0.0081	0.9514
Fusion via PCR6$^+$	**0.9581 ± 0.0148**	**0.9138 ± 0.0190**	**0.9825 ± 0.0080**	**0.9515**

✔ **Both PCR6$^+$** and **Shannon entropy** yield a small consistent improvement in the Mean IoU
10-fold cross-validation

Discounting fusion: DS and imprecise SPOTIS

Two evidential late-fusion strategies for DeepLabV3+ and LiteSeg



Imprecise SPOTIS - workflow example

Alternatives $= \{R, V, B\}$
Criteria $= \{C_{s_1}, C_{s_2}\}$
Interval decision
$\Rightarrow$ distance-to-ideal ranking

Direct evidence (BBAs)

	C_{s_1}	C_{s_2}
$m(R)$	0.20	0.05
$m(V)$	0.10	0.20
$m(B)$	0.10	0.05

Partial evidence

	C_{s_1}	C_{s_2}
$m(R \cup V)$	0.03	0.10
$m(R \cup B)$	0.07	0.20
$m(V \cup B)$	0.30	0.30
$m(\Theta)$	0.20	0.10

Build imprecise scores

	C_{s_1} $[Bel, Pl]$	C_{s_2} $[Bel, Pl]$
R	[0.20, 0.50]	[0.05, 0.45]
V	[0.10, 0.63]	[0.20, 0.70]
B	[0.10, 0.67]	[0.05, 0.65]

SPOTIS output

Distances (per class):

$$\mathbf{d} = [d_R, \mathbf{d_V}, d_B]$$

$$\mathbf{d_W} = [0.707, \mathbf{0.610}, 0.654]$$

$\arg\min d_W$

Closeness matrix Df

Final output (ε):

$$Df = \begin{bmatrix} |\mathbf{d_R} - \mathbf{d_R}| & |d_R - d_V| & |d_R - d_B| \\ |d_V - d_R| & |\mathbf{d_V} - \mathbf{d_V}| & |d_V - d_B| \\ |d_B - d_R| & |d_B - d_V| & |\mathbf{d_B} - \mathbf{d_B}| \end{bmatrix}$$

Masses $\rightarrow$ intervals $[\mathrm{Bel}, \mathrm{Pl}]$ $\rightarrow$ SPOTIS distances $\mathbf{d}$ (one per class), **simple to compute**.

SPOTIS and DS fusion: Fold-10 results

Mean IoU with uncertainty-aware fusion (discounted models)

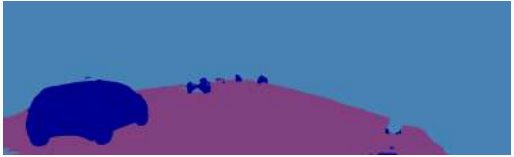
Model	Road	Vehicle	Background	Mean IoU
LiteSeg	0.9680	0.9343	0.9874	0.9632
DeepLabV3+	0.9696	0.9195	0.9874	0.9589
SPOTIS	0.9728	0.9378	**0.9888**	0.9665
DS Rule	**0.9735**	0.9374	**0.9890**	**0.9666**

Key idea: DS and SPOTIS fusion $\rightarrow$ consistent IoU gain over LiteSeg/DeepLabV3+
$\rightarrow$ predictions and expressing uncertainty.

Imprecise SPOTIS: visual results

Threshold $\epsilon = 0.05$. Example, *if* $|d_R - d_V| < \epsilon \rightarrow R \cup V$


(a) Best case SPOTIS, only singletons


(b) Worst case SPOTIS, only singletons

(c)Best case SPOTIS, all possible solutions

(d) Worst case SPOTIS, all possible solutions

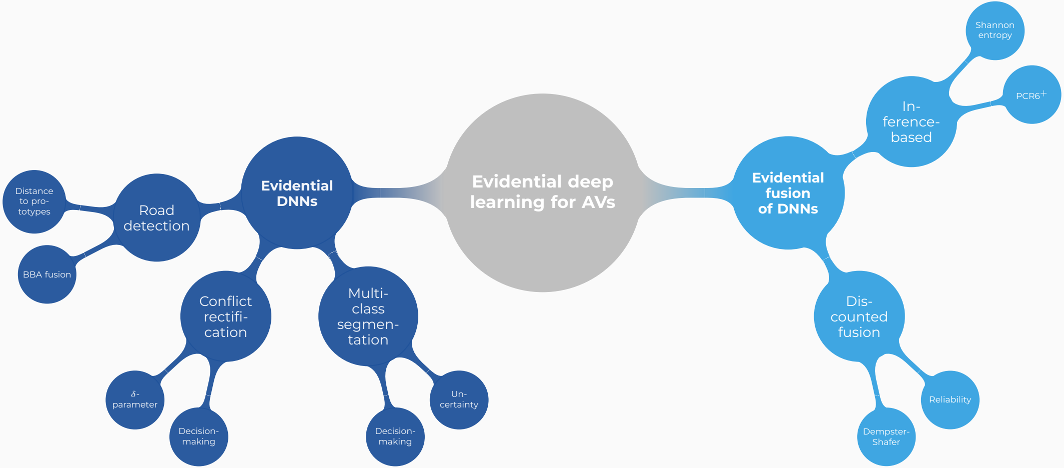
Conclusion on evidential fusion of DNNs

Evidential fusion of deep neural networks for semantic segmentation

- **Late fusion**: DeepLabV3+ and LiteSeg combined via evidential reasoning;
- **Fusion**: Inference-based (Shannon, PCR6$^+$); Discounted fusion (SPOTIS, DS rule);
- **Discounting** information as a reliability factor;
- Fast **computation** alternatives for fusion and decision-making.

D-V. Giurgi et al., *Fusion of Semantic Segmentation Models for Vehicle Perception Tasks*, **FUSION 2024**
D-V. Giurgi et al., *Evidential fusion of deep neural networks for multi-class vehicle perception*, *WIP*.

General conclusions

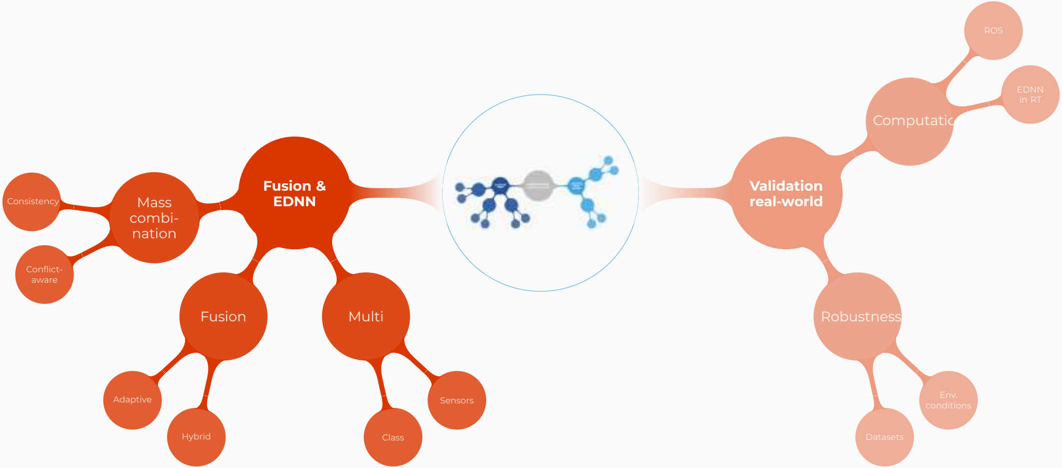


Research directions and their contributions

Evidential deep neural networks for autonomous vehicles

Evidential fusion of deep neural networks for multi-class segmentation

Future challenges



Perspectives

EDNN: BBA (consistency, conflict-aware), fusion (hybrid, adaptive), multi-sensors (radar) or multi-class
Real-time world: computation (EDNN in RT, ROS), robustness (datasets, environmental conditions)

THANK YOU FOR YOUR ATTENTION!

Evidential deep neural networks:
application in semantic analysis for autonomous vehicles

PhD Thesis Defence, February 10, 2026

Presented by
Dănuţ-Vasile GIURGI

Disseminations

- **1** international journal publication (IJAR)
- **1** book chapter contribution (DSmT Book Vol. 5, 2023)
- **8** conferences (**5** international, **3** national)