SOUTENANCE DE THESE
THESIS DEFENSE

Monsieur Maxime Chaveroche

Unité de Recherche **: Laboratoire Heudiasyc, Labex MS2T**

soutiendra sa thèse de **Doctorat** sur le sujet **:**

Perception collaborative décentralisée et efficace pour le véhicule autonome

A l'université de technologie de Compiègne
Le mercredi 29 septembre 2021 à 14h
bâtiment Blaise Pascal, salle GI 42

Devant le jury composé de :

- **M. Stéphane CANU**, professeur, membre examinateur, INSA de Rouen
- **M. Thierry DENOEUX**, professeur, membre examinateur, Université de technologie de Compiègne, laboratoire Heudiasyc, Compiègne
- **M. Jérémie MARY,** maître de conférences, membre rapporteur, CRITEO Al Lab, Paris
- **M. Frédéric PICHON,** professeur, membre rapporteur, Université d'Artois, LGI2A, Béthune
- **Mme Véronique CHERFAOUI**, professeur des universités, directeur de thèse, Université de technologie de Compiègne, laboratoire Heudiasyc, Compiègne
- **M. Franck DAVOINE**, chargé de recherche CNRS, directeur de thèse, Université de technologie de Compiègne, laboratoire Heudiasyc, Compiègne

Summary :

Recently, we have been witnesses of accidents involving autonomous vehicles and their lack of sufficient information at the right time. One way to tackle this issue is to benefit from the perception of different view points, namely collaborative perception.

We propose here a decentralized collaboration, i.e. peer-to-peer, in which the agents are active in their quest for full perception by asking for specific areas in their surroundings on which they would like to know more. Ultimately, we want to optimize a trade-off between the maximization of knowledge about moving objects and the minimization of the total information received from others, to limit communication costs and message processing time.

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To this end, we chose to use Dempster-Shafer Theory (DST) in order to identify different types of uncertainties. In particular, DST allows us to distinguish what has never been perceived (out of range or occluded area) -- which is mainly what collaborative perception tries to reduce -- from what is debated among different sources (conflict arising from fusion of sensors or other vehicles perceptions). More generally, DST takes into account the specificity of evidence, meaning that it provides information about the reliability of an agent's belief, which is crucial for safety. DST also features the advantage of easily dealing with data incest, a problem inherent to the decentralized approach, with its *Cautious* and *Bold* fusion rules. However, DST comes with high spatial and computational complexities, especially for dealing with data incest in fusion, which limits its usage to random experiments with few possible outcomes.

Thus, we first proposed an exact method to compute the decompositions needed for this *Cautious/Bold* fusion [1]. Then, we generalized this method to any Möbius transform in any partially ordered set, including most transformations exploited in DST. This also had the side effect of enabling us to propose generalizations of the decompositions required by the Cautious/Bold fusion [2]. These generalized decompositions allow one to use these fusion rules in more cases, in particular cases where an agent has gathered very specific evidence (dogmatism). This enhances both accuracy and computational stability in consecutive fusions. However, algorithms naively implementing our formulas would have intractable worst-case complexities. For that reason, we proposed optimizations in Boolean lattices [3], always outperforming the optimal complexity tied to algorithms that do not consider the function to transform. We then generalized these optimizations to distributive lattices [4], beyond the scope of the usual definitions of DST.

After this work on the fusion process itself, we tackled the issue of redundancy and irrelevance in decentralized collaborative perception. For this, we proposed a way to learn a communication policy that reverses the usual communication paradigm by only requesting from other vehicles what is unknown to the ego-vehicle, instead of filtering on the sender side [5]. We tested three different models to be taken as base for a Deep Reinforcement Learning (DRL) algorithm and compared them to a broadcasting policy and a random policy. More precisely, we slightly modified a state-of-the-art generative model named Temporal Difference VAE (TD-VAE) to make it sequential. This variant, namely Sequential TD-VAE (STD-VAE), was one of these three models. We also proposed Locally Predictable VAE (LP-VAE), inspired by STD-VAE, designed to enhance its prediction capabilities. We showed that LP-VAE produced better belief states for prediction than STD-VAE, both as a standalone model and in the context of DRL. The last model we tested was a simple state-less model (Convolutional VAE).

Policies learned based on LP-VAE featured the best trade-off, as long as future rewards were taken into account. Our best models reached on average about 25% of the maximum information gain while requesting only about 5% of the space around the ego-vehicle to others. We also provided interpretable hyperparameters controlling the reward function, which makes this trade-off adjustable (e.g. allowing greater communication costs).

Publications :

[1] Calcul exact de faible complexité des décompositions conjonctive et disjonctive pour la fusion d'information. M. Chaveroche, F. Davoine and V. Cherfaoui, XXVIIème Colloque GRETSI, 2019.

[2] Focal points and their implications for Möbius transforms and Dempster-Shafer Theory. M. Chaveroche, F. Davoine and V. Cherfaoui, Information Sciences, Elsevier, Volume 555, Pages 215-235, 2021.

[3] Efficient Möbius Transformations and their applications to Dempster-Shafer Theory. M. Chaveroche, F. Davoine and V. Cherfaoui, LFA - Rencontres francophones sur la Logique Floue et ses Applications, 2019.

[4] Efficient Möbius Transformations and their applications to D-S Theory. M. Chaveroche, F. Davoine and V. Cherfaoui, SUM - International Conference on Scalable Uncertainty Management, 2019.

[5] Learning to implicitly prioritize unknown areas for collaborative perception. M. Chaveroche, F. Davoine and V. Cherfaoui, Journal paper in preparation.

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