Effective Communications in the Goal-Oriented Semantic Signal Processing Framework: A Case Study in Cooperative Driving

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Abstract

This paper presents an effective communications demonstration in a simulated smart city environment built on a previously developed goal-oriented semantic signal processing framework. We specifically focus on a simplified cooperative driving application where an ego vehicle navigates to a point under speed and safety constraints, using the vehicle's own sensors and city-bound sensors transmitting semantic information. We show that the vehicle can take the optimal actions using very low network resources under different complexities of simulated environments. Moreover, by using the semantic representations in training instead of raw sensor outputs, we show that the training of the agents can be simplified greatly.

Keywords: Effective communications, semantic signal processing, semantic communications, goal-oriented communications, cooperative driving

1. Introduction

The next generation of wireless communications networks are expected to focus more on massive machine-type communications (mMTC), requiring efficient management of extreme numbers of interconnected IoT devices, such as sensors, radars, lidars, and cameras [1]. The number of sensors and resulting sensor-generated data are expected to increase at a faster rate than the available bandwidth at the air interface, leading to increasingly stringent efficiency requirements for communications systems [2].

In his seminal work on Classical Information Theory (CIT), Shannon classified the communication problem with three levels: the technical problem, the semantic problem, and the effectiveness problem [3]. The technical problem is concerned with the reliable transmission of symbols over an imperfect channel, whereas the semantic problem is concerned with whether the correct intended meaning of the symbols are correctly

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transmitted or not [4–6]. Finally, at the effectiveness level, the question is how well the communicated information achieves its intended goals.

Historically, both academia and industry have predominantly concentrated on the technical level, where we are nearing the theoretical limits at practical systems [7–10]. Recently, the advances in artificial intelligence and machine learning techniques, as well as the the incredible proliferation of available data, have enabled learning-based methods to infer *meaning* in the sensor signals, leading to many works focusing on the semantic level of communications. Several notable works on semantic communications have demonstrated a significant reduction in the overall communication throughput is possible compared to the conventional technical communications [11–14]. Specifically in [11, 15], the authors have proposed a goal-oriented semantic signal processing framework based on graph signals that can be tailored to any sensor modality application for reliable semantic extraction and transmission. The goal-oriented nature of semantic communications can address the effectiveness problem as well if the communication goals can be defined dynamically within the application, ensuring high efficiency in semantic transmissions, although this is not addressed explicitly in [11].

The work on the effectiveness problem is still in its infancy, with several promising works showing potential implementations in specific applications [16–19]. Specifically in [16], the authors propose a partially observable Markov decision process model trained with multi-agent reinforcement learning that allows multiple agents to reach their destination in a 5-by-5 grid while communicating as effectively as possible in a noisy channel. All of the aforementioned works focus on developing an effective communications from the ground-up, employing complex deep learning algorithms on the sensor and channel information to build a joint source-channel-effectiveness encoding/decoding scheme.

In this paper, we use a hierarchical approach to address the problem of effective communications based on the 3-level classification of Shannon in his CIT, i.e., we propose an effective communications proof-of-concept based on the semantic signal processing and communications framework presented in [11]. Specifically, We demonstrate a cooperative driving case study where an agent vehicle in a smart city is navigating under safety goals, with sensors onboard the vehicle and around the city are generating semantic information based on [11]. We train both the smart city and the vehicle using only semantic information and tabular learning, and show that the agents can effectively reach their destinations while reducing the overall communication throughput. This dual training approach facilitates the vehicle in taking the most effective actions and asking efficient questions, while the smart city environment learns to send only the pertinent information that can effect the actions of agents. Thanks to training on semantic representations, we show that the both the training and the deployment can be performed much more efficiently than the current state-of-the-art for autonomous and cooperative driving models.

The rest of the paper is organized as follows: In Section 2, we introduce our model of goal-oriented effective communications, tailored for cooperative driving applications. In Section 3, we describe the one-dimensional cooperative driving environment on which we prove our concept of effective communications. In Section 4, we introduce the realistic 3-D simulation environment, and discuss the semantic representation, and present our results demonstration of effective communications and actions. Concluding remarks and the future challenges for effective communications are given in Section 5.

2. Goal-Oriented Effective Semantic Communications for Cooperative Driving

Cooperative driving, also referred to as cooperative automated driving, envisions vehicles engaging in communication with infrastructure, traffic management systems, and other vehicles to enhance safety, efficiency, and user experience in traffic with minimal human intervention [20]. This paradigm relies on both vehicle-to-vehicle and vehicle-to-infrastructure communications [21]. The models for cooperative driving strive to bolster safety, reduce traffic accidents and their severity, enhance fuel efficiency, and improve the overall user experience by alleviating traffic congestion. Evaluation of cooperative driving models revolves around their effectiveness in achieving these objectives [22].

In our cooperative driving model, our primary focus is to demonstrate effective communications. Therefore, we simplify the action space of the ego vehicle (EV) to go in a straight line from point-A to point-B, meaning the only actions the vehicle can take are to accelerate or decelerate. We then assume that pedestrians can run into the road at any point randomly, although there are several crosswalks that the pedestrians will use predominantly. This concept is illustrated in Fig. 1. We assume the car, and any sensors the city has can extract semantic information that can identify and locate pedestrians around them. The EV semantic sensors and its acceleration capabilities are chosen so that the car will need external information to reach its destination more quickly.

Based on the proposed simple cooperative driving concept, we introduce three main effectiveness metrics, focusing on speed, safety, and communications in the form of the following loss function:

$$\min_{\theta} \quad T(\theta) + \lambda R(\theta), \tag{1}$$

$$\text{s.t.} \quad \min\left(D(\theta)\right) \geq D_{min}, \tag{2}$$

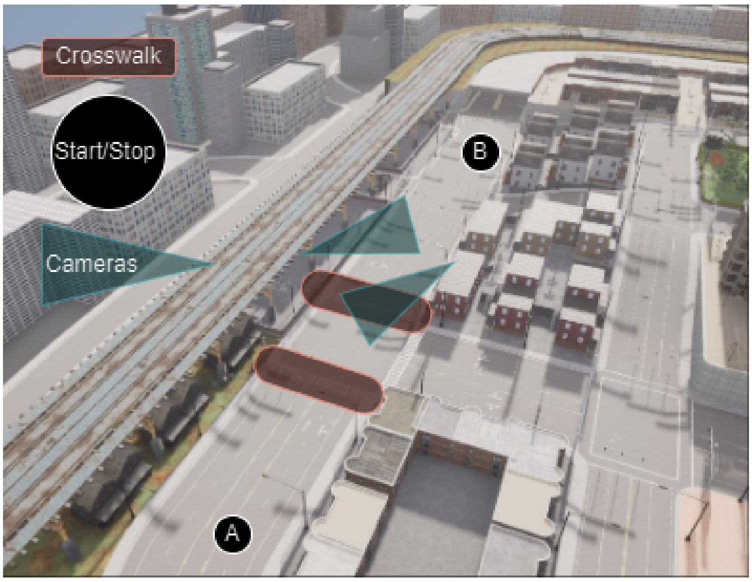

Figure 1: Cooperative driving concept. The ego vehicle (EV) starts at point-A and aims to reach point-B. The red overlays indicate crosswalks where the pedestrians will cross predominantly, and the green triangles represent the smart city cameras looking over the road.

where θ is the parameter set that include vehicle actions and transmission decisions, $T(\theta)$ is the total time of navigation, $R(\theta)$ is the average rate of transmissions with λ as the regularization factor, and $D(\theta)$ is the list of distances to the observed pedestrians in front of the vehicle with D_{min} as a minimum safety distance. As seen in (1) and (2), we aim to minimize the navigation time and the rate of communication while ensuring a minimum distance to pedestrians as the vehicle operates.

To demonstrate the effective communications problem posed in (1) and (2), we introduce two simulation environments to train cooperative driving models. The first environment is a one-dimensional (1D) representation of a smart city, comprising cells representing a section of a smart-city-observed road with randomly crossing pedestrians. Optimal policies can be derived from two state tables, one for the vehicle and one for the smart city, facilitating model training without the need for convolutional neural networks [23]. The second environment is a three-dimensional (3D) CARLA environment [24] as seen in Fig. 1, with a two-dimensional (2D) semantic representation extracted using [11, 15] that offers a simplified but effective information content for the city and the vehicle to act on, as shown in Fig. 2. Employing tabular learning over the semantic representation allows us to train our model without convolutional neural networks, significantly reducing training times and costs. After training, we map back to the CARLA simulation environment for testing, ensuring realistic assessments in a 3D context. In the following sections, we describe each simulation environment in detail and present the resulting effective cooperative driving models.

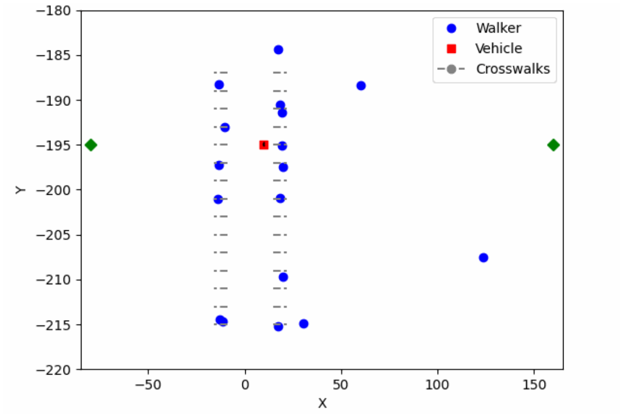

Figure 2: Two-dimensional semantic representation. Green dots represent point-A and point-B from Fig. 1. X and Y coordinates are grid indices from the simulation environment. Pedestrians cross mostly from crosswalks but may cross at any point with a relatively low probability.

3. Effective Communications and Cooperative Driving in a 1D Environment

To demonstrate effective communications over goal-oriented semantic communications, we first implement a simple 10,000 cells-long 1D environment, a simple representation of which is given in Fig. 3. The EV starts at the 1st node and aims to reach the end of the line. EV can take the following actions at each time step: stay idle, move forward 1 cell, move forward 5 cells.

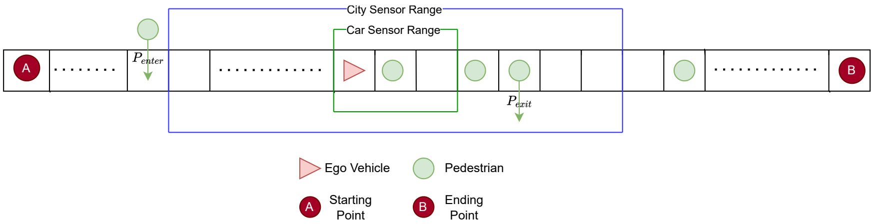

Figure 3: One-dimensional simulation environment for cooperative driving

Across each of the 10,000 cells, pedestrians (or other safety hazards) can enter and exit the scene with the following state transition matrix:

$$\Phi = \begin{bmatrix} 1 - P_{enter} & P_{enter} \\ P_{exit} & 1 - P_{exit} \end{bmatrix}, \tag{3}$$

where $P_{enter} < 1$ and $P_{exit} < 1$ are the probabilities of a pedestrian entering and exiting the 1D environment for each cell $c \in [0\ 10000]$, respectively. As defined in (1) and (2), the EV must maintain a minimum distance of $D_{min} = 1$ to the pedestrians at all times.

We assume the EV has an onboard semantic sensor that can identify pedestrians within 2 cells, meaning that to reach its maximum speed of 5 cells/step, the EV needs to obtain external information. This information is provided by the external semantic sensors of the smart city, which can detect all pedestrians and vehicles in the range $c \in [2000\ 7500]$. Note that the observation range of the smart city sensors are kept limited intentionally, to contrast the behavior of the EV throughout different availability of semantic information. In this setting, the expectation is for the EV to be able to reach its maximum speed within the smart city communication network but exercise caution outside it, ensuring a swift arrival at the target without unnecessary risks.

Tabular learning is employed to train this cooperative driving model, utilizing two state tables, one for the vehicle and one for the smart city. Each state table comprises multiple states. The vehicle state table, given in Table 1, includes four states: S_0 (no pedestrians observed), S_1 (nearest pedestrian is 1 cell away), S_2 (nearest pedestrian is $2-5$ cells away), S_3 (nearest pedestrian is 5+ cells away). Note that D_{EV} is the estimated list of pedestrian distances by the EV, using its onboard sensors and any information coming from the smart city. In the case of no detections from the onboard sensor and no smart city information, D_{EV} is set to infinity.

Table 1: Vehicle Speed State Table and Expected Actions

State	**Expected Action**
$S_0 : D_{EV}(\theta) = \infty$	Slow (1 cell/step)
$S_1 : \min(D_{EV}(\theta)) = 1$	Idle: (0 cells/step)
$S_2 : 1 < \min(D_{EV}(\theta)) \leq 5$	Slow: (1 cell/step)
$S_3 : \min(D_{EV}(\theta)) > 5$	Fast: (5 cells/step)

On the smart city side, if the EV is within the sensor range, minimum distance to the pedestrians $\hat{D}_{EV}$ is measured and a subset of this list may be transmitted to the EV at each time step. Then the loss function in (1) and (2) are interpreted with the following reward values listed in Tables 2 and 3. Note that the smart

Table 2: Reward Values for the Ego Vehicle in the 1D Environment

Event	**Reward**
Collisions: $\min(D_{EV}) < D_{min}$	-50
Idling: 0 cells/step	-2
Slowly moving: 1 cell/step	+5
Fast moving: 5 cells/step	+15

Table 3: Reward Values for the Smart City in the 1D Environment

Event	Reward
Collisions ($\min(D) < D_{min}$)	-20
No transmission	+1
Transmission	-2 per each pedestrian

city is penalized for transmitting each pedestrian information (i.e., each entry in $\hat{D}_{EV}$) to enforce efficient transmissions.

We train the EV and the smart city actions with a tabular learning model initialized with a high exploration probability $\epsilon = 1$, with a gradually reducing exploration factor over time $\epsilon_{decay} = 0.9995$, a minimal level of exploration of $\epsilon_{min} = 0.001$, and a learning rate of 0.01. The training set includes 1,000 runs with randomized pedestrian entry and exit probabilities ranging from 0 to 0.5, we illustrate the model's performance across all efficiency metrics in Figs. 4, 5, and 6. Fig. 4 shows the EV's position for a test run with P_{enter} set at 0.01 and 0.05 with $P_{exit} = 0.5$, and compares the trained model with the optimal policy shown in Table 1. As expected, the trained model follows the optimal policy perfectly, and speeds up within the smart city environment due to the extra available information about the pedestrians.

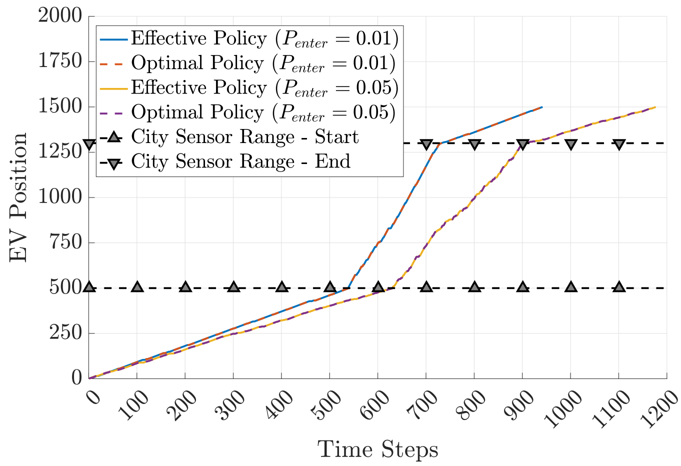

Figure 4: EV position for $P_{enter} = \{0.01, 0.05\}$ and $P_{exit} = 0.5$, compared to the optimal Policy. The horizontal lines represent the smart city observation range.

In Fig. 5, we illustrate the transmission rates for the same scenario shown in Fig. 4, and compare the trained model with full transmission of all sensor data at every time step. As expected from the optimal policy, the smart city learns to send only a single pedestrian information when the car is within the observation range, leading to an emergent effective communications. Also note that while a more dense pedestrians scenario leads to more semantic information traffic, the effective transmission policies are basically independent of the pedestrian density for this application.

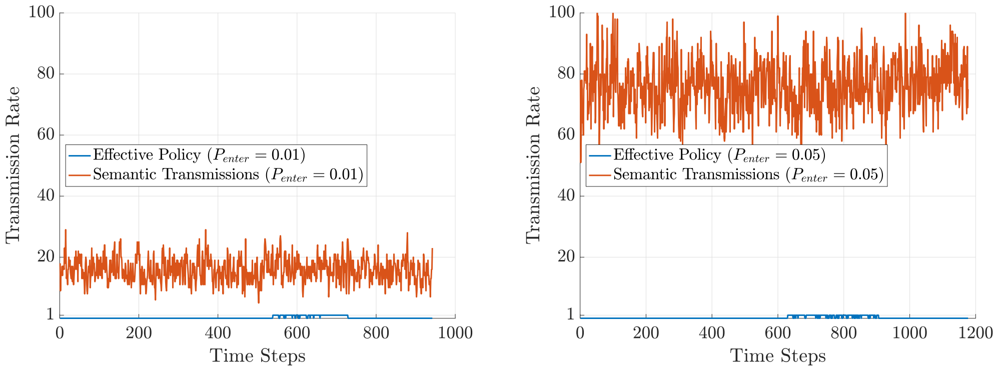

Figure 5: Transmission rates for $P_{enter} = 0.01$ (left) and $P_{enter} = 0.05$ (right) with $P_{exit} = 0.5$, compared to the full transmission of all semantic sensor data.

Finally, in Fig. 6 we illustrate the safety compliance of the EV policy through the D_{EV} metric. Throughout the test runs, EV successfully satisfies a minimum distance of 1 cell to all pedestrians, while adhering to an efficient communication and navigation policy.

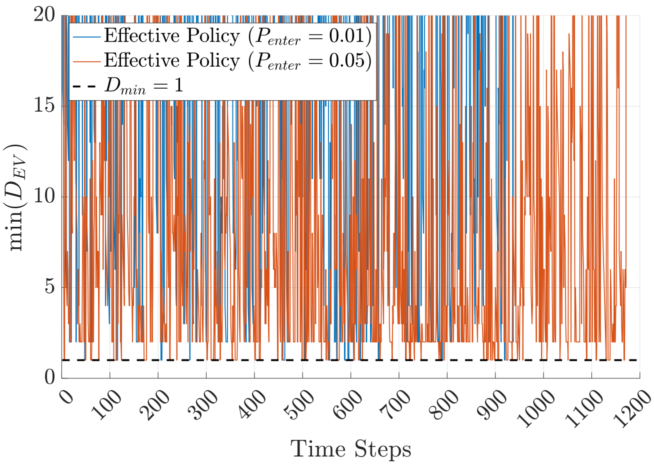

Figure 6: Minimum distance to pedestrians for $P_{enter} = \{0.01, 0.05\}$ and $P_{exit} = 0.5$.

In the following section, we extend our exploration to a more realistic 3D simulation environment in CARLA, paving the way for a comprehensive understanding of the goal-oriented effective communications framework in cooperative driving scenarios.

4. Effective Communications and Cooperative Driving in a 3D Environment

We now develop our 1D model into a more realistic 3D model. We use the semantic cameras provided in the CARLA environment to obtain a 2D semantic representation, as illustrated in Figs. 1 and 2. As indicated on in Fig. 1, we incorporate two semantic cameras positioned on poles to enhance the actions of the EV. These semantic cameras survey the regions around the crosswalks, seeking out various components of interest as shown in Fig. 7 and Fig. 8 for the first and second semantic camera, respectively. In the semantic segmented images, the color scheme corresponds to the classification results: red for pedestrians, blue for vehicles, and magenta for the road, etc.

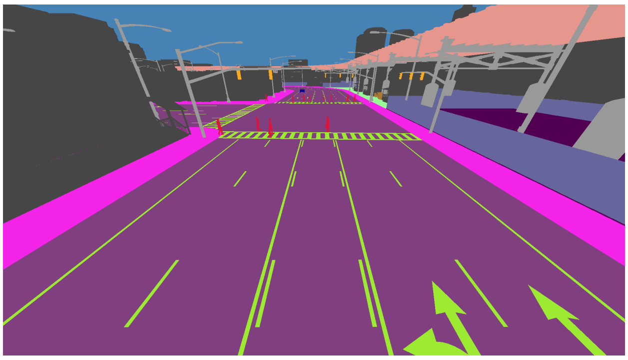

Figure 7: First semantic camera point-of-view. Different colors corresponds to different classes.

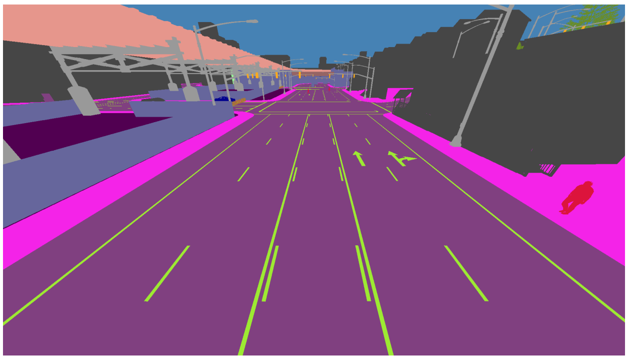

Figure 8: Second semantic camera point-of-view. Different colors corresponds to different classes.

Similar to the 1D case, we assume that the EV needs to travel along a straight path while avoiding pedestrians. This means that the only actions of the car can take is to accelerate and decelerate, while the city sensors can decide to transmit semantic information (pedestrian locations) as in the 1D case. The extracted semantic information from the city cameras are mapped to a 2D semantic grid of 250 cells along x direction (c_x) and 30 cells along y direction (c_y), representing the straight patch of road that the EV wants to traverse within the CARLA environment. Each cell is a square of 1 m edge length. Smart city can extract semantic pedestrian information within cells $c_x \in [60\ 180]$.

In figure 9, we provide a visual representation of the two-dimensional environment, where the green circles represent pedestrians, and the red triangle represents the EV that aims to navigate from point A to point B. The EV has three distinct speed values that can be set: 0 m/s, 1 m/s, and 5 m/s, all of which we assume can be attained within a time step of the simulation. The EV again has a limited sensing range: it can only detect pedestrians up to 2 meters (cells) ahead. The safety requirement D_{min} is set to 3 m (or 3 cells) to ensure safe distance from the pedestrians. At each time step, we generate pedestrians with probability P_{enter}, then place them either on the crosswalks with P_{xw} probability, or on other parts of the road with $1 - P_{xw}$ probability. In our simulation P_{xw} is set to 0.8 to generate most of the pedestrians on the crosswalks while allowing some pedestrians to cross on random parts of the road. Each generated pedestrian is assigned to a velocity along the y-axis that is uniformly sampled from $[0.5\, m/s,\ 1\, m/s]$.

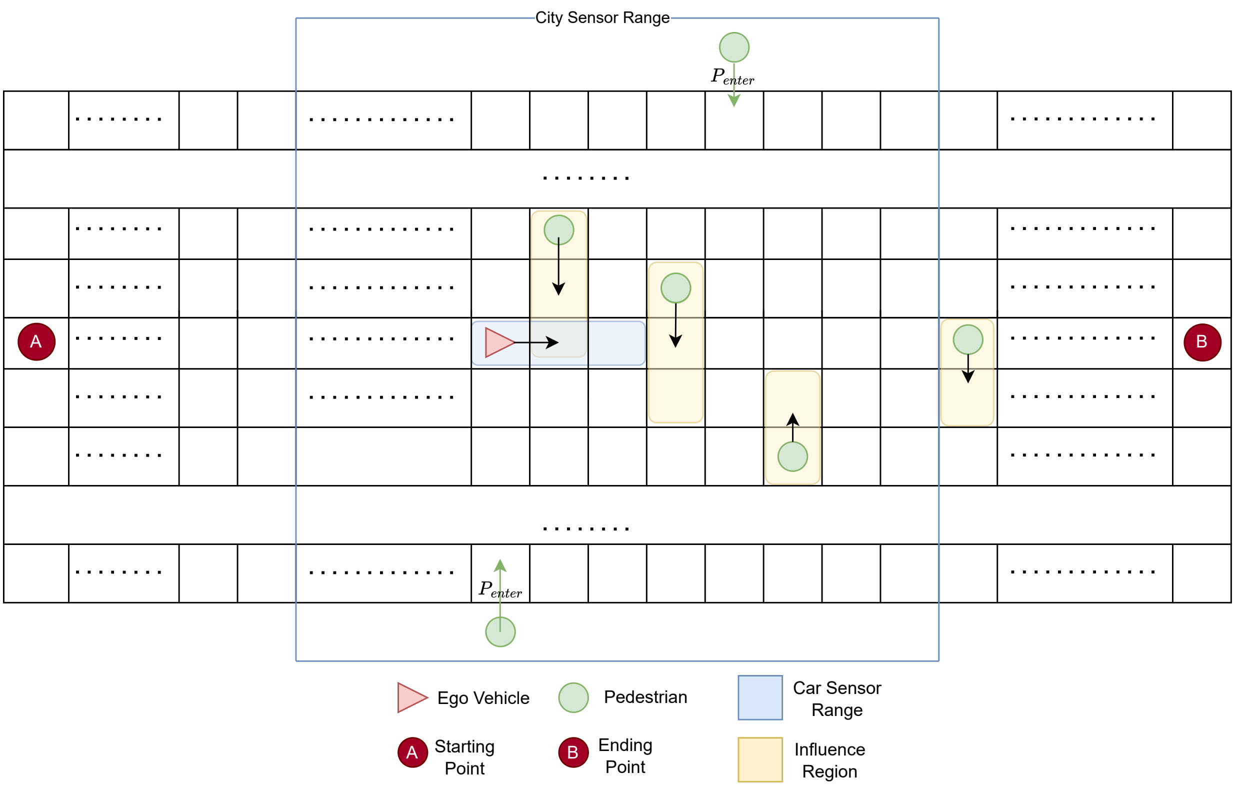

Figure 9: Two-dimensional semantic representation for cooperative driving

As shown in Fig. 9, we also incorporate *influence regions* to define safe distances to pedestrians in the 2D semantic representation. Each pedestrian and the EV are characterized by dynamic regions of influence, represented by their position and velocity vectors. Let the position and velocity of the EV be $\mathbf{r^{EV}} = (r_x^{EV}, r_y^{EV})$, $\mathbf{v^{EV}} = (v_x^{EV}, v_y^{EV})$, and the position and velocity of pedestrian-i be $\mathbf{r_i^P} = (r_{i,x}^P, r_{i,y}^P)$, $\mathbf{v_i^P} = (v_{i,x}^P, v_{i,y}^P)$, respectively. Then, we define the estimated list of projected distances to nearby pedestrians as

$$D_{EV} = \left\{ \left\| \left(\mathbf{r^{EV}} + \mathbf{v^{EV}}\right) - \left(\mathbf{r_i^P} + \mathbf{v_i^P}\right) \right\|_2 \mid \forall i \right\}. \tag{4}$$

Note that in (4), we estimate the next position of the EV and the pedestrians by a first order approximation.

We again use the same tabular learning approach in the 1D case with a more strict collision penalty to account for the changing environment, summarized in Table 4 and Table 5.

Table 4: Reward Values for the Ego Vehicle in the 1D Environment

Event	**Reward**
Collisions ($\min(D) < D_{min}$)	-200
Idling (0 cells/step)	-2
Slowly moving (1 cell/step)	+5
Fast moving (5 cells/step)	+15

Table 5: Reward Values for the Smart City in the 1D Environment

Event	**Reward**
Collisions ($\min(D) < D_{min}$)	-50
No transmission	+1
Transmission	-2 per each pedestrian

We train the EV and the smart city actions with the same parameters of: $\epsilon = 1$, $\epsilon_{decay} = 0.9995$, $\epsilon_{min} = 0.001$, and a learning rate of 0.01. Note that with the proposed model, the learning and the actions are taking place in the 2D semantic representation, while the actual events are simulated/realized in the 3D environment. We use the same efficiency metrics in the 1D model in 1,000 runs with randomized pedestrian entry and exit probability rates to test the model's success.

We illustrate the 2D-trained models performance in the 3D CARLA environment in Figs. 10–12. In Fig. 10, we show the EV's position for a test run with P_{enter} set at 0.35 and 0.45, and compare the trained model with the optimal expected policy. As expected, the trained model follows the optimal policy perfectly, and speeds up within the smart city environment due to the extra available information about the pedestrians. Also note that there are two extended period where the car barely moves at all, corresponding to the two crosswalks that have a significantly high pedestrian crossing rate.

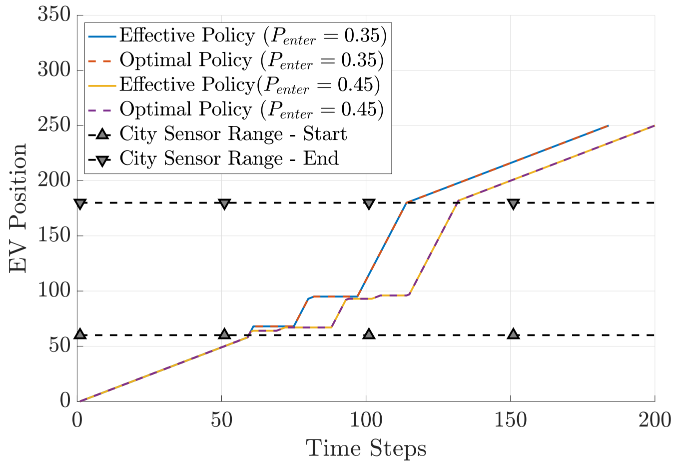

Figure 10: EV position for $P_{enter} = \{0.35, 0.45\}$, compared to the optimal Policy. The horizontal lines represent the smart city observation range.

In Fig. 11, we illustrate the transmission rates for the same scenario shown in Fig. 10, and compare to the full transmission of all sensor data at every time step. As expected from the optimal policy, the smart city again learns to send only a single pedestrian information when the car is within the observation range, leading to an emergent effective communications in a realistic 3D environment. Also note that since pedestrian generation is done at every step with zero pedestrians in the beginning, we have an increasing trend for full semantic transmission, and a steady state once the outgoing pedestrians counterbalance the newly generated ones. On the other hand, the effective transmission policies are again shown to be independent of the pedestrian density.

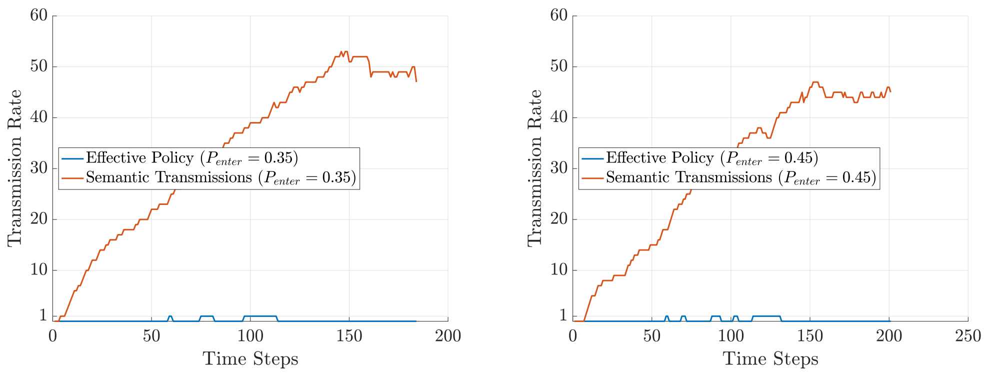

Figure 11: Transmission rates for $P_{enter} = 0.35$ (left) and $P_{enter} = 0.45$ (right), compared to the full transmission of all semantic sensor data.

Finally, in Fig. 12 we illustrate the safety compliance of the EV policy through the D_{EV} metric defined in (4). Throughout the test runs, EV successfully satisfies a minimum distance of 3 cells to all pedestrians, while adhering to an efficient communication and navigation policy as shown in Fig. 10 and Fig. 11.

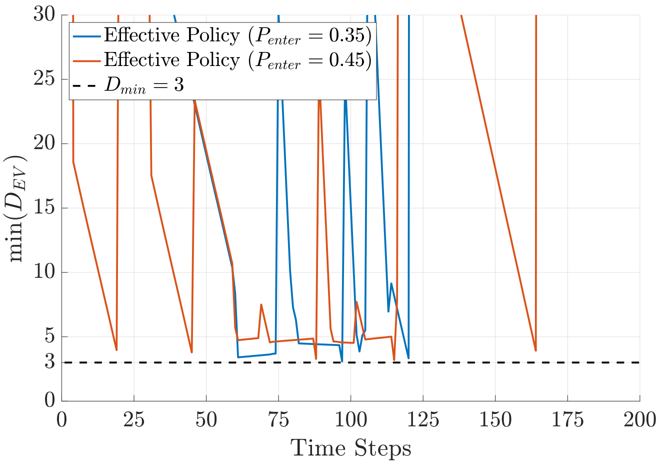

Figure 12: Minimum distance to pedestrians for $P_{enter} = \{0.35, 0.45\}$ with $D_{min} = 3m$

5. Conclusions and Future Research Directions

This paper introduces a semantic signal processing approach to address the effectiveness problem communications, with a simple demonstration on cooperative driving applications within a smart city environment. With a tabular learning model trained on simple 1D or 2D semantic representations of complex 3D environments, we show that the computational complexity of training and implementation can be greatly reduced, while observing emergent effective communications that reduces the overall throughput between sensor nodes.

Future research directions may extend the framework to more realistic and dynamic smart city environments, considering additional factors such as weather conditions, road infrastructure, and diverse traffic scenarios. Additionally, investigating the impact of communication delays and uncertainties in the smart city environment on communication effectiveness is a promising avenue for future exploration.

References

[1] W. Saad, M. Bennis, M. Chen, A vision of 6g wireless systems: applications, trends, technologies, and open research problems, IEEE Network 34 (3) (2020) 134–142. doi:10.1109/mnet.001.1900287.

[2] E. C. Strinati, S. Barbarossa, 6G networks: Beyond Shannon towards semantic and goal-oriented communications, Computer Networks 190 (2021) 107930.

[3] C. E. Shannon, A mathematical theory of communication, The Bell system technical journal 27 (3) (1948) 379–423.

[4] Y. Bar-Hillel, R. Carnap, Semantic information, The British Journal for the Philosophy of Science 4 (14) (1953) 147–157.

[5] J. Bao, P. Basu, M. Dean, C. Partridge, A. Swami, W. Leland, J. A. Hendler, Towards a theory of semantic communication, in: Proceedings of the 2011 IEEE 1st International Network Science Workshop, 2011, pp. 110–117.

[6] M. Kountouris, N. Pappas, Semantics-empowered communication for networked intelligent systems, arXiv preprint arXiv:2007.11579.

[7] S. L. Ariyavisitakul, Turbo space-time processing to improve wireless channel capacity, IEEE Transactions on Communications 48 (8) (2000) 1347–1359. doi:10.1109/26.864172.

[8] P. Oswald, A. Shokrollahi, Capacity-achieving sequences for the erasure channel, IEEE Transactions on Information Theory 48 (12) (2002) 3017–3028. doi:10.1109/TIT.2002.805067.

[9] A. Eslami, H. Pishro-Nik, A practical approach to polar codes, in: 2011 IEEE International Symposium on Information Theory Proceedings, 2011, pp. 16–20. doi:10.1109/ISIT.2011.6033837.

[10] O. Dizdar, E. Arıkan, A high-throughput energy-efficient implementation of successive cancellation decoder for polar codes using combinational logic, IEEE Transactions on Circuits and Systems I: Regular Papers 63 (3) (2016) 436–447. doi:10.1109/TCSI.2016.2525020.

[11] M. Kalfa, M. Gok, A. Atalik, B. Tegin, T. M. Duman, O. Arikan, Towards goal-oriented semantic signal processing: Applications and future challenges, Digital Signal Processing 119 (2021) 103134. doi:https://doi.org/10.1016/j.dsp.2021.103134.
URL https://www.sciencedirect.com/science/article/pii/S1051200421001731

[12] M. Kountouris, N. Pappas, Semantics-empowered communication for networked intelligent systems, IEEE Communications Magazine 59 (6) (2021) 96–102.

[13] H. Xie, Z. Qin, X. Tao, K. B. Letaief, Task-oriented multi-user semantic communications, IEEE Journal on Selected Areas in Communications 40 (9) (2022) 2584–2597.

[14] P. Jiang, C.-K. Wen, S. Jin, G. Y. Li, Wireless semantic communications for video conferencing, IEEE Journal on Selected Areas in Communications 41 (1) (2022) 230–244.

[15] M. Kalfa, S. Y. Yetim, A. Atalik, M. Gök, Y. Ge, R. Li, W. Tong, T. M. Duman, O. Arıkan, Reliable extraction of semantic information and rate of innovation estimation for graph signals, IEEE Journal on Selected Areas in Communications 41 (1) (2023) 119–140. doi:10.1109/JSAC.2022.3221950.

[16] T.-Y. Tung, S. Kobus, J. P. Roig, D. Gündüz, Effective communications: A joint learning and communication framework for multi-agent reinforcement learning over noisy channels, IEEE Journal on Selected Areas in Communications 39 (8) (2021) 2590–2603. doi:10.1109/JSAC.2021.3087248.

[17] G. He, S. Cui, Y. Dai, T. Jiang, Learning task-oriented channel allocation for multi-agent communication, IEEE Transactions on Vehicular Technology 71 (11) (2022) 12016–12029.

[18] G. He, M. Feng, Y. Zhang, G. Liu, Y. Dai, T. Jiang, Deep reinforcement learning based task-oriented communication in multi-agent systems, IEEE Wireless Communications 30 (3) (2023) 112–119.

[19] M. A. Gutierrez-Estevez, Y. Wu, C. Zhou, Learning to communicate with intent: An introduction, in: 2023 IEEE 34th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), IEEE, 2023, pp. 1–7.

[20] D. Chen, X. Xiong, Y. Zhou, Y. Zhang, Y. Zhang, R. Zhu, The cooperative car-following model with consideration of the stimulatory effect of lane-changing types, IEEE Access 9 (2021) 92374–92385. doi:10.1109/ACCESS.2021.3092755.

[21] M. Hasan, S. Mohan, T. Shimizu, H. Lu, Securing vehicle-to-everything (v2x) communication platforms, IEEE Transactions on Intelligent Vehicles 5 (4) (2020) 693–713. doi:10.1109/TIV.2020.2987430.

[22] D. Jia, D. Ngoduy, Platoon based cooperative driving model with consideration of realistic inter-vehicle communication, Transportation Research Part C: Emerging Technologies 68 (2016) 245–264. doi:https://doi.org/10.1016/j.trc.2016.04.008.
URL https://www.sciencedirect.com/science/article/pii/S0968090X16300122

[23] R. Shwartz-Ziv, A. Armon, Tabular data: Deep learning is not all you need, Information Fusion 81 (2022) 84–90. doi:https://doi.org/10.1016/j.inffus.2021.11.011.
URL https://www.sciencedirect.com/science/article/pii/S1566253521002360

[24] A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, V. Koltun, CARLA: An open urban driving simulator, in: Proceedings of the 1st Annual Conference on Robot Learning, 2017, pp. 1–16.