感知因素框架：
迈向自主系统的可靠感知

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Abstract— **未来的自动化系统承诺带来显著的社会利益，但它们的部署也引发了关于安全性和可信性的担忧。一个关键的问题是如何保证机器人感知的可靠性，因为感知是安全决策的基础。感知失败通常是由于复杂但常见的环境因素造成的，并可能导致事故，从而削弱公众信任。为了解决这个问题，我们引入了 SET （自我、环境和目标）感知因素框架。我们设计这一框架以系统地分析天气、遮挡或传感器限制等因素如何对感知产生负面影响。为此，该框架采用 SET 状态树来分类这些因素的起源，并利用 SET 因素树来建模这些来源和因素如何影响物体检测或姿态估计等感知任务。接着，我们利用这两种树开发感知因素模型，以量化给定任务的不确定性。我们的框架旨在通过提供一种透明和标准化的方法来识别、建模和传达感知风险，以促进严格的安全保证，并培育公众对自动化系统更大的理解和信任。**

I. 介绍

像物体检测这样的感知任务通常会引导计划和动作 [1] 。因此，从自动驾驶汽车到护理机器人这样的自主系统，必须准确感知其周围环境，以安全可靠地运行。然而，由于能见度差、遮挡或眩光等因素，感知常常会失败（图 1 ）。这些失败可能会扭曲系统对世界的认知，导致不安全的行动、（严重的）事故以及降低公众信任 [2]–[4] 。

为了减轻感知故障及其后果，量化感知不确定性至关重要——即一个系统对其当前感知预测有多么不确定。机器人学界几十年来一直在广泛研究感知不确定性（简要回顾见 III 节）。然而，我们缺乏一个统一的框架来系统地识别、分类、分析和传达导致感知故障的因素、这些因素的来源及其影响。这种缺口减缓了稳健的安全保证的发展，并使机器人工程师、监管者和公众难以讨论感知风险。

我们提出了 SET 感知因素框架来解决这个空缺，其中 SET 代表自我（感知主体）、环境和目标。该框架提供了一种结构化、易于理解的方法来：1）识别和建模影响感知任务（例如检测或定位）的感知因素（如眩光）；2）确定各种来源（如感知相机、太阳和目标车）如何影响这些因素；以及 3）创建感知因素模型（PFM），以量化给定输入因素或状态的感知不确定性。

II. SET 感知因素框架

SET 框架的目标是模拟人类可理解因素及其来源如何影响感知不确定性。该框架由三个组件组成：SET 状态树、SET 因子树和 PFM。

A. SET 状态树：不确定性的详细来源

SET 状态树列举了产生感知因素并影响感知不确定性的来源（物体或现象）（图 2 ）。这棵树帮助我们和感知

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Fig. 1. 感知失败损害了安全和信任。例如，雾霾（左）和雪（右）等不利天气可能导致 YOLOv8 [5] 未能检测到车辆（图像来自 DAWN 数据集 [6], [7] ）。如果一辆自动驾驶汽车仅依赖于这些失败的检测，汽车可能会误判安全性，可能导致事故（例如，在左转弯时），伤害乘客，并侵蚀公众信任。

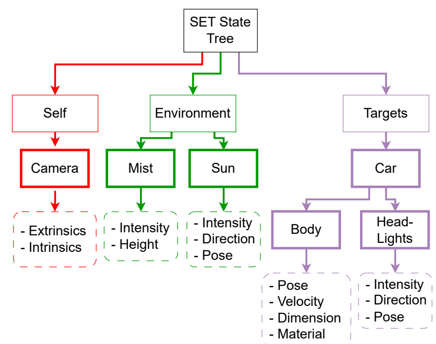

Fig. 2. 该图展示了一个样本 SET 状态树。该树模型化了可能影响汽车检测任务（如图 1 左侧所示）来源的起源（对象或现象）。这个树也在 SET 因子树中展示了相同的来源（如图 3 ）。这里，“self” 表示感知代理的摄像头，而目标是路上的其他汽车。我们用粗体框表示来源，用虚线框表示描述来源状态的变量。

代理回答：世界和我自己的哪些属性（即来源及其状态）可能导致感知失败？我们将来源组织在三个分支下：

- 自我：包括其传感器（例如，参见图 2 中的“自我”）以及可能影响不确定性的代理的其他部分（例如，可能导致眩光的反射车辆表面）的感知代理本身。
- 环境：除感知主体（自我）和目标之外的任何物体或现象，例如天气状况（如雨或雾）、光源（如路灯）以及物体（如树木和建筑物）。
- 目标：智能体旨在感知的物体或现象（例如，图 1 中的车辆）。

B. SET 因素树：不确定性的链条

SET 因素树模型展示了源和因素如何影响感知不确定性（图 3 ），显示了一条从源到因素再到感知任务的链条，以回答两个问题。首先，源如何创造因素？其次，因素如何定量地影响不确定性（即，降低任务）？我们可以使用确定性或概率的方法来层次化地建模这些关系：

1) 来源：树的叶子，表示来源于状态树的对象或现象。
2) 感知因素：中间节点表示因素，如眩光强度和运动模糊幅度。这些因素源于不同来源之间的相互作用。例如，眩光是由于阳光（环境）射入相机（自身），

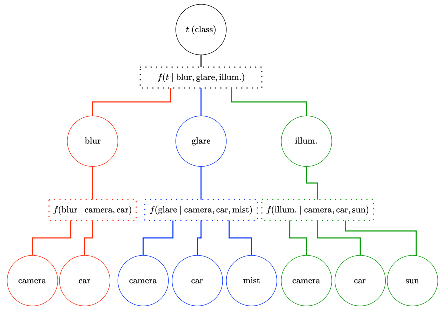

Fig. 3. 这张图展示了一个用于图 1 左侧目标检测任务的示例 SET 因子树。YOLOv8 可能未能检测到汽车（目标）是由于感知因素，例如运动模糊、车头灯的眩光和（低）照明。这些因素可能是由于相机、汽车、雾气和太阳等来源引起的。我们用虚线框表示因子节点，用圆圈表示变量节点（观测、感知因素和来源）。

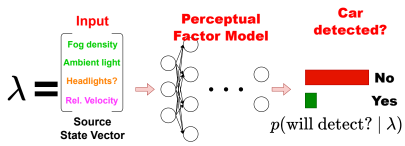

Fig. 4. 此图展示了一个样本 SET 感知因素模型，该模型用于基于图 1 的汽车检测任务。模型预测感知算法（如 YOLOv8）是否会在给定来源状态 λ [8]–[10] 的情况下检测到汽车。输入向量展示了来源状态的示例。

导致图像饱和，从而妨碍了其他车辆（目标）的检测。

3) 感知任务：树的根节点，表示我们正在模拟的任务（例如，物体检测），其确定性受到感知因素的影响。

C. SET 感知因子模型：量化不确定性

我们现在创建一个 SET 感知因子模型（PFM），根据源（如 [8], [9], [11] ）的状态或因素（如 [10] ）的大小量化感知不确定性（图 4 ）。PFM 可以是神经网络、高斯过程 [12] ，或其他概率模型。无论 PFM 的输入是状态还是因素，它们的值可以是估计值、真实值或混合的。例如，PFM 可以输出检测车辆任务的检测概率，或者在给定源状态（如相机参数、雾强度和环境光照等大气条件）以及潜在目标车辆的情况下输出定位任务的姿态分布。对于任何任务，我们可以通过使用感知车辆上的卡尔曼滤波器提供给 PFM 相机的状态，使用车载传感器或在线天气报告提供雾强度，通过车载环境光（光电探测器）传感器提供环境光照，以及估计的目标（车辆）状态，这假设了我们感兴趣的车辆的状态。

D. 总结：SET + 公众对自主系统的信任

该框架以多种方式促进可信自主性。SET 状态树使我们能够系统地识别各种操作环境中感知失败的来源，与临时测试相比，减少了被忽视的风险。明确的结构（即树和 PFM）促进了透明的沟通和保证，使我们能够清楚地陈述已考虑的因素、它们的建模影响和量化的性能（例如，“在大雨中检测概率下降到 90 %”）用于安全案例，取代模糊的断言。此外，状态树和 PFM 指导有针对性的数据收集（真实的或模拟的）朝向最具挑战性和安全关键的场景。最后，将该框架与诸如失效模式和效应分析 [13] 等其他框架结合，一个成熟的安全工程实践，促进了感知中更高水平的严格分析。

III. 相关工作

简要概述：分析信息源和感知因素如何影响知觉有着悠久的历史。早期的主动视觉研究 [14], [15] 探讨了影响经典物体或特征检测方法的几何和光学参数（例如相机姿态、遮挡和视场）[16]–[26] 。眩光 [27] 、背光 [28], [29] 和低光照 [19], [30], [31] 等光照因素也被广泛研究。随着深度学习检测器的流行度持续增长，已经创建了数据集来减轻各种视觉感知因素的影响 [32]–[46] 。最后，研究人员还对导致在自我定位 [8], [9] 、主动感知 [10], [47], [48] 、SLAM [49] 和检测任务 [50], [51] 中产生异方差观测噪声的信息源和感知因素进行了建模。

SET 框架的不同之处：我们的框架通过 SET 树提供了一种清晰的语言和结构，用于交流感知因素如何影响感知不确定性以及这些因素如何从 SET 来源之间的相互作用中产生。这种统一的方法建立在相关工作 [8]–[10] 的基础上，通过明确地建模因素的影响和起源。这与那些主要集中于不可解释特征 [49] 、观察相关性 [47], [52] 、特定推理类型 [50] 或有限因素 [51] 的方法有所不同。

厘米

References

[1] R. Siegwart, I. R. Nourbakhsh, and D. Scaramuzza, Introduction to Autonomous Mobile Robots. MIT press, 2011.

[2] “Tesla Autopilot feature was involved in 13 fatal crashes, US regulator says,” Apr 2024.

[3] J. Nelken-Zitser, “A robot crushed a man to death after it mistook him for a box of vegetables: Reports,” Nov 2023.

[4] The Wall Street Journal, “The hidden autopilot data that reveals why teslas crash.” YouTube Video, Dec 2024. Accessed: 2025-04-25.

[5] G. Jocher and J. Qiu, “Ultralytics yolo11,” 2024.

[6] M. A. Kenk and M. Hassaballah, “DAWN: Vehicle Detection in Adverse Weather Nature Dataset,” CoRR, vol. abs/2008.05402, 2020.

[7] M. KENK, “Dawn,” 2020.

[8] T. Williams and Y. Sun, “Learning State-Dependent, Sensor Measurement Models for Localization,” in 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 3090–3097, 2019.

[9] Y. Sun and T. Williams, “Learning State-Dependent Sensor Measurement Models for Localization,” 2 2020.

[10] D. Morilla-Cabello, J. Westheider, M. Popovic, and E. Montijano, “Perceptual Factors for Environmental Modeling in Robotic Active Perception,” 2023.

[11] T. Williams and Y. Sun, “Learning State-Dependent Sensor Measurement Models with Limited Sensor Measurements,” in 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 86–93, 2021.

[12] C. Williams and C. Rasmussen, “Gaussian Processes for Regression,” in Advances in Neural Information Processing Systems, vol. 8, MIT Press, 1995.

[13] D. H. Stamatis, Failure Mode and Effect Analysis : FMEA from Theory to Execution. Milwaukee, Wisc.: ASQC Quality Press, 1995.

[14] R. Bajcsy, “Active perception,” Proceedings of the IEEE, vol. 76, no. 8, pp. 966–1005, 1988.

[15] M. J. Swain and M. A. Stricker, “Promising directions in active vision,” International Journal of Computer Vision, vol. 11, no. 2, pp. 109–126, 1993.

[16] C. Cowan and P. Kovesi, “Automatic sensor placement from vision task requirements,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 10, no. 3, pp. 407–416, 1988.

[17] C. Cowan, “Model-based synthesis of sensor location,” in Proceedings. 1988 IEEE International Conference on Robotics and Automation, pp. 900–905 vol.2, 1988.

[18] S. Hutchinson, R. Cromwell, and A. Kak, "Planning sensing strategies in a robot work cell with multi-sensor capabilities," in Proceedings. 1988 IEEE International Conference on Robotics and Automation, pp. 1068–1075 vol.2, 1988.

[19] K. Tarabanis, R. Tsai, and P. Allen, "Automated sensor planning for robotic vision tasks," in Proceedings. 1991 IEEE International Conference on Robotics and Automation, pp. 76–82 vol.1, 1991.

[20] K. Tarabanis and R. Tsai, "Computing viewpoints that satisfy optical constraints," in Proceedings. 1991 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 152–158, 1991.

[21] K. Tarabanis and R. Tsai, "Computing occlusion-free viewpoints," in Proceedings 1992 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 802–807, 1992.

[22] K. Tarabanis, R. Tsai, and A. Kaul, "Computing occlusion-free viewpoints," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 18, no. 3, pp. 279–292, 1996.

[23] E. Trucco, M. Umasuthan, A. Wallace, and V. Roberto, "Model-based planning of optimal sensor placements for inspection," IEEE Transactions on Robotics and Automation, vol. 13, no. 2, pp. 182–194, 1997.

[24] F. Kececi, M. Tonko, H.-H. Nagel, and V. Gengenbach, "Improving visually servoed disassembly operations by automatic camera placement," in Proceedings. 1998 IEEE International Conference on Robotics and Automation (Cat. No.98CH36146), vol. 4, pp. 2947–2952 vol.4, 1998.

[25] P. Lehel, E. Hemayed, and A. Farag, "Sensor planning for a trinocular active vision system," in Proceedings. 1999 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (Cat. No PR00149), vol. 2, pp. 306–312 Vol. 2, 1999.

[26] A. Farag and A. Abdel-Hakim, "Image content-based active sensor planning for a mobile trinocular active vision system," in 2004 International Conference on Image Processing, 2004. ICIP '04., vol. 5, pp. 2913–2916 Vol. 5, 2004.

[27] B. Kisacanin and T. J. Newman, "Illumination and imaging system with glare reduction and method therefor," 2006.

[28] C. Schroeter, M. Hoechemer, S. Mueller, and H.-M. Gross, "Autonomous robot cameraman - Observation pose optimization for a mobile service robot in indoor living space," in 2009 IEEE International Conference on Robotics and Automation, pp. 424–429, 2009.

[29] C.-T. Lin and C.-L. Chin, "Using fuzzy inference and cubic curve to detect and compensate backlight image," International Journal of Fuzzy Systems, vol. 8, no. 1, pp. 2–13, 2006.

[30] K. Tarabanis, R. Tsai, and P. Allen, "The MVP sensor planning system for robotic vision tasks," IEEE Transactions on Robotics and Automation, vol. 11, no. 1, pp. 72–85, 1995.

[31] K. Tarabanis, P. Allen, and R. Tsai, "A survey of sensor planning in computer vision," IEEE Transactions on Robotics and Automation, vol. 11, no. 1, pp. 86–104, 1995.

[32] Y. Zhang, A. Carballo, H. Yang, and K. Takeda, "Perception and sensing for autonomous vehicles under adverse weather conditions: A survey," ISPRS Journal of Photogrammetry and Remote Sensing, vol. 196, pp. 146–177, 2023.

[33] E. O. Appiah and S. Mensah, "Object detection in adverse weather condition for autonomous vehicles," Multimedia Tools and Applications, vol. 83, no. 9, pp. 28235–28261, 2024.

[34] T. Hara, H. Saito, and T. Kanade, "Removal of Glare Caused by Water Droplets," in 2009 Conference for Visual Media Production, pp. 144–151, 2009.

[35] A. Marathe, D. Ramanan, R. Walambe, and K. Kotecha, "Wedge: A multi-weather autonomous driving dataset built from generative vision-language models," in Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pp. 3318–3327, 2023.

[36] G. Batchuluun, J. K. Kang, D. T. Nguyen, T. D. Pham, M. Arsalan, and K. R. Park, "Deep Learning-Based Thermal Image Reconstruction and Object Detection," IEEE Access, vol. 9, pp. 5951–5971, 2021.

[37] Y. Chen, F. Liu, and K. Pei, "Self-supervised Sun Glare Detection CNN for Self-aware Autonomous Driving," in Machine Learning for Autonomous Driving Workshop at the 35th Conference on Neural Information Processing System, 2021.

[38] K. Yoneda, N. Ichihara, H. Kawanishi, T. Okuno, L. Cao, and N. Suganuma, "Sun-Glare region recognition using Visual explanations for Traffic light detection," in 2021 IEEE Intelligent Vehicles Symposium (IV), pp. 1464–1469, 2021.

[39] O. Mazhar, R. Babuška, and J. Kober, "GEM: Glare or Gloom, I Can Still See You –End-to-End Multi-Modal Object Detection," IEEE Robotics and Automation Letters, vol. 6, no. 4, pp. 6321–6328, 2021.

[40] N. Gray, M. Moraes, J. Bian, A. Wang, A. Tian, K. Wilson, Y. Huang, H. Xiong, and Z. Guo, "GLARE: A Dataset for Traffic Sign Detection in Sun Glare," IEEE Transactions on Intelligent Transportation Systems, vol. 24, no. 11, pp. 12323–12330, 2023.

[41] L. Yahiaoui, M. Uřičář, A. Das, and S. Yogamani, "Let the sunshine in: Sun glare detection on automotive surround-view cameras," Electronic Imaging, vol. 2020, no. 16, pp. 80–1, 2020.

[42] M. A. Esfahani and H. Wang, "Robust Glare Detection: Review, Analysis, and Dataset Release," arXiv preprint arXiv:2110.06006, 2021.

[43] M. Z. Alam, Z. Kaleem, and S. Kelouwani, "Glare Mitigation for Enhanced Autonomous Vehicle Perception," IEEE Transactions on Intelligent Vehicles, pp. 1–15, 2024.

[44] I. Morawski, Y.-A. Chen, Y.-S. Lin, and W. H. Hsu, "NOD: Taking a Closer Look at Detection under Extreme Low-Light Conditions with Night Object Detection Dataset," 2021.

[45] C.-J. Lin and Y.-C. Liu, "Image backlight compensation using neuro-fuzzy networks with immune particle swarm optimization," Expert Systems with Applications, vol. 36, no. 3, Part 1, pp. 5212–5220, 2009.

[46] X. Hong, B. Cui, W. Chen, Y. Rao, and Y. Chen, "Research on multi-ship target detection and tracking method based on camera in complex scenes," Journal of Marine Science and Engineering, vol. 10, no. 7, 2022.

[47] W. L. Teacy, S. J. Julier, R. De Nardi, A. Rogers, and N. R. Jennings, "Observation Modelling for Vision-Based Target Search by Unmanned Aerial Vehicles," in Proceedings of the 2015 International Conference on Autonomous Agents and Multiagent Systems, AAMAS '15, (Richland, SC), p. 1607–1614, International Foundation for Autonomous Agents and Multiagent Systems, 2015.

[48] T. Williams, P.-L. Chen, S. Bhogavilli, V. Sanjay, and P. Tokekar, "Dynamically Finding Optimal Observer States to Minimize Localization Error with Complex State-Dependent Noise," 2022.

[49] S. Rabiee and J. Biswas, "IV-SLAM: Introspective Vision for Simultaneous Localization and Mapping," in Conference on Robot Learning, pp. 1100–1109, PMLR, 2021.

[50] V. Tchuiev and V. Indelman, "Inference Over Distribution of Posterior Class Probabilities for Reliable Bayesian Classification and Object-Level Perception," IEEE Robotics and Automation Letters, vol. 3, no. 4, pp. 4329–4336, 2018.

[51] Y. Feldman and V. Indelman, "Bayesian Viewpoint-Dependent Robust Classification Under Model and Localization Uncertainty," in 2018 IEEE International Conference on Robotics and Automation (ICRA), pp. 3221–3228, 2018.

[52] J. Velez, G. Hemann, A. S. Huang, I. Posner, and N. Roy, "Modelling Observation Correlations for Active Exploration and Robust Object Detection," Journal of Artificial Intelligence Research, vol. 44, pp. 423–453, 2012.