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Environmental Perception and Sensing Systems for Intelligent Control: Multi-sensor Fusion and Closed-Loop Control Methods

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Abstract. This paper reviews how perception systems in intelligent systems evolve from single sensing to multi-source collaboration and then to participation in closed-loop control. Sensors such as vision, LiDAR, radar, and IMU differ in spatial coverage, accuracy, and environmental adaptability, making fusion necessary; time synchronization and spatial alignment are its prerequisites. Each of the data-level, feature-level and decision-level fusion is appropriate to certain tasks. Calibration of sensors, degradation detection, and fault detection in complex conditions guarantee long-term reliability, and machine learning enhances the extraction of information. Control decisions are becoming more and more driven by perception information via state feedback such that quadruped robots are using multi-IMU proprioception to drive MPC switching and connected vehicles are modulating intersection control by sharing perception. The computational latency of complex fusion algorithms can be reduced by model compression, edge computing and hierarchical information processing to reduce real-time pressure on the algorithm, architecture and scheduling levels. Overall, the deep integration of perception and control is both an inevitable technological trend and a key path toward higher autonomy and reliability in unstructured environments.

Keywords: Multi-Sensor Fusion, perception and control, edge computing, model compression, cooperative perception

1. Introduction

Autonomous robots, intelligent vehicles, and similar systems need to continuously acquire information about the external environment and their own states in ever-changing complex environments, and adjust their operating states in real time according to environmental changes. However, a single sensor is highly susceptible to interference from factors such as lighting, weather, occlusion, noise, and measurement range, making it difficult for it to provide complete and reliable environmental information on its own. Therefore, environmental perception is gradually shifting from reliance on a single sensor to multi-sensor collaborative perception. By fusing the complementary information from different sensors, the stability of the system under complex conditions can be effectively improved, and the perception range can be expanded.

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Within the context of collaborative perception, once data of various sensors are subjected to temporal and spatial resolution and feature recognition, it can not only be utilized to create an overall environmental model, but also it can also play a direct role in state perceptions and control of intelligent systems. Using the case of the vehicle-road cooperative system, connected autonomous vehicles may exchange information via vehicle-to-vehicle communication and vehicle-to-road communication, including detected data related to the target position, speed, and type, to enhance the perception range of a single vehicle and address the blind spots in its view. Likewise, in intelligent surface vessels, automated identification system (AIS) and radar data, once converted to coordinates and trajectory, can be immediately utilized to identify the target, evaluate risk of collision and control navigation in a closed loop between perception and control [1]. Moreover, in studies of quadruped robots, a multiple inertial measurement units (IMU)-based proprioceptive perception network [2]. This combined sense of perception and control allows the system to actively change its behavior in the complex settings and not to be so dependent on one kind of information.

Recent studies are primarily interested in the heterogeneous sensor data fusion, sensor calibration, performance degradation compensation, and machine learning use in environmental information processing. As an illustration, LiDAR-vision fusion can be used to enhance the precision of 3D object detection, and the ability of radar and AIS data to provide association can enhance the tracking capabilities of long-range targets. These techniques take advantage of the complementary nature of the various sensors in order to effectively increase the stability and perception limits of the system [3]. Multi-sensor fusion is able not only to improve the situational awareness of the system, but also more reliable state information to control the closed-loop. Research has revealed that, following the comparison of the AIS paths with visual detection outcome, precision and recall of target detecting is greatly enhanced. In soft robot studies, with motion-force multimodal estimator, by combining limited motion sensing information, the robot can predict the distribution of contact forces in real time and adapt its control strategy to autonomously avoid obstacles and maximally accurately grasp [4]. Altogether, multi-source collaborative perception is a significant technological trend towards making intelligent systems more autonomous and adaptable. Perception data is slowly changing not to passively give references, but to actively participate in a control, become an important connection in the intelligent decision-making and control loops.

According to this relationship, Chapter 1 of this paper primarily examines the reliability problems of multi- sensor collaborative perception in complex environments, and how technologies like spatiotemporal synchronization of heterogeneous sensors, feature-level fusion, sensor calibration, and performance degradation compensation can guarantee the accuracy and stability of perception information. Chapter 2 also explains the role of sensing feedback in control decisions, and how edge computing and model lightweighting can relieve the pressure of real-time computing introduced by multi-source data, thus enabling efficient conversion of perception information into control commands.

A systematic review of the entire technical chain of perception-fusion-feedback-control, this paper concludes that sensing systems are slowly transforming out of the old traditional information sources of collection and reporting into organic parts of intelligent closed-loop control systems. The results of perception are not only employed to build environmental models, but are also directly involved in the creation/generation and online tuning of control variables. This is more pronounced in the more sophisticated control structures like the switched model predictive control and reinforcement learning-based strategies. The main idea that streamlines through the two chapters is that the deep integration of perception and control is not merely a necessary option of intelligent

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systems to address the dynamic and uncertain environments, but also a way of increasing system autonomy, as well as encouraging the ongoing development of intelligent systems.

2. Multi-sensor collaborative environmental perception

2.1. Heterogeneous sensing information fusion

Multi-sensor fusion is based on the principle of capitalizing on the respective benefits of various sensors to produce complementarity with respect to spatial coverage, measurement precision and environmental flexibility, and finally constructing a more comprehensive view of the environment. Visual sensors are capable of giving rich texture and semantic information, and their performance in the night or during heavy fog is dismal. LiDAR is capable of measuring the spatial distances in three dimensions accurately, but it cannot detect color or texture as well as it is sensitive to rain and fog. Radar is able to penetrate well, and can work in rain, snow, smoke, and fog, but the point cloud data is sparse, which makes it hard to tell what an item is. IMUs are able to constantly measure their own motion states and are not influenced by the external environment but their position errors increase over time. The four kinds of these sensors possess distinct advantages and disadvantages in the distance of sensing, accuracy and the ability to adjust to the environment, hence data presented by various sources will have to be combined to offset the drawbacks of the others.

Two basic issues have to be resolved first to achieve a perfect fusing of multi-sensor data: Temporal synchronization and spatial alignment. The sampling frequencies of different sensors differ considerably. Thus, one will require approaches of interpolation, nearest-neighbor matching, or triggering by hardware so that the data are aligned to the same time frame. Moreover, the coordinate system of each sensor is different and thus calibration needs to be conducted before it can be utilized to calculate transformation matrices and convert all measurements to either a common world coordinate system or vehicle body coordinate system. Based on this, fusion strategies can be broken down into three levels. Data-level fusion directly overlaps raw data in place, preserving the maximum information, but it also has the greatest computational complexity, and the most demanding spatiotemporal coincidences. The feature-level fusion compares feature firstly on the information of every sensor and subsequently does association and integration in the feature space, which is a trade-off between information retention and computational efficiency. Decision-level fusion requires all sensors to initially perform detection or estimation independently, then fuse the outcomes and it is the most flexible and convenient to combine different kinds of sensors although some information may be lost as a result of conflicts between separate judgments [5]. These three levels can be made flexibly depending on the task at hand to strike a balance between perception accuracy, real time performance and system stability.

In order to integrate multi-sensor data, Boxing Zhang et al. conducted a systematic review of technical framework of multi-sensor fusion of intelligent surface vehicles [1]. They categorized fusion strategies into four types: early fusion, intermediate fusion, late fusion, and hybrid fusion, and made a comparative study on these based on various dimensions, such as, the cost of computation, flexibility, the size of data, and environmental adaptability. The team tested the conditions of various fusion strategies that apply in real maritime situations by using multi-sensor information extracted in a real situation and discovered that late fusion and hybrid fusion is more applicable to heterogeneous sensor systems. We quote this source due to the fusion strategy classification framework it proposes, which can be directly applied to the situation when ground mobile robots and autonomous driving are involved, which will provide the framework of the discussion in the present paper regarding the

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trade-off between the reliability of the perception and the real-time performance, and which will also make it easier to analyze the edge computing and lightweighting of the models.

Tai Fei et al. fully surveyed spatial environmental perception and sensing technologies in automated systems, including various modalities such as vision, radar, LiDAR, acoustics, and Wi-Fi sensing, but specifically addressed key connections needed to ensure the long-term robust performance of perception systems, like sensor calibration, performance degradation analysis, and fault detection and diagnosis [5]. The team has used a systematic analysis of benefits and drawbacks of different technologies to quantitatively characterize the degradation of sensor performance when exposed to poor weather conditions- say, the LiDAR range of detection reduces by about 25 percent in rain and fog. This is the reason why we cite this review since it investigates the perception reliability through the lens of the entire system lifecycle, i.e. the entire chain of calibration, degradation, and diagnosis that fits well with the beginning of this section, which is the discussion of perception reliability in complex environments. Simultaneously, its discussion of the depreciation processes of perception systems in unfavorable circumstances also offers the direct proof of the argument presented in this paper about the need to have multi-sensing fusion and spatiotemporal synchronization.

In the meantime, Keyu Li et al. suggested a closed loop magnetic manipulation scheme involving an external permanent magnet. The group combined both internal IMU measurements as well as external magnetic field sensor array measurements to obtain real-time estimation of the six-degree-of-freedom pose of the probe and five-degree-of-freedom closed-loop control and confirmed the positioning accuracy of the system and tracking behavior using a phantom heart [6]. We provide this reference because it illustrates an actual example of employing IMU and external sensory data to make accurate state estimates and closed-loop control in a dynamic setting which supports the argument in this paper that the IMU is the key to internal state perception. The sensor fusion methodology employed in the current paper- a combination of internal motion measurements and external environment measurements to enhance the accuracy of the state estimation- is in line with the reasoning of multi-sensor collaborative perception addressed in this section.

Sanket Lokhande et al. have suggested a switched model predictive control model with multi-IMU proprioception. The group put up several IMUs on critical locations on the torso and legs of a quadruped robot, constructed a context-sensitive two-layer hybrid dynamics model and on this platform MPC switching control via terrain classification [2]. It was experimentally found that this approach is still capable of stabilising locomotion control in the absence of GPS, or in a situation where visual sensors are malfunctioning. We reference this source as it confirms that an IMU network can indeed deliver credible state information where external perception is restricted, just as this section focuses on the IMU being resistant to external environmental influence and the ability to constantly measure its own state of motion. Meanwhile, the tendency of the perception information becoming single sensor-based to networked and distributed is also demonstrated in this paper.

Di Ding et al. in the paper Vision-Based Contact Force Sensing in Robotic Surgery: A Technical Review comprehensively reviewed the use of the vision-based contact force sensing technology in surgical robots [7]. The group reviewed force perception techniques that rely on tissue deformation analysis, biomechanical modelling, and machine learning focusing on the benefits of only vision-based solutions in escaping the challenge of integration and sterilization of physical sensors, but also noting that still-challenges in real-time performance, robustness of illumination, and cross-task generalization capability exist. We quote this reference as it shows that a visual sensor can replace a physical sensor in the tasks in which a physical sensor is used, which will give us a parallel case to our discussion in this paper of the versatility and constraints of a visual sensor in dynamic

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environments, and even greater in the outdoor dynamic environment. In its turn, this, again, emphasizes the need of multi-sensor fusion.

Sanket Lokhande et al. have suggested a switched model predictive control model with multi-IMU proprioception. The team installed several IMUs at important locations on the torso and legs of a quadruped robot, created a context-sensitive two-layers hybrid dynamics model, and on this foundation performed MPC switching control founded on the classification of terrains. Experimental findings demonstrated that this approach can continue to ensure stable locomotion control in the absence of GPS or failure of visual sensors. This reference is cited as it confirms that an IMU network can autonomously supply credible state information when there is little external perception, which is precisely what this section is concerned with; that the IMU is resistant to external environmental influence and that it can always measure its own state of motion. Concurrently, the current paper demonstrates the tendency of perception information to evolve to networked and distributed types as well.

2.2. Methods for enhancing the robustness of perception systems

In complex environments, improving perception reliability can be approached mainly through three categories of research methods: sensor calibration and error compensation, performance degradation analysis and fault diagnosis, and machine learning-assisted perception enhancement. These three types of methods have different emphases when dealing with issues such as environmental interference, sensor drift, and local failure—calibration methods mainly make sensor measurement results more accurate and more consistent; degradation and fault diagnosis focus on the operating state of the sensor itself, checking whether it can no longer function; learning methods rely on data features to better extract environmental information under complex conditions.

The basis to the quality of measurements is sensor calibration and error compensation. Environmental factors, including temperature, humidity, and lighting affect sensors during operation and their output values can slowly drift. Fei et al. in their review noted that the sensor calibration was supposed to traverse the overall life cycle of the system. Conventional static calibration is easy to carry out, yet it can only be precise under certain environmental conditions; dynamic calibration on the other hand can constantly change the parameters under some environmental conditions that are near the actual operating environment [5]. In practice, through setting up a sensor measurement model and error model, and then interpolating or filtering the raw data to correct the error, the error brought about by environmental changes may be minimized to some level. The merit of this kind of approach is that theoretically, it has grown up and its computation burden is relatively cheap yet it is not able to deal with the abrupt variation of sensor performance or extreme environmental interference.

The performance degradation analysis and fault diagnosis is concerned with the changes of states when sensor is used over the long-term. The performance of sensors degrades with time; in the case of LiDAR, the range of detection can decrease by approximately one quarter during rain and fog weather, and vision sensors also show significantly lower performance when the lens is dirty, or when bright light directly illuminates the sensors. Degradation analysis provides an approximation of the time that a sensor will continue to be utilized by tracking trends in changes in its key indicators, and fault diagnosis can be used to quickly discover where the issue originated when anomalies appear. This kind of approach can provide warnings prior to a sensor entirely failing, allowing the system time to switch or enter a degraded state, but the assumption is that the degradation process should be modeled correctly, and in real complex systems models frequently do not work. Another approach to unreliable measurements is taken by Wang et al. who employed

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Kalman filtering with elliptical gating mechanism to filter out abnormal sensor measurements to enhance mobility-tracking robustness in the case of unstable measurements [8].

Machine learning-assisted perception enhancement has developed rapidly in recent years. Unlike traditional methods that rely on manually designed features and fixed thresholds, machine learning methods can automatically learn the patterns of environmental change from large amounts of data and maintain relatively high perception accuracy in conditions such as rain and fog, low light, and occlusion. Applying deep learning to sensor fault detection and diagnosis can effectively extract the nonlinear features in data and adapt to dynamic changes in the system. However, this type of method relies heavily on high-quality labeled data, and the computational cost of model training and inference is not low, so deployment on edge devices with limited computing power remains difficult. Singh et al. fused IMU and UWB measurements for warehouse-robot localization and compared LSTM, CNN-LSTM, MLP, and CNN models; the CNN-LSTM fusion achieved the lowest positioning error among the tested models [9].

3. Intelligent control driven by perceptual information

3.1. Multi-source sensory feedback and control adjustment

Perception systems are gradually moving beyond merely acquiring environmental information and are becoming embedded in closed-loop control, serving as an important basis for controllers to judge operating conditions and adjust strategies. External sensors (such as cameras, LiDAR, and radar) are responsible for acquiring geometric and semantic information about the surrounding environment, while proprioceptive sensors such as IMUs continuously measure the robot's own motion states, including acceleration and angular velocity. After time synchronization and coordinate unification, the two types of information form state feedback, based on which the controller determines whether the current operating conditions have changed and accordingly adjusts control parameters or switches control modes.

Sanket Lokhande et al. proposed a switching MPC framework enhanced by multi-IMU proprioception [2]. The team installed multiple IMUs on the torso and legs of a quadruped robot, built a context-aware two-layer hybrid dynamics model, identified terrain categories through proprioceptive feedback, and drove MPC to switch among different control modes. Experiments demonstrated that the approach has the ability to retain stable locomotion despite being deprived of GPS or seeing. We quote this work as it explicitly shows how the proprioceptive information can be used in control decisions-IMUs do not just give the state estimate, but become the basis of a trigger that the controller can use to detect a change in the environment and change control mode, which is very much in line with the logic of perception contributing in closed-loop control discussed in this section.

Elham Yazdani Bejarbaneh et al. conducted a systematic review of the technical framework of cooperative perception and cooperative control [3]. The authors have indicated that connected vehicles exchange the information about the perception via V2V and V2I communication, which allows the controllers to be aware of the state and intentions of other vehicles at the intersection, thus dynamically changing crossing order and speed paths. The article subdivides cooperative control into the centralized and distributed types, and notes that the only way in which control strategies can be effective is by sharing perception information in real-time. The reason we cite this review is that it details at the systems level the extension of perception information to the control loop beyond a single vehicle, which gives support in the framework of understanding the joint development of state feedback by external environmental information, and by proprioceptive

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information. Rong et al. also generalized the concept of multi-vehicle collaborative planning as a procedure between perception, communication, path planning, motion planning and local feedback control with the focus on the importance of real-time environmental data in mutual car decision making [10].

To conclude, it is demonstrated in both cases: either a quadruped robot with multi-IMU proprioceptive feedback to drive MPC switching, or connected vehicles with shared perception to modify intersection control strategies, that the perception system has ceased to be an autonomous information acquisition system, but an inseparable feedback loop in closed-loop control.

3.2. Edge computing and real-time perception control

Complex fusion algorithms have the advantage of enhancing the accuracy and stability of the perception, but it is also associated with the apparent issue of latency in computation. In the process of fusing multi-sensor data, the data should undergo stages like time synchronization, transformation of coordinates, feature extraction and multi-level fusion and the volume of data and the amount of computation required is very high. Using the case of autonomous driving, cameras, LiDAR, millimeter-wave radar, and IMUs run in parallel and the processing of every frame of data requires many computations, which can easily delay the perception to control response. This time lag can be directly related to the safety of control in high-speed motion or dynamic situations and even lead to wrong decisions. Thus, the question of reducing response time with limited computing capacity and maintaining perception accuracy and real-time is one of the main issues in the implementation of multi-sensor fusion systems.

Three key directions to solve this issue are model compression, edge computing, and hierarchical information processing. Pruning can be used to compress the model, deleting unimportant parameters of a network to reduce computation and storage, knowledge distillation enters a large model to train a small model to achieve a relatively high accuracy, and quantization represents high-precision floating-point parameters by low-precision representations, which further compresses the number of parameters [1]. This discussion indicates that these techniques could be employed singly or together to address the requirements of various computing platforms. Indicatively, in intelligent surface vehicles, pruning and distillation together cut down on model parameters by a considerable margin, which is accompanied by a significant number of inference speed, although the decrease in perception accuracy is minimal. It demonstrates that model compression has a significant potential of reducing the response time, and the compression ratio should be selected with caution since over compression can result in a loss of accuracy.

The latency issue is solved by edge computing in terms of computing architecture. Conventional cloud processing involves sending huge volumes of raw data to distant computers which has huge transmission latency and causes severe bandwidth congestion. Edge computing transfers some of the fusion and inference processing capabilities of the cloud to the edge devices near the data source, eliminating additional steps in data transmission and enhancing response time. The review also notes edge devices lack computing power and must compromise between accuracy and speed, trading between real-time performance and perception quality with a reasonable trade-off between offloading tasks and resources. An example of this is to put computationally intensive feature fusion computations on edge servers and lightweight decision inference on onboard terminals, creating a collaborative division of labor in computing. Naturally, edge computing has its share of problems, including resource allocation, task priority, and computing power has to be distributed dynamically based on the urgency of tasks.

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The hierarchical information processing maximizes the response time in terms of scheduling tasks. Various perception tasks may have varying real time needs, higher frequency control tasks can be prioritized, and lower frequency environmental modeling tasks can be put in the back background [3]. This review highlights that the precondition to control strategies to work is real-time exchange of perception information in cooperative control, yet the various kinds of information can have varying timeliness demands. To take an example, the position and speed of vehicles at intersections require high-frequency update of their real-time values, whereas the semantic map of the environment around can be updated with low frequency. The system is able to guarantee the speed of key control links response without necessarily processing all the information in a high frequency thus minimizing the total burden of computations. This scheme is complementary to model compression, and edge computing, and the three create a technical system to reduce the perception-to-control response time.

Altogether, model compression, edge computing and hierarchical information processing have various focuses, but the aim is the same, with limited computing resources, to make the time between the perception and the control as short as possible without neglecting the accuracy and real-time performance. Model compression minimizes the computation at the algorithm level, edge computing minimizes the transmission latency at the architecture level and hierarchical information processing minimizes resources allocation at the scheduling level. The three are not mutually exclusive, but can be used in combination. In the future, as hardware performance increases and algorithm optimization techniques become established, a combination of the three techniques can be the key to actually implementing complex fusion algorithms in real world systems.

4. Conclusion

Centered on the main thread of environmental perception and control in intelligent systems, this paper starts from the fundamental issues of multi-sensor fusion and sorts out the development trajectory of how perception systems evolve from single sensing to multi-source collaboration, and then to participation in closed-loop control. Each sensor possesses its advantages and disadvantages in terms of spatial coverage, accuracy and environmental flexibility. The complementary nature of the vision, LiDAR, radar and IMU defines the need of fusion, and time synchronization and spatial alignment are the requirements of fusion. Data-level, feature-level and decision-level fusion all possess their scenarios that are applicable and should be chosen according to the need of the task flexibly. In complicated situations, sensor calibration, performance degradation analysis, and fault diagnosis are used to guarantee the long-term stability of perception, whereas machine learning can provide an additional opportunity to extract information. The information of perception is not applied to the environment modeling anymore, but is directly involved in control decisions with state feedback. The quadruped robots which use multi-IMU proprioceptive feedback to drive the MPC switching and the connected vehicles which use common perception to modify the intersection control strategies are both common representations of this trend. At the same time, the computational latency problem brought by complex fusion algorithms cannot be ignored. Model compression, edge computing, and hierarchical information processing collaboratively alleviate real-time pressure from three levels: algorithm, architecture, and scheduling.

In the future, perception and control will be more closely integrated. On the one hand, multi-sensor fusion needs to develop to a deeper level, moving from the current feature-level fusion toward dynamic adaptive fusion of multimodal information, so that the system can automatically adjust fusion strategies and sensor weights according to environmental changes. On the other hand, the combination of edge computing and lightweight models will become more mature, and the

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collaborative optimization of model pruning, knowledge distillation, and hardware acceleration is expected to achieve higher-precision real-time inference on platforms with limited computing power. In addition, perception systems need to have online learning and adaptive capabilities to cope with new scenarios and edge cases not covered by training data. With the improvement of vehicle-road-cloud collaborative architectures, cross-platform sharing of perception information will support cooperative control on a larger scale. Overall, the deep integration of perception and control is not only an inevitable direction of technological evolution, but also a key path for intelligent systems to achieve higher autonomy and reliability in unstructured environments.

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