Active Control Method of Sensor Data Selection for Autonomous Mobile Robot

Dmitry G. Korzun, Olga I. Bogoiavlenskaia
Petrozavodsk State University (PetrSU)
Petrozavodsk, Russia
{dkorzun, olbgvl}@cs.karelia.ru

***Abstract*—An autonomous mobile robots have been discovering recently a wide range of applications in various areas of human activities, including industry, commerce, social life, environmental projects, health care, science, education, agriculture, housekeeping. The amount of sensors carried by a robot normally is rather considerable. In the sensor data stream the items are not equally important. We propose a method for data selection which is based on Additive Increase Multiplicative Decease Algorithm and could reduce the amount of data passed to the data fusion module.**

I. Background

An autonomous mobile robots have been discovering recently a wide range of applications in various areas of human activities, including industry, commerce, social life, environmental projects, health care, science, education, agriculture, housekeeping. For several decades the efforts of the research community in the area is directed to the development of methods and technologies that could make such devices able to navigate in a completely or partly unknown environment without any or with a restricted supervision of a human distant operator, e.g. [1], [2].

Autonomous mobile robot as a system operates in the environment which is either completely unknown and to be discovered or is partly described by a map and a path within the map the robot has to follow. Also the environment can change during the operation and those changes could be unpredictable. For the proper operation of the system the changes should be detected and a reaction should be designed. For these reasons an autonomous navigation is based upon sensors data which provide varied information about surrounding objects and inner information that could be useful for locomotion and navigation.

Nowadays there exists a wide variety of sensors that deliver diverse multitude of raw data. The sensors could be classified by the nature of the data they perceive, e.g., spatial, temporal, electromagnetic, mechanical and others, or by the nature of the sensor activity, e.g. inner (battery level, wheel angle) external (distance to the obstacle), active (sonar sensor), passive (camera). A range of classifications exists in the literature as well. Basically using sensor assumes that further processing of the sensors data could infer some information about the world around necessary for a robot safe navigation and mission completion. There are two major problems to be solved:

1) The raw sensors data carry uncertainty due to the lack of precision, external factors intervention or noise of the signal (Gaussian of non Gaussian).
2) The amount of sensors carried by a robot normally is rather considerable. Hence the amount of the information they produce is rather considerable as well. In the data stream the items are not equally important. Some of them are critical for the device integrity, some are essential for it's proper operation and some are useless. In many cases the attributes enumerated above could not be attached to a particular sensor (if so, dismount it). Let's consider a battery level sensor. If the battery level is high there is no need to monitor it on the regular basis. But if the charge is low or it is high but decreases faster than expected these data should be examined by the inference modules.

To deal with the first problem the methods of control theory are widely used. The sensor producers and the robot designers apply filters to smooth raw data. Different variations of the Kalman filter [3] could be applied for the state estimation if there is a linear low that bounds observed variables, e.g. velocity and acceleration, or distance and velocity. Another major method is Particle Filer [4] which is sequential Monte-Carlo technique. Due to the computation complexity of these two methods simple techniques as moving arithmetical average, median, mode filters are widely used in practice as well.

Smoothed data are further processed by sensor fusion algorithms [5], [4], which combine data from several sensors and relevant information from corresponding databases to produce more precise and specific inference about the surrounding environment. Meanwhile Kalman filter and Partical filter could be treated as fusion technique as well, e.g. [6].

Although the first problem enlisted above is researched extensively, the second problem is to be solved now by the choice of sensors set and their allocation. Meanwhile the battery charge and the computational facilities of an autonomous device are restricted and fusion useless data from the stream remains an important problem. We propose an approach to data selection which is based on Additive Increase Multiplicative Decease (AIMD) Algorithm and could reduce the amount of data passed to the data fusion module. The selection algorithms could be applied before, if possible, or after raw data smoothing stage and dynamically control the data flow passed to further processing.

II. Data Selection Algorithms

Let's consider a sensor as a mapping $S_m \mapsto S_n$, where $S_m \subset \mathbb{R}^m$ and $S_n \subset \mathbb{R}^n$. In most cases $|S_m| > |S_n|$. This inequality forms one of the main sources of uncertainty for the raw sensor data since the actual mapping is many to one. The set S_m represents the real world phenomenon. It could be continuous or discrete. Also it could be a conjunction of several continuous intervals or be any other subset of $\mathbb{R}^m$. The set S_n is discrete in most cases due to the sensor output granularity. Smoothing raw data done internally by the sensor producer or by the robot computing facilities still keeps it discrete due to the discrete nature of the computing architecture but the latter transforms $S_n \mapsto \tilde{S}_n$ and $|S_n| \leq |\tilde{S}_n|$.

Let's consider $x, y \in S_n$ and introduce the norm $||x - y|| \in \mathbb{R}$ which defines the distance between two values measured by a sensor. The norm is additive and $||ax|| = a||x||$, $a \in R$, $x \in S_n$. Then let's denote a sequence $s^i = \{s^i_0, s^i_1, \dots\}$, $s^i_k \in \tilde{S}_n$ of data produced by ith sensor and a sequence $t^i = \{t^i_0, t^i_1, \dots\}$ of timestamps that label the corresponding elements of the sequence s^i.

The selection method maintains the geometrical average of s^i sequence i.e.

$$||\hat{s}^i_k|| = \kappa||\hat{s}^i_{k-1}|| + (1-\kappa)||\hat{s}^i_k||, \tag{1}$$

where $0 < \kappa < 1$. This additional filter is applied if primary filters don not succeed. Otherwise the primary filter output could bu used as $\hat{s}^i$ sequence. The filter is not applied for periodical or fluctuating data. Also we consider which presents a feedback Then let's define a delay τ_n which is applied before the sensor data are passed to the inference modules.

The delay is dynamically adjusted depending on the properties of the data in the stream. Also it evaluates according to the feedback which selection algorithms obtain from the inference module. The feedback is presented as a sequence $\{k_n\}^\infty_{n=0}$, where k_n estimates importance and usefulness of the selected data sent after t_n interval. The value $k_n \in \mathbb{R}$ and $0 < k_n \leq 1$. It evaluates a measure of new information about the environment brought by the new portion of data selected.

In the scale 1 means crucial or very important and 0 means useless. If there is a lack of computing facilities the discrete or even binary value crucial/useless could be applied. Also we define one special signal k_{urgent} which means that sensors data should be sent immediately. The general scheme of the interaction is presented at Fig. 1.

Hence the delay t_n evaluates dynamically as follows:

$$\tau_{n+1} = \begin{cases} \dfrac{\alpha}{k_n + 1}\tau_n, & \text{if specified events has happened} \\ \tau_n + \delta, & \text{otherwise} \end{cases} \tag{2}$$

Here $0 < \alpha < 1$ is a delay decrease factor and $\delta > 0$ is a constant that increases the delay. So the method reduces the sending rate if the device operation is stable and increases it if the environment or the operation mode had changed. The decrease rate stays within the limits $[\alpha/2, \alpha]$.

The specified events are one of the following

1) The value of $||\hat{s}^i_k - \hat{s}^i_{k-1}|| > 0$ for ν time in the row, where ν is a parameter.

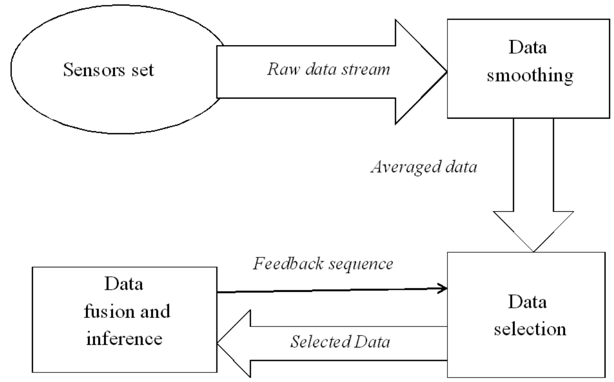

Fig. 1. The sensors data processing stages.

2) The $||\hat{s}^i_k|| = (1+\beta)||\hat{s}^i_{k-1}||$, where $\beta > 0.5$ is a parameter.
3) If KF or PF are used the event is: the error evaluated before a correction step does not change sign ν' times in a row.
4) A critical event is identified. The list of the critical events is formed in advance and normally they mean something which needs immediate reaction, e.g. sharp increase of acceleration.

At the end of τ_n interval the current value $\hat{s}^i_k$ is passed to the inference facility.

Thus if the sensor data are stable, uniform and correspond the current operation of the autonomous mobile robot they don't contain new insight about the environment and hence are not passed to the data fusion modules. If noticeable change happen then the data could be significant and are passed to the inference facility.

If the feedback is not taken into account than (2) transforms into AIMD algorithm as follows:

$$\tau_{n+1} = \begin{cases} \alpha\tau_n, & \text{if specified events has happened} \\ \tau_n + \delta, & \text{otherwise} \end{cases} \tag{3}$$

III. Conclusion

In this work the method of sensor data selection is proposed. It identifies data significant for autonomous mobile robot inference subsystem and reduces the amount of data processed. The method also employs feedback exchange between selection algorithms and the sensor data fusion methods as well.

Acknowledgment

The work is implemented within the Government Program of Flagship University Development for Petrozavodsk State University (PetrSU) in 2017-2021.

References

[1] F. Rubio, F. Valero, and C. Llopis-Albert, "A review of mobile robots: Concepts, methods, theoretical framework, and applications," *International Journal of Advanced Robotic Systems*, vol. 16, p. 172988141983959, 03 2019.

[2] R. Barber, J. Crespo, C. Gómez, A. C.Hernámdez, and M. Galli, "Mobile robot navigation in indoor environments: Geometric, topological, and semantic navigation," 2018.

[3] W. van Drongelen, "Chapter 19 - kalman filter," in *Signal Processing for Neuroscientists (Second Edition)*, second edition ed., W. van Drongelen, Ed. Academic Press, 2018, pp. 361 – 374. [Online]. Available: http://www.sciencedirect.com/science/article/pii/B9780128104828000199

[4] Y. Raaj, A. John, and T. Jin, "3d object localization using forward looking sonar (fls) and optical camera via particle filter based calibration and fusion," *OCEANS 2016 MTS/IEEE Monterey*, pp. 1–10, 2016.

[5] K. Nagla, M. Uddin, and D. Singh, "Multisensor data fusion and integration for mobile robots: A review," *IAES International Journal of Robotics and Automation (IJRA)*, vol. 3, 09 2014.

[6] A. T. Erdem and A. . Ercan, "Fusing inertial sensor data in an extended kalman filter for 3d camera tracking," *IEEE Transactions on Image Processing*, vol. 24, no. 2, pp. 538–548, 2015.