Intelligent Data Selection in Robot Movement

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Abstract—**Autonomous mobile robots have been discovering recently a wide range of applications in various areas of human activities. A robot uses many data sources (sensors) to recognize its current situation, including video, inertial, acoustic, mechanical stress. The data flows from such sources are redundant, with high rate, and contain much information about the ongoing events. Recognized events are input for the robot movement control. The number of ongoing events can be large. They have different importance for the movement control. In this work-in-progress paper, we consider a method for intelligent data selection. The method is based on the Additive Increase Multiplicative Decrease (AIMD) algorithm. The effect is in filtering the most significant information to forward to the robot movement control.**

I. Background

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 [1]. 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 operate in a completely or partly unknown environment without any or with a restricted supervision of a human distant operator, e.g., see [2], [3].

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. 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 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 the 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 us 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 [4] 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 [5] 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 [6], [5], 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., see [7].

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 a method for data selection which is based on the well-known Additive Increase Multiplicative Decrease (AIMD) algorithm [8]. The increase/decrease rules imitate the human cognition function, when a fault in decision leads to the strong reaction (multiplicative decrease) and a positive sign leads to small reaction (additive increase).

The method reduces the amount of data passed to processing for the robot movement control. The selection is applied before, if possible, or after the raw data smoothing phase. The effect is in filtering the most significant information.

II. Data Selection

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 $|S_n| \leq |\tilde{S}_n|$.

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 $s^i = \{s_0^i, s_1^i, \dots\}$, $s_k^i \in \tilde{S}_n$ of data produced by ith sensor and a sequence $t^i = \{t_0^i, t_1^i, \dots\}$ 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.,

$$||\hat{s}_k^i|| = \kappa||\hat{s}_{k-1}^i|| + (1 - \kappa)||\hat{s}_k^i||, \qquad (1)$$

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 us 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 $\{k_n\}_{n=0}^{\infty}$, 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. Then we define one special signal k_{urgent} which means that sensors data should be sent immediately. The general scheme of the interaction is presented in Fig. 1.

Hence the delay t_n evaluates dynamically as follows:

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

$$(2)$$

Here $0 < \alpha < 1$ is a delay decrease factor and $\delta > 0$ is a constant that increases the delay. Hence 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 $||\hat{s}_k^i - \hat{s}_{k-1}^i|| > 0$ for ν time in the row, where ν is a parameter.
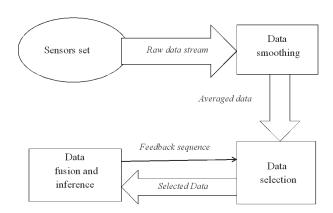

Fig. 1. The sensors data processing stages.

2) The $||\hat{s}_k^i|| = (1 + \beta)||\hat{s}_{k-1}^i||$, 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 $\hat{s}_k^i$ is passed to the inference facility.

Therefore, if the sensor data are stable, uniform and correspond the current operation of the autonomous mobile robot they do not 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 then (2) transforms into AIMD algorithm as follows:

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

III. Conclusion

This work introduced a new method of sensor data selection. The novelty is in using the AIMD algorithm, which previously used in other problem domains. The method intelligently recognizes the most significant information for autonomous mobile robot movement control. The amount of data to process is reduced. The method also employs feedback exchange between selection algorithms and the sensor data processing as well. The intelligence is in the selection strategy—the selection is close to the rules that human applies in solving a similar selection problem.

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