Wireless Agent Guidance of Remote Mobile Robots: Rough Integral Approach to Sensor Signal Analysis

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Abstract. A rough integral multiple sensor fusion model for wireless agent guidance of remote mobile robots is presented in this paper. A rough measure of sensor signal values provides a basis for a discrete form of rough integral that offers a means of aggregating sensor values and to estimate by means of a sensor signal how close robot is to a target region of space. By way of illustration, the actions of a collection of robots are controlled by a wireless system that connects a web agent (called a Guide Agent or GA) written in Java and pairs of Radio Packet Controller (RPCs) modules (one attached to a workstation and a second RPC on board a robot). The web GA analyzes robot sensors signals, communicates robot movement commands and assists other web agents in updating some parts of a web page that implements a real-time robot traffic control system. This web page displays the current configuration of a society of mobile robots (stopping, direction of movement, avoiding, wandering, mapping, and planning). Only a brief description of the web GA is given in this paper.

1 Introduction

Considerable work has already been carried out in the study of various forms of agents in the context of rough sets (e.g., [12]-[15]), rough mereology (e.g., [1]-[2]), approximate reasoning by agents (e.g., [3]-[5]), and sensor fusion (e.g., [6]-[9]). An agent is an independent process capable of responding to stimuli from its environment and communicating with other agents in its society. In this paper, the focus is on the design of a form of web agent called a Guide Agent (GA). The web GA described in this paper receives and analyzes robot sensors signals, communicates robot movement commands (usually originating from a human robot traffic controller) and assists other agents in updating some parts of a web page that implements a real-time robot traffic control system. The web page displays the current configuration of a society of mobile robots (stopping, direction of movement, avoiding, wandering, mapping, and planning). The contribution

N. Zhong et al. (Eds.): WI 2001, LNAI 2198, pp. 413–422, 2001.

of this paper is the modeling of web agents that classify sensor signals using rough integration to measure the effectiveness of a navigation plan to achieve an objective. This paper is structured as follows. The basic concepts underlying sensor signal analysis by a web-based guide agent are briefly presented, namely, set approximation and rough membership functions (Section 2), rough measures (Section 3) and discrete rough integrals (Section 4). Multi-sensor fusion, identification of relevant sensors, a model of a web guide agent, and an example of a web-based wireless system for guiding the actions of mobile robots are presented in Section 5.

2 Basic Concepts of Rough Sets

Rough set theory offers a systematic approach to set approximation [13]. To begin, let $S = (U, A)$ be an information system where U is a non-empty, finite set of objects and A is a non-empty, finite set of attributes, where $a : U \to V_a$ for every $a \in A$. For each $B \subseteq A$, let there is associated an equivalence relation $Ind_A(B)$ such that

$$Ind_A(B) = \{(x, x') \in U^2 \mid \forall a \in B.a(x) = a(x')\}$$

If $(x, x') \in Ind_A(B)$, we say that objects x and x' are indiscernible from each other relative to attributes from B. The notation $[x]_B$ denotes equivalence classes of $Ind_A(B)$. Further, partition $U/Ind_A(B)$ denotes the family of all equivalence classes of relation $Ind_A(B)$ on U. For $X \subseteq U$, the set X can be approximated only from information contained in B by constructing a B-lower and B-upper approximation denoted by $\underline{B}X$ and $\overline{B}X$ respectively, where $\underline{B}X = \{x \mid [x]_B \subseteq X\}$ and $\overline{B}X = \{x \mid [x]_B \cap X \neq \emptyset\}$.

Definition 1. *Let $S = (U, A)$ be an information system. Further, let $\wp(U)$ denote the powerset of U, $B \subseteq A$, $u \in U$ and let $[u]_B$ be an equivalence class of an object $u \in U$ of $Ind_A(B)$. The set function*

$$\mu_u^B : \wp(U) \to [0, 1], \text{where } \mu_u^B(X) = \frac{|X \cap [u]_B|}{|[u]_B|} \quad \text{for any } X \in \wp(U)$$

is called a rough membership function.

A rough membership function provides a classification measure inasmuch as it tests the degree of overlap between the set X in $\wp(U)$ and equivalence class $[u]_B$. The form of rough membership function in Def. 1 is slightly different from the classical definition where the argument of the rough membership function is an object x and the set X is fixed [14].

3 Rough Measures

Let $S = (U, A)$ be an information system, $X \subseteq U$, $B \subseteq A$, and let $Ind_A(B)$ be the indiscernibility relation on U. The tuple $(X, \wp(X), U/Ind_A(B))$, where $\wp(X)$ denotes the family of subsets of X and $U/Ind_A(B)$ denotes a set of all equivalence classes determined by $Ind_A(B)$ on U, is called an *indiscernibility space* over X and B. Let $u \in U$. A non-negative and additive set function $\rho_u : \wp(X) \to [0, \infty)$ defined by $\rho_u(Y) = \rho'(Y \cap [u]_B)$ for $Y \in \wp(X)$, where $\rho' : \wp(X) \to [0, \infty)$ is called a *rough measure* relative to $U/Ind_A(B)$ and u on the indiscernibility space $(X, \wp(X), U/Ind_A(B))$. The tuple $(X, \wp(X), U/Ind_A(B), \{\rho_u\}_{u \in U})$ is a *rough measure space* over X and B.

*Example 1 (*Sample Non-Negative Set Function). The rough membership function $\mu_u^B : \wp(X) \to [0, 1]$ is a non-negative and additive set function.

Proposition 1. [19] $(X, \wp(X), U/Ind_A(B), \mu_u^B)$ is a rough measure space over X and B.

Other rough measures based on upper {lower} approximations are possible but consideration of these other measures is outside the scope of this paper.

4 Discrete Rough Integral

Rough integrals were introduced in [15], and elaborated in [19]. In what follows, let $X = \{x_1, \ldots, x_n\}$ be a finite, non-empty set with n elements. The elements of X are indexed from 1 to n. The notation $X_{(i)}$ denotes the set $\{x_{(i)}, x_{(i+1)}, \ldots, x_{(n)}\}$ where $i \geq 1$ and $n = card(X)$. The subscript (i) is called a permutation index because the indices on elements of $X_{(i)}$ are chosen after a reordering of the elements of X. This reordering is "induced" by an external mechanism. Next, we use a functional defined by Choquet in 1953 in capacity theory [16] to define a discrete rough integral.

Definition 2. *Let ρ be a rough measure on X where the elements of X are denoted by $x_1, \ldots, x_n$. A particular form of a discrete rough integral of $f : X \to \Re^+$ with respect to the rough measure ρ is defined by*

$$\int f \, d\rho = \sum_{i=1}^{n} (f(x_{(i)}) - f(x_{(i-1)}))\rho(X_{(i)})$$

where $\bullet_{(i)}$ specifies that indices have been permuted so that $0 \leq f(x_{(i)}) \leq \ldots \leq f(x_{(n)})$, $X_{(i)} := \{x_{(i)}, \ldots, x_{(n)}\}$, and $f(x_{(0)}) = 0$.

This definition of a discrete rough integral is a variation of the definition given in Pawlak et al. [19] and a formulation of the Choquet integral by Grabisch [17]. It should be observed that in general the Choquet integral has the effect of "averaging" the values of a measurable function. This averaging closely resembles the well-known Ordered Weighted Average (OWA) operator [18].

Proposition 2 (Pawlak et al. [19]). Let $0 < s \leq r$. If $a(x) \in [s, r]$ for all $x \in X_a$, then $\int a \, d\mu_u^e \in (0, r]$ where $u \in U$.

5 Multi-sensor Fusion

Consider, next, the case where there is interest in discovering which sensor is more relevant among a set of sensors. The term relevance in this context denotes the "closeness" of a set of experimental sensor values relative to a set of a pre-calibrated, target sensor values that are considered important in a classification effort. The identification of relevant sensors provides a form of sensor fusion. The term sensor fusion generally refers to some process of combining sensor readings [11]. Further, assume that each of the sensors have the same model with essentially the same accuracy. At this stage, we will ignore the issue of the accuracy of a sensor, and trust that each sensor in a set of sensors produces output with low error.

5.1 Relevant Sensors

Assume that a denotes a proximity sensor that responds to stimuli (energy from a reflecting surface) with distance measurements. Let $\{a\} = B \subseteq A$ where $a : U \rightarrow [0, 0.5]$ where each sample sensor value $a(x)$ is rounded to two decimal places. Let $(Y, U - Y)$ be a partition defined by an expert and let $[u]_e$ denote a set in this partition containing u for a selected $u \in U$. We further assume the elements of $[u]_e$ are selected relative to an interval $(u - \varepsilon, u + \varepsilon)$ for a selected $\varepsilon \geq 0$. We assume a decision system (X_a, a, e) is given for any considered sensor a such that $X_a \subseteq U,\ a : X_a \rightarrow \Re^+$ and e is an expert decision restricted to X_a defining a partition $(Y \cap X_a, (U - Y) \cap X_a)$ of X_a. Moreover, we assume that $X_a \cap [u]_e \neq \emptyset$. The set $[u]_e$ is used to classify sensors and is given the name "classifier". By way of illustration, we give the following two tables.

Let $u = 0.425$ and $\varepsilon = 0.2$, and obtain $[0.425]_e$ with values in the interval $[a(0.225), a(0.625)] = [0.2, 0.6]$. The aim is to fuse the sample values in each signal using a rough integral, and evaluate the rough integral value relative to $[u]_e$. From Table 1(a) compute $\int a \, d\mu_u^e = 0.1$ and $\int a \, d\mu_u^e = 0.239$ from Table 1(b). The first integral value lies outside the target interval [0.2, 0.6] and the second integral value falls inside [0.2, 0.6]. Let $\bar{u}$ denote the average value in the

Table 1. (a)

$X\backslash\{a,e\}$	a	e
$x_1 = 0.203$	0.2	0
$x_2 = 0.454$	0.45	1
$x_3 = 0.453$	0.45	1
$x_4 = 0.106$	0.11	0
$x_5 = 0.104$	0.10	0

Table 1. (b)

$X\backslash\{a,e\}$	a	e
$x_2 = 0.454$	0.45	1
$x_9 = 0.455$	0.46	1
$x_{10} = 0.401$	0.4	1
$x_{11} = 0.407$	0.41	1
$x_{12} = 0.429$	0.43	1

classifier $[u]_e$, and let $\delta \in [0,1]$. Then, for example, the selection R of the most relevant sensors in a set of sensors is found using

$$R = \left\{ a_i \in B \; : \; \left| \int a_i \, \mu_u^e - a(\bar{u}) \right| \leq \delta \right\}$$

In effect, the integral $\int a_i \, d\mu_u^e$ serves as a filter inasmuch as it "filters" out all sensors with integral values not close enough to $a(\bar{u})$.

5.2 Guide Agent

A web-based guide agent (GA) is a web-based independent process that interacts with external devices via the internet and radio packet interfaces.

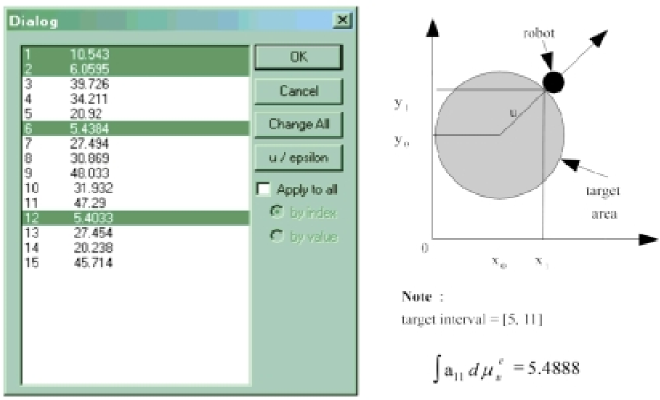

Fig. 1. Tracking Mobile Robot

The form of GA described in this article engages in sensor signal analysis and communicates navigation commands that direct an external device (e.g., a mobile robot) to navigate inside a specified region of space. The GA also provides input to other agents responsible for updating and maintaining a web page used to monitor the changing configuration of a system of commanded devices (e.g., motors on robots). Sample output in the form of a group of 15 range sensor readings from a sensor named a_{11} onboard an external device is shown in Fig. 1. Let a_{11} be the name of a robot ranging sensor (e.g., let a_{11} be an ultrasonic sensor that computes the distance L_0 travelled by an emitted sound wave that reflects back from an object where $L_0 = (vtcos\,\theta)/2)$ [10]. For simplicity, we assume that the velocity v of a sound wave in a medium is fixed, and θ (the angle of separation between transmitter and receiver in relation to a detected object) is also fixed. Then $[u]_e$ is a finite set of sample durations $\{u, t_1, t_2, \ldots\}$ considered representative of ideal timings by an expert. Sample output from a moving robot that monitors groups of 15 sensor readings at a time is shown in Fig. 1. In this case, the agent learns that the robot is maintaining an average distance of 5 cm from the center of a circle with radius 12 cm. At some point, the agent diverged from the center a distance of 39 cm (reading 3), then, after adjusting its position three times (readings 4 and 5), it slips back into the desired circle. Ideally, the integral value should equal $a_{11}(\bar{u})$ when the robot is navigating correctly.

5.3 Basic Guide Agent Algorithm

A guide agent begins with a universe of objects reflecting possible sensor values, a set of sensors, classifier set $[u]_e$, signal value threshold u, boundary value δ, and time limit t. A sensor signal measures the distance between a robot and a reflecting medium such as a wall in corridor where a mobile robot is navigating.

5.4 Example: Web-Controlled Mobile Robots

A pair of mobile robots exchanging information with a web GA (sensor signals from robot, commands from web agent) is shown in Fig. 2(a) and 2(b). Each robot is equipped with compass (module at the top of the "tower" of each robot in Fig. 2(a)), 6 ranging sensors, and Radiometrix Radio Packet Controller or RPC [20]. A RPC can send {receive} to {from} another RPC. It communicates at 40 Kbits/s over 433.92 MHz channels in the UHF band. Each robot RPC (Fig. 2(a)) communicates with a companion RPC (Fig. 2(b)) plugged into a Dallas Semiconductor TINI board that connects to an I/O port on a computer [21]. The TINI board has its own computer programmable in Java and makes it possible to web-enable remote electrical devices connected to ports on the TINI board. In this article, an ideal view of each robot is given where each robot is equipped with 6 ranging sensors to measure distances between the robot and the approximate center of a bounded region. We also assume that the bounded region is approximately circular. A GA monitors the direction of travel and relative position of a particular robot. It is also assumed that boundaries periodically move. Each robot has its own web GA and 6 ranging sensors. Each sensor provides

Guide Agent Algorithm

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Input:       U, A, [u]_e, δ, t;          // universe, sensors, classifier, bound, ms delay
Constraint:  |∫ a dρ − a(ū)| ≤ δ        // sensor signal within an acceptable range
Output:      R                           // measured response to selected sensor
while (true) {
   delay(t); sample = integrate(read(sensorSignal));
   switch (sample) {
      (|sample − a(ū)| ≤ δ):{
         turnLeft; moveForward; stop;              // begin zigzag movement
         sample = integrate(read(a));
         switch (sample) {
            (|sample − a(ū)| ≤ δ):
               turnRight; moveForward; stop;    // zigzag
            (|sample − a(ū)| > δ): stop; u = calibrate(sample, u);
         } // switch
      (|sample − a(ū)| > δ): stop; u = calibrate(sample, u);
   } // switch
} // while (End Algorithm)
end Algorithm
```

distance measurements making it possible to estimate of the relative position of the robot.

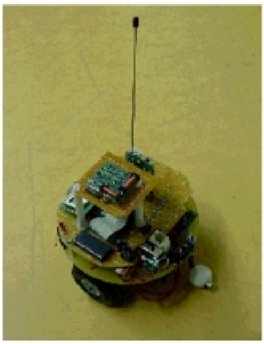

Fig. 2. (a) Web Guided Robot

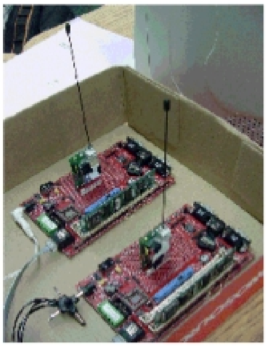

Fig. 2. (b) Radio Control Pack Modules

Assume that each sensor has a detection range from 0.1 cm to 30 cm and that sensor readings are made continuously and stored in a queue. Let $a_i, a_i(t)$ be the i^{th} sensor and i^{th} sensor reading at time t, respectively. Sensor queues are analyzed for each collection of 10 readings. Assume we are interested in sensor readings in the range 30 cm $\pm$ 6cm where 30 is the approximate center of a circular "ambling" region for a robot whose mission is to explore its bounded environment. A summary of the integral values for two separate experiments with sensor signal samples gathered over time is given in the control chart in Fig. 3, where the Upper {Lower} Control Limits 30.87{6.03} have been chosen arbitrarily. Since the average integral value is inside the target interval, the web GA continues using the same circular region in guiding robot actions. If one of the boundaries were to move (e.g., a door opens) and the robot is able to move beyond the boundary of the circular region, the web GA would calibrate u (we assume u is a parameter such as duration in the model for an ultrasonic sensor) to facilitate new exploration by the robot.

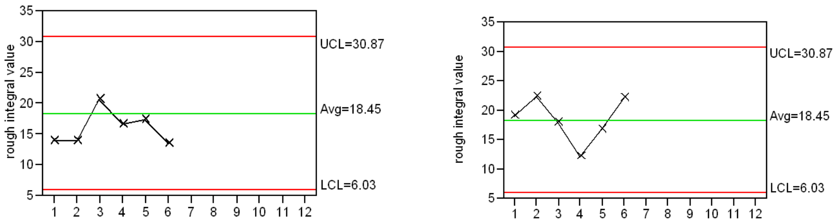

Fig. 3. Sample Navigation Control Charts for Rough Integral Values

Remark. Suppose we are interested in estimating for a considered period of time if an agent moving around in a circular region with obstacles such as walls. The meaning of this can be estimated by an expert looking at the plot in Fig. 3 relative to the requirement stipulated by $[u]_e$. We can imagine a decision table with sample sensor signals (not single sample signal values but a set of sample signal values) where a decision to view a signal as acceptable is approximated by $\int a\, d\rho$, which is deemed "close enough" to $a(\bar{u})$ for sensor a. That is, the integral value tends to reflect (approximate) an expert decision about the appropriateness of robot movements relative to the target region. That is, the integral computes the aggregative effect reflected by sensor values relative to the "walking region". The set $[u]_e$ provides a basis for classifying sensor signals.

6 Conclusion

This article presents an application of a discrete form of rough integral in the design of a web guide agent that guides the actions of a mobile robot. This integral computes an ordered weighted average and provides a means of sensor fusion. The rough integral is superior to other known forms of weighted averaging because it is computed relative to a classification requirement reflected in $[u]_e$. Further, the set $[u]_e$ makes it possible to classify sensor signals inasmuch as it prescribes "ideal" parameter values for a ranging sensor in a required region of space considered safe for the movements of the robot being controlled by a navigation agent. In a sense, $[u]_e$ provides a schema that mediates between the sensors and planner for a web agent responsible for guiding the movements of a remote mobile robot. In this context, the term *schema* denotes a mediating representation. Hence, $[u]_e$ is also called a classification schema, a fundamental feature in the intelligence of an agent. In a complete web-based robot control system, a collection of robots would be controlled remotely (e.g., a web page accessed in control centers in Tokyo and other cities in Japan could be used to monitor and control a collection of robots designed to inspect railway tracks).

Acknowledgment. The research of Sheela Ramanna and James Peters has been supported by the Natural Sciences and Engineering Research Council of Canada (NSERC) research grant 194376 and research grant 185986, respectively. The research of Maciej Borkowski has been supported by a grant from Manitoba Hydro. The research of Andrzej Skowron has been supported by grant 8 T11C 025 19 from the State Committee for Scientific Research (KBN) and from a grant from the Wallenberg Foundation.

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