APPROXIMATE SENSOR FUSION IN A NAVIGATION AGENT

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A multiple sensor fusion model for a navigation agent based on rough integration is given in this paper. A rough measure of sensor signal values provides a basis for a discrete form of rough integral. This integral computes a form of ordered weighted average using a weighting factor determined by a classifier in the form of a set of "ideal" sensor values. In this paper, the focus is on classifying sensor signals relative to a classification interval of interest in guiding the navigation of a mobile robot. A navigation agent "looks" for rough integral values representing sensor signals to determine appropriate movements in a particular region of space. A navigation algorithm used by an agent to govern the movements of a mobile robot is given.

1 Introduction

An agent is an independent process capable of responding to stimuli from its environment and communicating with other agents in its society. The aim of the current research is to study one form of navigation by an agent based on rough set theory [2]-[3], recent work with sensors, filters and sensor fusion [5]-[7], rough measures and integrals [4], and approximate reasoning by agents [8]. The contribution of this paper is the modeling of agents that classify sensor signals using rough integration to measure the effectiveness of a navigation plan needed to achieve an objective.

This paper is structured as follows. Section 2 provides a brief presentation of the basic concepts underlying sensor signal analysis by a navigation agent, namely, set approximation, rough membership functions and rough measures. Discrete rough integrals and identification of relevant sensors are briefly presented in Sections 3 and 4. A navigation algorithm for an agent is given in Section 5.

2 Basic Concepts of Rough Sets

Rough set theory offers a systematic approach to set approximation [2]. 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 $B \subseteq A$, there is associated an equivalence relation $Ind_A(B)$ such that

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

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 $Ind_A(B)$.

Definition 2.1 Let $S = (U, A)$ be an information system, $B \subseteq A$, $u \in U$ and let $[u]_B$ be an equivalence class of an object $u \in U$ of $Ind_A(B)$. The set function

$$\mu_u^B : \wp(U) \to [0,1], \text{where } \mu_u^B(X) = \frac{card\,(X \cap [u]_B)}{card\,([u]_B)} \tag{1}$$

for any $X \in \wp(U)$ is called a *rough membership function (rmf)*.

The form of rough membership function in Def. 2.1 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 [3].

Definition 2.2 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 rough membership function $\mu_u^B : \wp(X) \to [0, 1]$ is a non-negative set function [4].

Proposition 2.1 (Pawlak et al. [4]) The rough membership function μ_u^B as defined in Definition 2.1 (formula (1)) is additive on U.

3 Rough Integrals

Rough measure-based integrals were introduced in [4], and applied in [5-7]. In this section, we introduce a particular form of a discrete rough integral defined relative to a rough measure.

Definition 3.1 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 the discrete rough integral is based on a formulation of the Choquet integral in Grabisch [1].

Proposition 3.1 (Pawlak et al. [4]) 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 $u \in U$.

4 Relevance of a Sensor

In this section, we consider the measurement of the relevance of a sensor using a rough integral. A sensor is considered relevant in a classification effort in the case where $\int a \, d\mu_u^e$ for a sensor a is close enough to some threshold in a target interval of sensor values.

Example 4.1 Assume that a denotes a sensor that responds to stimuli with measurements that govern the actions of an agent. Let $\{a\} = B \subseteq A$ where $a : U \to [0, 0.5]$ 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 $X_a \subseteq U$, $a : X_a \to \Re^+$ 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". Consider the following decision tables.

Table 1(a)

$X \backslash A \cup \{d\}$	a	d
$x_1 = 0.203$	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)

$X \backslash A \cup \{d\}$	a	d
$x_2 = 0.454$	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

Let $u = 0.425$ and $\varepsilon = 0.2$, and obtain $[0.425]_e$ with values in the interval [0.225, 0.625]. 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 [0.225, 0.625] and the second integral value falls inside [0.225, 0.625]. Let $\bar{u}$ denote the average value in the 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 Basic Navigation Algorithm

A navigation agent begins with a universe of objects reflecting possible sensor values, a set of sensors, classifier set $[u]_e$, signal value threshold u, boundary values ε and δ, and time limit t.

Navigation Algorithm

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Input:       U, A, [u]_e, u, ε, δ, t;   // universe, sensors, classifier, threshold,
                                        // bounds, 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) && (sample < u ): moveForward;
    (sample < u − ε): stop; u = calibrate(sample, u, ε);
    (|sample − a(ū)| ≤ δ) && (sample ≥ u): stop; moveBackward;
    (sample > u + ε): stop; u = calibrate(sample, u, ε);
} }
```

6 Conclusion

This article presents an application of a discrete form of rough integral in the design of a navigation agent for a mobile robot. This integral computes an ordered weighted average and provides a means of sensor fusion. For a value u in the universe of sensor values and bound ε on a classification interval, the selection of an appropriate u and ε needed to construct $[u]_e$ is important. The set $[u]_e$ makes it possible to classify sensor signals inasmuch as it prescribes 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 of an intelligent agent. 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. By comparing the integral value and the average value in [u]e, a navigation agent can decide when the calibration of u is necessary to align the movements of a robot within the required "walking" region.

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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