From Empirical Data to Multi-Modal Control Procedures*

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Summary. In this paper we study the problem of generating control programs, i.e. strings of symbolic descriptions of control-interrupt pairs (or modes) from input-output data. In particular, we take the point of view that such control programs have an information theoretic content and thus that they can be more or less effectively coded. As a result, we focus our attention on the problem of producing low-complexity programs by recovering the strings that contain the smallest number of distinct modes. An example is provided where the data is obtained by tracking ten roaming ants in a tank.

1 Introduction

As the complexity of many control systems increases, due both to the system complexity (e.g. manufacturing systems, [6]) and the complexity of the environment in which the system is embedded (e.g. autonomous robots [1, 17]), multi-modal control has emerged as a useful design tool. The main idea is to define different modes of operation, e.g. with respect to a particular task, operating point, or data source. These modes are then combined according to some discrete switching logic and one attempt to formalize this notion is through the concept of a *Motion Description Language* (MDL) [5, 9, 15, 18].

Each string in a MDL corresponds to a control program that can be operated on by the control system. Slightly different versions of MDLs have been proposed, but they all share the common feature that the individual atoms, concatenated together to form the control program, can be characterized by control-interrupt pairs. In other words, given a dynamical system

$$\begin{aligned} \dot{x} &= f(x,u),\ x \in \mathbb{R}^N,\ u \in U \\ y &= h(x),\ y \in Y, \end{aligned} \tag{1}$$

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together with a control program $(k_1, \xi_1), \ldots, (k_z, \xi_z)$, where $k_i : Y \to U$ and $\xi_i : Y \to \{0, 1\}$, the system operates on this program as $\dot{x} = f(x, k_1(h(x)))$ until $\xi_1(h(x)) = 1$. At this point the next pair is read and $\dot{x} = f(x, k_2(h(x)))$ until $\xi_2(h(x)) = 1$, and so on[3].

Now, a number of results have been derived for such (and similar) systems, driven by strings of symbolic inputs, i.e. when the control and interrupt sets are finite. For example, in [4], the set of reachable states was characterized, while [10] investigates optimal control aspects of such systems. In [8, 15, 18], the connection between MDLs and robotics was investigated. However, in this paper we continue the development begun in [3], where the control programs are viewed as having an information theoretic content. In other words, they can be coded more or less effectively. Within this context, one can ask questions concerning minimum complexity programs, given a particular control task.

But, in order to effectively code symbols, drawn from a finite alphabet, one must be able to establish a probability distribution over the alphabet. If such a distribution is available then Shannon's celebrated source coding theorem [20] tells us that the minimal expected code length l satisfies

$$\mathcal{H}(\mathcal{A}) \leq l \leq \mathcal{H}(\mathcal{A}) + 1, \tag{2}$$

where $\mathcal{A}$ is the alphabet, and where the *entropy* is given by

$$\mathcal{H}(\mathcal{A}) = \sum_{a \in \mathcal{A}} p(a) \log_2 \frac{1}{p(a)}, \tag{3}$$

where $p(a)$ is the probability of drawing the symbol a from $\mathcal{A}$. The main problem that we will study is how to produce an empirical probability distribution over the set of modes, given a string of input-output data. Such a probability distribution would be useful when coding control procedures since a more common mode should be coded using fewer bits than an uncommon one. The ability to code control programs effectively has a number of potential applications, from teleoperated robotics, control over communication constrained networks, to minimum attention control.

The outline of this paper is as follows: In Section 2 we introduce motion description languages, and in Section 3, we define the problem at hand and show how this can be addressed within the MDL framework. In Section 4 we show how to find mode sequences that contain the smallest number of distinct modes, followed by a description of how these types of sequences can be modified for further complexity reductions, in Section 5. In Section 6, we give an example where the control programs are obtained from data generated by 10 roaming ants.

[3] Note that the interrupts can also be time-triggered, but this can easily be incorporated by a simple augmentation of the state space.

2 Motion Description Languages

The primary objects of study in this paper are so called *motion description languages* (MDLs). Given a finite set, or alphabet, $\mathcal{A}$, by $\mathcal{A}^\star$ we understand the set of all strings of finite length over $\mathcal{A}$, with the binary operation of concatenation defined on $\mathcal{A}^\star$. Relative to this operation, $\mathcal{A}^\star$ is a semigroup, and if we include the empty string in $\mathcal{A}^\star$ it becomes a monoid, i.e. a semigroup with an identity, and a *formal language* is a subset of the free monoid over a finite alphabet. (See for example [12] for an introduction to this subject.)

The concept of a *motion alphabet* has been proposed recently in the literature as a finite set of symbols representing different control actions that, when applied to a specific system, define segments of motion [5, 7, 11, 14, 18]. A MDL is thus given by a set of strings that represent such idealized motions, i.e. a MDL is a subset of the free monoid over a given motion alphabet. Particular choices of MDLs become meaningful only when the language is defined relative to the physical device that is to be controlled, as shown in Equation (1).

Now, in order to make matters somewhat concrete, we illustrate the use of MDLs with a navigation example, found in [8]. What makes the control of mobile robots particularly challenging is the fact that the robots operate in unknown, or partially unknown environments. Any attempt to model such a system must take this fact into account. We achieve this by letting the robot make certain observations about the environment, and we let the robot dynamics be given by

$$\begin{aligned} &\dot{x} = u,\ \ x, u \in \mathbb{R}^2 \\ &y_1 = o_d(x),\ \ y_2 = c_f(x), \end{aligned}$$

where o_d is an odometric (possibly quantized) position estimate of x, and c_f is the (possibly quantized) contact force from the environment. The contact force could either be generated by tactile sensors in contact with the obstacle or by range sensors such as sonars, lasers, or IR-sensors.

Relative to this robot it is now possible to define a MDL for executing motions that drive the robot toward a given goal, located at x_F, when the robot is not in contact with an obstacle. On the other hand, when the robot is in contact with an obstacle, it seems reasonable to follow the contour of that obstacle in a clock-wise or counter clock-wise fashion, as suggested in [13]. We let the MDL be given by the set $\sigma_{GA} \cdot (\sigma_{OA} \cdot \sigma_{GA})^\star$, where GA and OA denote "goal-attraction" and "obstacle-avoidance" respectively, and where $a^\star = \{\emptyset, a, aa, aaa, ...\}$. The individual modes $\sigma_{GA} = (k_{GA}, \xi_{GA})$ and $\sigma_{OA} = (k_{OA}, \xi_{OA})$ are furthermore given by

$$\begin{cases} k_{GA}(y_1, y_2) = \kappa(x_F - y_1) \\ \xi_{GA}(y_1, y_2) = \begin{cases} 0 \text{ if } \langle y_2, x_F - y_1 \rangle \geq 0 \\ 1 \text{ otherwise} \end{cases} \end{cases}$$

$$\begin{cases} k_{OA}(y_1,y_2) = cR(-\pi/2)y_2 \\ \xi_{OA}(y_1,y_2) = \begin{cases} 0 \text{ if } \langle y_2, x_F - y_1\rangle < 0 \text{ or } \angle(x_F - y_1, y_2) < 0 \\ 1 \text{ otherwise.} \end{cases} \end{cases}$$

The idea here is that the goal is located at x_F, and when the robot is not in contact with an obstacle, x_F is taken as a set-point in a proportional feedback law, provided by the mapping $k_{GA}(y_1,y_2) = \kappa(x_F - y_1)$, with $\kappa > 0$. When the robot is in contact with an obstacle, no set-point is needed, and $k(y_1,y_2)$ is simply given by $cR(-\pi/2)y_2$, where $c > 0$, $R(\theta)$ is a rotation matrix, and the choice of $\theta = -\pi/2$ corresponds to a clockwise negotiation of the obstacle. Note that in this example, the interrupts trigger as new obstacles are encountered, and in the definition of the interrupts, $\angle(\gamma,\delta)$ denotes the angle between the vectors γ and δ. An example of using this multi-modal control sequence is shown in Figure 1.

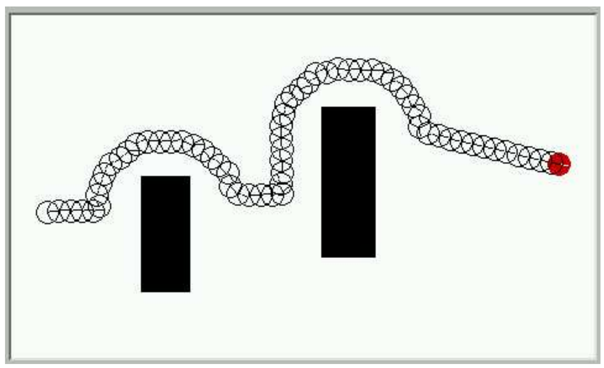

Fig. 1. A multi-modal input string is used for negotiating two rectangular obstacles. Depicted is a simulation of a Nomadic Scout in the Nomadic `Nserver` environment.

3 Specification Complexity

If we now assume that the input and output spaces (U and Y respectively) in Equation (1) are finite, which can be justified by the fact that all physical sensors and actuators have a finite range and resolution, the set of all possible modes $\Sigma_{total} = U^Y \times \{0,1\}^Y$ is finite as well. We can moreover adopt the point of view that a data point is measured only when the output or input change values, i.e. when a new output or input value is encountered. This corresponds to a so called *Lebesgue sampling*, in the sense of [2]. Under this sampling policy, we can define a mapping $\delta : \mathbb{R}^N \times U \rightarrow \mathbb{R}^N$ as $x_{p+1} = \delta(x_p, k(h(x_p)))$, given the control law $k : Y \rightarrow U$, with a new time update occurring whenever a new output or input value is encountered. For such a system, given the input string $(k_1,\xi_1),\ldots,(k_z,\xi_z) \in \Sigma^*$ where $\Sigma \subseteq \Sigma_{total}$, the evolution is given by

$$\begin{cases} x(q+1) = \delta(x(q), k_{l(q)}(y(q))),\ y(q) = h(x(q)) \\ l(q+1) = l(q) + \xi_{l(q)}(y(q)). \end{cases} \tag{4}$$

Now, given a mode sequence of control-interrupt pairs $\sigma \in \Sigma^\star$, we are interested in how many bits we need in order to specify σ. If no probability distribution over Σ is available, this number is given by the *description length*, as defined in [19]:

$$\mathcal{D}(\sigma, \Sigma) = |\sigma| \log_2(card(\Sigma)),$$

where $|\sigma|$ denotes the length of σ, i.e. the total number of modes in the string. This measure gives us the number of bits required for describing the sequence in the "worst" case, i.e. when all the modes in Σ are equally likely. However, if we can establish a probability distribution p over Σ, the use of optimal codes can, in light of Equation (2), reduce the number of bits needed, which leads us to the following definition:

Definition (Specification Complexity): *Given a finite alphabet Σ and a probability distribution p over Σ. We say that a word $\sigma \in \Sigma^*$ has specification complexity*

$$\mathcal{S}(\sigma, \Sigma) = |\sigma| \mathcal{H}(\Sigma).$$

An initial attempt at establishing a probability distribution over $\Sigma \subseteq U^Y \times \{0,1\}^Y$ was given in [3]. In that work, the main idea was to recover modes (and hence also the empirical probability distribution) from empirical data. For example, supposing that the mode string $\sigma = \sigma_1\sigma_2\sigma_1\sigma_3$ was obtained, then we can let $\Sigma = \{\sigma_1, \sigma_2, \sigma_3\}$, and the corresponding probabilities become $p(\sigma_1) = 1/2,\ p(\sigma_2) = 1/4,\ p(\sigma_3) = 1/4$. In such a case where we let Σ be built up entirely from the modes in the sequence σ, the empirical specification complexity depends solely on σ:

$$\mathcal{S}^e(\sigma) = |\sigma| \mathcal{H}^e(\sigma) = -\sum_{i=1}^{M(\sigma)} \lambda_i(\sigma) \log_2 \frac{\lambda_i(\sigma)}{|\sigma|}, \tag{5}$$

where $M(\sigma)$ is the number of distinct modes in σ, $\lambda_i(\sigma)$ is the number of occurrences of mode σ_i in σ, and where we use superscript e to stress the fact that the probability distribution is obtained from empirical data.

Based on these initial considerations, the main problem, from which this work draws its motivation, is as follows:

Problem (Minimum Specification Complexity): *Given an input-output string $S = (y(1), u(1)), (y(2), u(2)), \ldots, (y(n), u(n)) \in (Y \times U)^n$, find the minimum specification complexity mode string $\sigma \in \Sigma_{total}^*$ that is consistent with the data. In other words, find σ that solves*

$$\mathrm{P}(\Sigma_{total}, \boldsymbol{y}, \boldsymbol{u}) : \begin{cases} \min_{\sigma \in \Sigma_{total}^*} \mathcal{S}^e(\sigma) \\ \text{subject to } \forall q \in \{1, \ldots, n\} \\ \begin{cases} \sigma_{l(q)} = (k_{l(q)}, \xi_{l(q)}) \in \Sigma_{total} \\ k_{l(q)}(y(q)) = u(q) \\ \xi_{l(q)}(y(q)) = 0 \Rightarrow l(q+1) = l(q), \end{cases} \end{cases}$$

where the last two constraints ensure consistency of σ with the data S, and where $\boldsymbol{y} = (y(1), \ldots, y(n))$, $\boldsymbol{u} = (u(1), \ldots, u(n))$ give the empirical data string.

Note that this is slightly different than the formulation in Equation (4) since we now use $\sigma_{l(q)}$ to denote a particular member in $U^Y \times \{0,1\}^Y$ instead of the $l(q)$-th element in σ.

Unfortunately, this problem turns out to be very hard to address directly. However, the easily established property

$$0 \leq \mathcal{H}^e(\sigma) \leq \log_2(M(\sigma)), \ \forall \sigma \in \Sigma^\star_{total}$$

allows us to focus our efforts on a more tractable problem. Here, the last inequality is reached when all the $M(\sigma)$ distinct modes of σ are equally likely.

As a consequence, we have $\mathcal{S}^e(\sigma) \leq |\sigma| \log_2(M(\sigma))$ and thus it seems like a worth-while endeavor, if we want to find low-complexity mode sequences, to try to minimize either the length of the mode sequence $|\sigma|$ or the number of distinct modes $M(\sigma)$. In fact, minimization of $|\sigma|$ was done in [3], while the minimization of $M(\sigma)$ is the main pursuit in this paper:

Problem (Minimum Distinct Modes):
Given an input-output string $S = (y(1), u(1)), (y(2), u(2)), \ldots, (y(n), u(n)) \in (Y \times U)^n$, find σ that solves

$$\mathrm{Q}(\Sigma_{total}, \boldsymbol{y}, \boldsymbol{u}) : \begin{cases} \min_{\sigma \in \Sigma^*_{total}} M(\sigma) \\ \text{subject to } \forall q \in \{1, \ldots, n\} \\ \begin{cases} \sigma_{l(q)} = (k_{l(q)}, \xi_{l(q)}) \in \Sigma_{total} \\ k_{l(q)}(y(q)) = u(q) \\ \xi_{l(q)}(y(q)) = 0 \Rightarrow l(q+1) = l(q). \end{cases} \end{cases}$$

4 Always Interrupt Sequences

Definition (Always Interrupt Sequence): *We will refer to any mode string $\sigma = \sigma_1 \ldots \sigma_n \in \Sigma^*_{total}$ such that*

$$\begin{cases} M(\sigma) \triangleq card\{\sigma_i \mid \sigma_i \in \sigma\} \\ \qquad\quad \triangleq card\{l(q) \mid q = 1, \ldots, n\} \qquad (6) \\ \qquad\quad = \max_{y \in Y}(card\{u \mid (y,u) \in S) \\ \xi_{l(q)}(y(q)) = 1, \qquad q = 1, \ldots, n \qquad (7) \end{cases}$$

as an Always Interrupt Sequence (AIS)[4]

[4] Note that given a finite set C, by $card(C)$ we understand the number of different elements in C, e.g. $card(\{c_1, c_2, c_1, c_3\}) = 3$.

Here, Equation (6) means that the total number of distinct modes $M(\sigma)$ used in the AIS is equal to the maximum number of different input values u associated with an output value y in the sense that (u, y) appears as an input-output pair in the data string. One direct consequence of Equation (7) is that the length of an AIS is equal to the length n of the input-output string it is consistent with.

Existence: *Given an input-output string $S \in (Y \times U)^n$ there always exist an Always Interrupt Sequence consistent with the data.*

Proof: The consistency of a mode string with the data S is ensured by the two conditions :

$$\forall q \in \{1, \ldots, n\}, \begin{cases} k_{l(q)}(y(q)) = u(q) \\ \xi_{l(q)}(y(q)) = 0 \Rightarrow l(q+1) = l(q) \end{cases}$$

Let M denote $\max_{y \in Y}(card\{u \mid (y, u) \in S\})$. For every $y \in Y$, there exist $m \leq M$ distinct values of u such that $(y, u) \in S$. One possible way to construct an AIS consistent with the data is to associate one distinct mode from the M available modes with each of the different values of u, i.e.

$$\forall (i, j) \text{ such that } y(i) = y(j),\ u(i) \neq u(j) \Rightarrow l(i) \neq l(j)$$

By doing so for every value of y encountered in S, we ensure that

$$\forall (i, j), \begin{cases} l(i) = l(j) \\ y(i) = y(j) \end{cases} \Rightarrow u(i) = u(j)$$

so that the first condition is met. The second condition is always met since by definition of the AIS, $\xi_{l(q)}(y(q)) = 1,\ q = 1, \ldots, n$.
Hence we have constructed an AIS that is consistent with the data S. ∎

One important fact should be noted here. In the proof, we proposed one particular AIS but there are many different ways to construct an AIS consistent with the data.

Example. Given the following input-output string

y	0	0	1	2	2	0	1	1	0	1	2	2	1	2	1	0	2	0	2	1
u	4	2	1	2	3	0	3	3	1	1	4	4	0	2	3	4	4	0	1	0

We have $Y = \{0, 1, 2\}$ and:

$$card\{u \mid (0, u) \in S\} = card\{4, 2, 0, 1, 4, 0\} = 4$$
$$card\{u \mid (1, u) \in S\} = card\{1, 3, 3, 1, 0, 3, 0\} = 3$$
$$card\{u \mid (2, u) \in S\} = card\{2, 3, 4, 4, 2, 4, 1\} = 4$$

so that an AIS will use $M = \max\{4, 3, 4\} = 4$ modes here.

As seen in the previous proof for existence, one way to build an AIS is to, for each $y \in Y$, establish an injective mapping between U and U^Y. For example, we can use:

mode	$y = 0$	$y = 1$	$y = 2$
1	$k_1(0) = 4$	$k_1(1) = 1$	$k_1(2) = 2$
2	$k_2(0) = 2$	$k_2(1) = 3$	$k_2(2) = 3$
3	$k_3(0) = 0$	$k_3(1) = 0$	$k_3(2) = 4$
4	$k_4(0) = 1$		$k_4(2) = 1$

Thus we get the following l-string:

y	0	0	1	2	2	0	1	1	0	1	2	2	1	2	1	0	2	0	2	1
u	4	2	1	2	3	0	3	3	1	1	4	4	0	2	3	4	4	0	1	0
l	1	2	1	1	2	3	2	2	4	1	3	3	3	1	2	1	3	3	4	3

and the corresponding mode sequence is $\sigma = \sigma_1\sigma_2\sigma_1\sigma_1\sigma_2\sigma_3\sigma_2\sigma_2\sigma_4\sigma_1\sigma_3\sigma_3\sigma_3\sigma_1$ $\sigma_2\sigma_1\sigma_3\sigma_3\sigma_4\sigma_3$.

Theorem: *Any mode string consistent with a given input-output string S is such that its number of modes is greater than or equal to*

$$M = \max_{y \in Y}(card\{u(q) \mid (y, u(q)) \in S,\ q \in \{1, \ldots, n\}\}).$$

Proof: Suppose that there exists a mode string σ consistent with the data using only $m < M$ modes. Consider the value of $y \in Y$ such that $card\{u(q) \mid (y, u(q)) \in S,\ q \in \{1, \ldots, n\}\} = M$ and label it y_M. In other words, there exist M different values of $u \in U$ such that $(y_M, u) \in S$. As $m < M$ there must exist two couples $(y_M, u(i))$ and $(y_M, u(j))$ in S with $u(i) \neq u(j)$ that are associated with the same mode, say $\sigma_x = \sigma_{l(i)} = \sigma_{l(j)}$. As the mode string is supposed to be consistent, we can write $k_x(y_M) = u(i)$ for the first couple and $k_x(y_M) = u(j)$ for the second one. But as $u(i) \neq u(j)$ we have a contradiction.
Consequently, any mode string consistent with a given input-output string S must use at least M modes. ■

Corollary. *Any AIS consistent with the data is a solution to the problem* $\mathrm{Q}(\Sigma_{total}, \boldsymbol{y}, \boldsymbol{u})$.

Proof: To be consistent with the data, a mode string must use at least M modes. An AIS consistent with the data uses exactly M modes. Thus it solves $Q(\Sigma_{total}, \mathbf{y}, \mathbf{u})$. ■

Theorem. *Given an input-output sequence $S \in (Y \times U)^n$ with a minimum number of distinct modes M, the number of possible AIS is bounded above by M^{n-M}.*

Proof: First, let us consider $y_M \in Y$ such that $card\{u(q) \mid (y_M, u(q)) \in S,\ q \in \{1, \ldots, n\}\} = M$ and $S_M = \{(y_M, u(q)) \in S,\ q \in \{1, \ldots, n\}\}$. To be consistent with the data, each distinct input-output pair in S_M must correspond to a different mode. There are $P_{S_M} = M!$ ways in which this can be achieved.
Now consider the other values of y. S_M contains at least M pairs $(y_M, u(q))$ so that we now have to look at the contribution of at most $n - M$ other pairs $(y(q), u(q))$ in S. Let S_m denote the corresponding set. Each element in S_m can potentially be associated with up to M modes so that S_m can add $P_{S_m} \leq M^{n-M}$ to the total number of possibilities in a multiplicative fashion. The total number of modes can thus be bounded by: $P = \frac{1}{M!} P_{S_M} P_{S_m} \leq M^{n-M}$, where the division by $M!$ avoids counting sequences that differ from one another by permutations of the mode indexes.
Note that this bound can be reached when S_M contains exactly M elements and S_m contains $n - M$ elements that all have a distinct value for y. ■

A conclusion to draw from this is that there is a large number of AIS and one question would be to pick the one that minimizes $\mathcal{S}^e(\sigma)$. However, as will be seen in the next section, there are potentially better ways of obtaining low complexity programs by abandoning the AIS structure.

5 Modified Mode Sequences

Here we introduce a method that reduces the length of a given AIS. The idea is to modify the interrupt function ξ of each mode and make it be equal to zero (i.e. no mode change) whenever possible. Ideally, a sequence like $\sigma = \sigma_1\sigma_1\sigma_2\sigma_2\sigma_2\sigma_1\sigma_1\sigma_1\sigma_2\sigma_2$ could then be reduced to $\sigma' = \sigma_1\sigma_2\sigma_1\sigma_2$. This method, if plausible, would not add any new modes. The resulting sequence would still use exactly M distinct modes and would thus be another solution to $Q(\Sigma_{total}, \mathbf{y}, \mathbf{u})$. But as the ξ functions are modified, the resulting mode sequence is no longer an AIS. In this matter, the resulting sequence will be referred to as a *Sometimes Interrupt Sequence* (SIS).

Algorithm (Sometimes Interrupt Sequence): *Given an AIS* $\sigma = \sigma_{l(1)}, \sigma_{l(2)}, \ldots, \sigma_{l(n)}$ *consistent with an input-output sequence* $S = (y(1), u(1)), \ldots, (y(n), u(n))$*, we construct the associated SIS by :*

1. *keeping* $\xi_x(y(q)) = 1$ *for all mode* σ_x *whenever* $\exists q \in \{1, \ldots, n\}$ *such that* $l(q) = x$ *and* $l(q+1) \neq x$,
2. *changing all the other values of* ξ *to zero, for all modes.*

Theorem. *The SIS derived from an AIS consistent with the data is consistent with the data.*

Proof: We recall here again the two conditions for consistency :

$$\forall q \in \{1,\ldots,n\}, \begin{cases} k_{l(q)}(y(q)) = u(q) \\ \xi_{l(q)}(y(q)) = 0 \Rightarrow l(q+1) = l(q). \end{cases}$$

The modifications of the AIS mode sequence only concern the ξ functions, i.e. the interrupts. Thus, we just have to prove that the modified sequence does not violate the second consistency condition.
Suppose we have a case where $\xi_{l(q)}(y(q)) = 0$ and $l(q+1) \neq l(q)$. This is impossible as it contradicts the first step in the construction of the SIS. Thus the second condition for consistency is always met and the SIS derived from an AIS which is consistent with the data is consistent with the data as well.■

Example. Consider the following input-output string and the given AIS mode sequence σ (or equivalently the l string) which is consistent with this data.

y	1	0	2	0	2	2	1	2	2	0	1	2
u	0	1	1	0	0	0	1	1	0	1	1	1
l	1 $\rightarrow$ 2		2 $\rightarrow$ 1		1	1 $\rightarrow$ 2		2 $\rightarrow$ 1 $\rightarrow$ 2			2	2

Now construct the associated SIS :

1. The arrows in the table show us whenever $l(q) \neq l(q+1)$, i.e. whenever we need to keep $\xi_{l(q)}(y(q)) = 1$. Here, we need to keep $\xi_1(1) = 1$, $\xi_1(2) = 1$ and $\xi_2(2) = 1$.
2. So we can set $\xi_1(0) = 0$, $\xi_2(0) = 0$ and $\xi_2(1) = 0$.

Consequently, the mode switches happening at $q = 2, 4, 7, 10$ and 11 have been suppressed and the above mode string has been reduced from $\sigma = \sigma_1\sigma_2\sigma_2\sigma_1\sigma_1\sigma_1\sigma_2\sigma_2\sigma_1\sigma_2\sigma_2\sigma_2$ with length $N = 12$ to $\sigma = \sigma_1\sigma_2\sigma_1\sigma_1\sigma_2\sigma_1\sigma_2$ with length 7.

It can be easily shown that the action of removing one element from a mode string σ strictly reduces its specification complexity $\mathcal{S}^e(\sigma)$. The SIS is thus a mode sequence with lower complexity than the AIS it is derived from.

6 What Are the Ants Doing?

In this section we consider an example where ten ants *(Aphaenogaster cockerelli)* are placed in a tank with a camera mounted on top, as seen in Figure 2. A 52 second movie is shot from which the Cartesian coordinates, x and y, and the orientation, θ, of every ant is calculated every 33ms using a vision-based tracking software. This experimental setup is provided by Tucker Balch and Frank Dellaert at the Georgia Institute of Technology Borg Lab[5] [16].

[5] http://borg.cc.gatech.edu

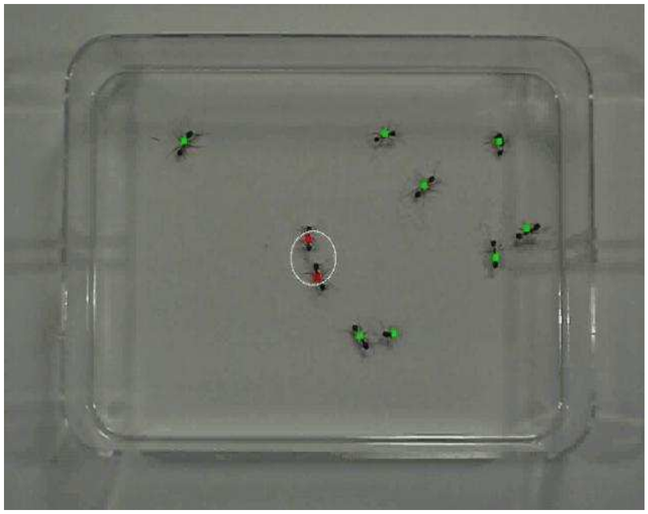

Fig. 2. Ten ants are moving around in a tank. The circle around two ants means that they are "docking", or exchanging information.

From this experimental data, an input-output string is constructed for each ant as follows: At each sample time k, the input $u(k)$ is given by $(u_1(k), u_2(k))$ where $u_1(k)$ is the quantized angular velocity and $u_2(k)$ is the quantized translational velocity of the ant at time k. Moreover, the output $y(k)$ is given by $(y_1(k), y_2(k), y_3(k))$ where $y_1(k)$ is the quantized angle to the closest obstacle, $y_2(k)$ is the quantized distance to the closest obstacle, and $y_3(k)$ is the quantized angle to the closest goal. Here, an *obstacle* is either a point on the tank wall or an *already visited* ant within the visual scope of the ant, and a *goal* is an ant that has not been visited recently. Figure 3 gives a good illustration of these notions of visual scope, goals and obstacles.

In this example, we choose to quantize $u_1(k), u_2(k), y_1(k), y_2(k)$ and $y_3(k)$ using 8 possible values for each. Thus $u(k)$ and $y(k)$ can respectively take 64 and 512 different values. For each ant, a mode sequence σ_1 with the shortest length , in the sense of [3], and the SIS associated with a particular choice of AIS σ_2 have been computed from the input-output string of length $n = 106$. Results including string length, number of distinct modes, entropy and specification complexity of these two sequences for each of the ten ants are given in Table I.

In Table I, results marked with a star are optimal. For σ_1, it is the length $|\sigma|$ that is minimized and for σ_2, it is the number of distinct modes $M(\sigma)$. It should however be noted that the length of σ_2 is in fact less than $n = 106$ as the mode sequence is not an AIS but a SIS.

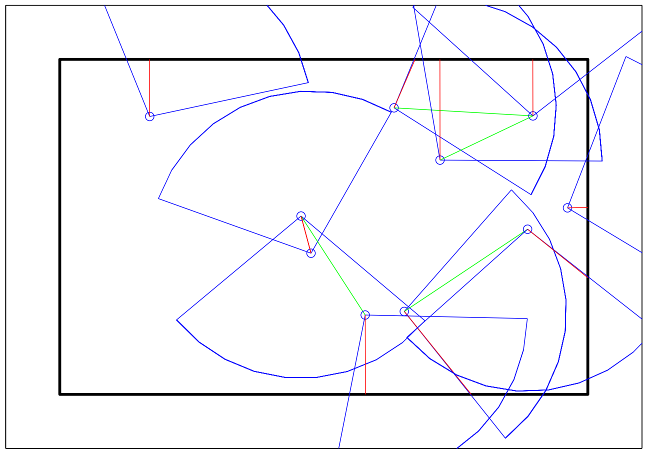

Fig. 3. This figure shows the conical visual scope as well as the closest obstacles (dotted) and goals (dashed) for each individual ant.

The minimum length sequence σ_1 has been constructed using the dynamic programming algorithm given in [3], in which every element of the mode sequence is a new mode. Consequently, $|\sigma_1| = M(\sigma_1)$. Moreover, the entropy of σ_1 is exactly equal to $\log_2(|\sigma_1|)$ as every mode is used only once in the sequence. The entropy of σ_2 is always smaller because the number of distinct modes is minimized and the modes are not equally recurrent in σ_2.

Finally, the specification complexity is smaller with σ_1 for five of the ten ants, and smaller with σ_2 for the five others. On the average, there is a little advantage for σ_2, with a total of 1152 bits compared to 1220 bits for σ_1.
An efficient way to ensure a low complexity coding would be to estimate both sequences for each ant and pick the one with lowest specification complexity. In our example, the total number of bits needed to encode the ten mode sequences using this coding strategy is 1064 bits.

It should be noted, however, that even though we have been able to recover mode strings, these strings can not be directly used as executable control programs without some modifications. Since the input-output string is generated from empirical data, measurement errors will undoubtedly be possible. Moreover, the dynamic system on which the control program is to be run (e.g. we have implemented mode strings obtained from the ant data on mobile robots) may not correspond exactly to the system that generated the data. Hence, a given input string might not result in the same output string on the original system and on the system on which the mode sequence is run.

For example, consider the case where we recovered the mode (k, ξ) and where the available empirical data only allows us to define the domain of k and ξ as a proper subset of the total output space Y, denoted here by Y_k

Table 1.

ant#	$\lvert\sigma\rvert$		$M(\sigma)$		$\mathcal{H}^e(\sigma)$		$\mathcal{S}^e(\sigma)$	
	σ_1	σ_2	σ_1	σ_2	σ_1	σ_2	σ_1	σ_2
1	21*	57	21	5*	4.4	1.4	92	82
2	34*	66	34	5*	5.1	1.5	172	99
3	25*	68	25	6*	4.6	2.0	116	139
4	33*	64	33	6*	5.0	1.8	166	116
5	20*	65	20	6*	4.3	1.9	86	121
6	26*	73	26	6*	4.7	1.8	122	133
7	33*	71	33	6*	5.0	2.0	166	145
8	19*	74	19	7*	4.2	2.2	80	166
9	25*	71	25	10*	4.6	2.4	116	169
10	23*	60	23	4*	4.5	1.7	104	102

or Y_ξ.[6] But, while executing this mode, it is conceivable that a measurement $y \notin Y_k$ is encountered, at which point some choices must be made. We here outline some possible ways in which this situation may be remedied:

- If $y_p \in Y_k$ and $\xi(y_p) = 0$, but the next measurement $y_{p+1} \notin Y_k$, we can replace $k(y_{p+1})$ with $k(y_p) \in U$ as well as let $\xi(y_{p+1}) = 0$. As would be expected, this approach sometimes produces undesirable behaviors, such as robots moving around indefinitely in a circular motion.
- If $y_p \notin Y_k$, but $y_p \in Y_{\tilde{k}}$ for some other mode pair $(\tilde{k}, \tilde{\xi})$ in the recovered mode sequence, we can let $k(y_p)$ be given by the most recurrent input symbol $\tilde{u} \in U$ such that $\tilde{k}(y_p) = \tilde{u}$. This method works as long as y_p belongs to the domain of at least one mode in the sequence. If this is not the case, additional choices must be made.
- If y_p does not belong to the domain of any of the modes in the sequence, we can introduce a norm on Y, and pick $\tilde{y}$ instead of y_p, where $\tilde{y}$ minimizes $\|y_p - \tilde{y}\|_Y$ subject to the constraint that $\tilde{y}$ belongs to the domain for at least one mode in the sequence.

Note that all of these choices are heuristic in the sense that there is no fundamental reason for choosing one over the other. Rather they should be thought of as tools for going from recovered mode strings to executable control programs. However, more research is needed on this topic.

7 Conclusions

In this paper, we present a numerically tractable solution to the problem of recovering modes from empirical data. Given a string of input-output pairs,

[6] From the construction of the modes, these two subsets are always identical, i.e. $Y_k = Y_\xi$.

the string with the smallest number of distinct modes that is consistent with the data is characterized algorithmically through the notion of an Always Interrupt Sequence. This has implications for how to generate multi-modal control laws by observing real systems, but also for the way the control programs should be coded. The algorithms for obtaining AIS and slightly modified derivatives of such strings can be thought of as providing a description of what modes are useful for solving a particular task, from which an empirical probability distribution over the set of modes can be obtained. This probability distribution can be put to work when coding the control programs, since a more common mode should be coded using fewer bits than an uncommon one. This work has thus a number of potential applications from teleoperated robotics, control over communication constrained networks, to minimum attention control.

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