Markov-optimal Sensing Policy for User State Estimation in Mobile Devices*

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ABSTRACT

Mobile device based human-centric sensing and user state recognition provide rich contextual information for various mobile applications and services. However, continuously capturing this contextual information consumes significant amount of energy and drains mobile device battery quickly. In this paper, we propose a computationally efficient algorithm to obtain the optimal sensor sampling policy under the assumption that the user state transition is Markovian. This Markov-optimal policy minimizes user state estimation error while satisfying a given energy consumption budget. We first compare the Markov-optimal policy with uniform periodic sensing for Markovian user state transitions and show that the improvements obtained depend upon the underlying state transition probabilities. We then apply the algorithm to two different sets of real experimental traces pertaining to user motion change and inter-user contacts and show that the Markov-optimal policy leads to an approximately 20% improvement over the naive uniform sensing policy.

Categories and Subject Descriptors

C.3 [**Special Purpose and Application Based Systems**]: Signal processing systems

General Terms

Algorithms, Design, Performance, Verification

Keywords

Energy efficiency, Mobile sensing, Optimal sampling policy, Markovian User state

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1. INTRODUCTION

Mobile devices permeate our daily lives and their utility is further enhanced with mobile applications and services. A growing number of these mobile services rely on accurate and automatic detection of user state. User state is obtained by sensing the user's surroundings and deriving contextual information from the sensed data. Current generation mobile devices integrate a wide range of sensing and networking features such as GPS, microphone, camera, light sensor, accelerometer, WiFi, Bluetooth, GPRS, and so on. These sensors collectively enable us to obtain user's contextual information, such as user's activity, location, background sound, and number of peering devices. Throughout our study, we use the term "user state" to represent human context information, which evolves over time.

While incorporating user's contextual information brings mobile application personalization to new levels of sophistication, a major impediment to collecting and determining user context is the limited battery capacity on mobile phones. Since the integrated sensors can consume significant amount of energy, continuously collecting context information through sensor activation will make even the most compelling mobile application less than desirable to users. For example, our experiments show that a fully charged battery on Nokia N95 device would be completely drained within six hours if its GPS is operated continuously [33]. Therefore, energy efficient mobile sensing is critical in order to maintain the lifetime of mobile device battery and to continue to take advantage of mobile applications and services.

This paper addresses the critical issue of energy efficient mobile sensing by making the following two contributions: First, we formulate the problem of sampling Markovian user state sequence under energy constraint as a constrained optimization problem. We develop a framework based on Constrained Markov Decision Process (CMDP) in order to obtain the Markov-optimal sensor sampling policy. Second, we analyze and evaluate the Markov-optimal policy, and compare its performance against uniform periodic sampling on real user state traces.

In our prior work [32], we studied how to energy efficiently sample a discrete time Markovian user state sequence by proposing a stationary deterministic sensor sampling policy. The policy assigns different but fixed duty cycles to the sensor at different user states. We investigated its performance in terms of the tradeoff between two conflicting performance metrics: the expected energy consumption and the expected user state estimation error. However, this prior work requires exponential run-time and computes a sub-optimal policy. Motivated by these shortcomings of the previous work, in this paper we address the following question: Given a certain device energy consumption budget and user state transition probabilities, what is the optimal sensor sampling policy that leads to the minimum expected state estimation error, while satisfying the energy budget constraint? We formulate this constrained optimization problem as an infinite-horizon CMDP. The expected average cost of the CMDP is considered as the cost criteria to be minimized (as compared to the discounted cost), with the sensor energy consumption serving as the constraint. Solving such CMDP yields a globally optimal sensor sampling policy u^* which guarantees the minimum expected user state estimation error while satisfying the given energy budget for Markovian user state transitions (we thus name this policy "Markov-optimal"). The Markov-optimal policy is stationary and randomized (shown in [2, 11, 12]) and can be obtained by solving the corresponding Linear Programming (LP) of the CMDP formulation, which requires only polynomial run-time for any number of user state inputs.

To evaluate the performance of the Markov-optimal policy, we compare it to uniform periodic sampling for Markovian user state transitions. The expected user state estimation error in both cases is computed for different transition probabilities and energy budget values. The numeric comparison results show that the Markov-optimal policy always leads to a non-negative gain over uniform sampling. We then apply both the Markov-optimal policy and periodic sampling to real user context data traces pertaining to user motion change ("Stable" vs. "Moving") and the status of user contact ("In contact" vs. "Not in contact"). We show that although the user state transitions in these real data traces are not strictly Markovian, the Markov-optimal policy still leads to approximately 20% improvement over uniform periodic sampling. The reason for energy efficiency improvement is that even when the state transitions do not strictly follow Markovian, Markov-optimal policy is able to reduce the expected estimation error by sampling more frequently when state transition is more uncertain, and on the other hand, increasing the length of the idle interval as state transition becomes more predictable.

Although in this paper, we limit the analysis and theory development to discrete user state transitions, it is worth mentioning that continuous context such as location can be divided into discrete space and thus fits in our framework well. In addition, while the approach presented in this paper is centered around mobile sensing, the problem formulation can be generalized easily to many other monitoring/detection/probing problems where certain performance metric needs to be optimized with energy consumption limitations. For example, in the field of environmental monitoring using wireless sensors, it is ideal to improve the detection accuracy while maintaining long device lifetime.

The rest of this paper is organized as follows. In section 2, we discuss relevant prior work. In section 3, we introduce the background of our study, including the model and assumptions, the mechanism that estimates user state for missing observations, the formal definition of expected energy consumption and expected user state estimation error, as well as the constrained optimization problem. In section 4, we propose our CMDP formulation and the algorithm that finds the optimal sensing policy and associated state estimation error by solving the corresponding LP. We also show some of the properties of the optimal policy for special Markov transition probabilities. In section 5, we compare the optimal policy with uniform periodic sampling both through numerical analysis and by applying them to real user state traces. Finally, we conclude and present directions for future work in section 6 and 7.

2. RELATED WORK

In the context of using mobile device to sense and recognize user state, it is worth noting that Schmidt *et al.* [25] first propose to incorporate low level sensors to mobile PDAs to demonstrate situational awareness. Several works have been conducted thereafter by using the commodity cell phones as sensing, computing or application platforms [5, 13, 20, 21, 27, 34]. For example, "CenceMe" [21] uses the integrated as well as external sensors to capture the user's status such as activity, disposition, and surroundings and enables members of social networks to share their sensing presence. Similarly, "Sensay" [27] is a context-aware mobile phone that uses data from a number of sources to dynamically change cell phone ring tone, alert type, as well as determine users' "un-interruptible" states.

The study of energy efficiency in mobile sensing has been conducted in works such as [18] and [17]. Krause *et al.* [18] investigate the topic of trading off prediction accuracy and power consumption in mobile computing, and the authors showed that even very low sampling rate of the accelerometer can lead to competitive classification results while device energy consumption can be significantly reduced. The hierarchical sensor management concept is explored by the "SeeMon" system [17], which achieves energy efficiency by only performing context recognition when changes occur during the context monitoring. More recently, energy management in personal health care system using mobile devices is studied by Aghera *et al.* [1]. The authors aim to address the tradeoff between energy efficiency and data uploading latency by implementing a task assignment strategy capable of selecting different levels of operation. Constandache *et al.* [9] study energy efficiency in mobile device based localization, and the authors show that human can be profiled based on their mobility patterns and thus location can be predicted. The proposed "EnLoc" system achieves good localization accuracy with a realistic energy budget.

Besides in mobile sensing, energy efficient monitoring and event detection has been widely studied in a much broader context such as communication, data collection, and so on. For example, Stabellini and Zander [29] propose a new energy efficient algorithm for wireless sensor networks to detect communication interference. Shin *et al.* [26] propose DEAMON, an energy efficient distributed sensor monitoring algorithm where sensors are controlled using a Boolean expression and energy is conserved by selectively turning on/off the nodes and limiting communication operations. Similarly, Silberstein *et al.* [28] investigate suppression technique (reducing the cost for reporting changes) and take advantage of temporal and spatial data correlation to reduce data reporting therefore enlarge the lifetime of sensors.

The work in this paper is originated from [33] and [32]. In [33], we present an Energy Efficient Mobile Sensing System (EEMSS) that recognizes user states as well as detects state transitions. EEMSS significantly improves device battery life, by powering a minimum set of sensors at any given time and applying appropriate sensor duty cycles. However, in [33], sensors still adopt pre-determined, fixed duty cycles whenever activated, which is not adjustable to different user behaviors. We address this issue in [32], where we model the user state as a discrete time Markov chain (DTMC), and propose a stationary deterministic sensing policy to increase energy efficiency by assigning different sensor duty cycles at different user states. In this paper, we study how sensor duty cycles can be optimized in order to minimize the expected user state estimation error, while maintaining an energy consumption budget. We propose an efficient algorithm that obtains the optimal sensing policy for Markovian user state, by formulating the constrained optimization problem as a infinite-horizon CMDP and solving its corresponding LP.

CMDP [2] is a variant of Markov Decision Processes [4] (MDP) which provides a framework for constructing optimal policies for a stochastic process. CMDP considers a situation where one type of cost is to be optimized while keeping others below some pre-defined bounds. For example, Lazar [19] used CMDP to analyze the problem of maximizing throughput subject to delay constraints in telecommunication applications. In traffic applications, Nain and Ross [23] studied the problem where different traffic types compete for the same resource. Some weighted sum of average delays of certain traffic types is to be minimized while some other traffic types need to satisfy certain delay constraints. More recent studies of CMDP include [10], where Dolgov and Durfee limit the optimal policy search to stationary deterministic policies coupled with a novel problem reduction to mixed integer programming, and the method yields an algorithm that finds computationally feasible policies (i.e., not randomized).

It has been shown by Feinberg and Shwartz [11, 12] that stationary deterministic policies are not guaranteed to be optimal due to the constraints added to the classical MDP model. In order to solve for the optimal stationary randomized policy in polynomial time, Kallenberg [16], and Heyman and Sobel [14], propose the use of LP where adding constraints with the same discount factor does not increase the complexity of the problem. In our study, we utilize this concept and rewrite the constrained optimization problem as an LP, and obtain the optimal randomized policy in polynomial time.

3. BACKGROUND

3.1 Model and assumptions

We assume that time is discretized and the user state evolves as a N-state discrete time Markov chain (DTMC) with transition probabilities $p_{ij}(i, j \in \{1, 2, ..., N\})$ from state i to j.The discrete time horizon is denoted as $T = \{t, t = 0, 1, 2, ...\}$. At each time slot during the process, a sensor may be sampled, in which case user state is detected with 100% accuracy and a unit of energy consumption is associated. On the other hand, the sensor can also stay idle to save energy. This process is illustrated in figure 1. We define O as the set of time slots when the sensor makes observation and O is thus a subset of T, as shown by figure 1. Ideally, if the sensor can be sampled in each time slot ($O = T$), the user state sequence can be obtained perfectly. However, in general, since sensor duty cycles are required to extend mobile device lifetime, there exist durations where user state needs to be estimated using only observed data and the knowledge of the user state transition dynamics.

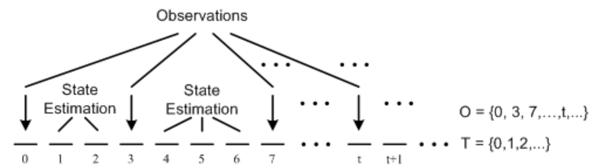


Figure 1: Illustration of the Markovian user state sequence, sampled at certain time slots.

3.2 User state estimation

A user state estimation mechanism has been proposed in one of our previous works [32]. Here we give a brief introduction of the method, which estimates the most likely user state for each time slot between two subsequent observations. In particular, given the sensor detects state i at time t_m, and detects state j at time t_n ($t_m, t_n \in T$ and $t_m < t_n$), the probability of being in state k ($k \in 1, 2, ..., N$) at time t ($t_m < t < t_n$), is given by:

$$p[s_t = k | s_{t_m} = i, s_{t_n} = j] \quad (1)$$

$$= \frac{p[s_t = k, s_{t_n} = j | s_{t_m} = i]}{p[s_{t_n} = j | s_{t_m} = i]} \quad (2)$$

$$= \frac{p[s_t = k | s_{t_m} = i] \cdot p[s_{t_n} = j | s_t = k]}{p[s_{t_n} = j | s_{t_m} = i]} \quad (3)$$

$$= \frac{P_{ik}^{(t-t_m)} \cdot P_{kj}^{(t_n-t)}}{P_{ij}^{(t_n-t_m)}} \quad (4)$$

where s_t denotes the true user state at time t. In order to select the "most likely" state (denoted by s'_t) at time t, the quantity given in (1) needs to be maximized:

$$s'_t = \underset{k}{\text{argmax}} \left\{ \frac{P_{ik}^{(t-t_m)} \cdot P_{kj}^{(t_n-t)}}{P_{ij}^{(t_n-t_m)}} \right\} \quad (5)$$

The expected estimation error for time slot t, denoted by e_t, is defined as the probability of incorrect estimation, which is given by:

$$e_t = 1 - p[s_t = s'_t | s_{t_m} = i, s_{t_n} = j] \quad (6)$$

$$= 1 - \max_k \left\{ \frac{P_{ik}^{(t-t_m)} \cdot P_{kj}^{(t_n-t)}}{P_{ij}^{(t_n-t_m)}} \right\} \quad (7)$$

3.3 Expected energy consumption $E[C]$ and expected user state estimation error $E[R]$

Throughout our study, we address two important performance metrics: (a) the expected energy consumption and (b) the expected user state estimation error. These two intrinsically conflicting metrics are fundamental performance measures of mobile sensing applications, as the former characterizes the device lifetime and the latter is directly related to the quality of the application in terms of providing high user state detection accuracy. The formal definitions of the two are given as follows:

Definition 1. *The expected energy consumption $E[C]$ of the user state sampling process is defined as*

$$E[C] = \frac{1}{E[I]} \tag{8}$$

where $E[I]$ is the expected sensor idle interval, i.e., the average number of time slots the sensor waits before the next sample.

Definition 2. *The expected user state estimation error $E[R]$ is defined as the long term average of per-slot estimation error:*

$$E[R] \quad = \quad \lim_{n\to\infty} \frac{\sum_{t=1}^{n} e_t}{n} \tag{9}$$

3.4 The optimization problem

In practical system operations, a device energy consumption budget is often specified in order to ensure a long enough device lifetime. We define ξ (where $0 \leq \xi \leq 1$) as the energy budget which is the maximum expected energy consumption allowed. Let u denote a sensor sampling policy, which specifies how sensor duty cycles should be assigned when different user states are detected, i.e., how long the sensor should stay idle after each observation. We investigate the following constrained optimization problem: *Considering a long user state evolving process, given a device energy consumption budget ξ and user state transition matrix P, what is the optimal sensor sampling policy u^* such that the expected user state estimation error $E[R]$ is minimized, and the expected energy consumption is maintained below the budget, i.e., $E[C] \leq \xi$?*

4. THE MARKOV-OPTIMAL POLICY

We formulate the optimization problem as a infinite-horizon CMDP with expected average cost. Solving such CMDP yields a Markov-optimal policy u^* which is stationary and randomized [2, 11, 12], i.e., u^* does not vary over time and decision is randomized over several actions. Meanwhile, the algorithm that finds the Markov-optimal policy u^* is computationally efficient, since u^* can be obtained by solving the corresponding LP, which is a polynomial time computation.

4.1 The CMDP formulation

We use an infinite-horizon CMDP to model the sensor duty cycle selection problem, whose major components are explained as follows:

- **Decision Epochs** O**.** Decision is made immediately after each sensing observation. The set of decision epochs is defined as $O = \{d, d = 1, 2, ...\}$. Note that this is the same O defined in section 3.1.
- **System State Space** X**.** The system state at decision epoch d is the detected user state s_d. The set of system states is denoted by $X = \{1, 2, ..., N\}$.
- **Action Space** A**.** The set of actions is denoted by A. An action $a \in A$ is the number of time slots the sensor waits until making the next observation. Note that the potential number of actions could be infinity, i.e., $A = \mathbb{N}^*$, the set of positive integers. However, in order to facilitate the study, we limit the set of actions to positive integers under some threshold a_m in our study. As ξ decreases, a_m needs to be increased in order to meet the energy budget constraint.
- **System Transition Probabilities** $\mathcal{P}$**.** Define $\mathcal{P}_{iaj}$ as the probability of moving from system state i to j, when action a is taken. Given the user state transition probability matrix P, it is easy to conclude that $\mathcal{P}_{iaj} = P_{ij}^{(a)}$.
- **Intermediate Cost** $c(y, a)$**.** The intermediate cost $c(y, a)$ is defined as the expected aggregate state estimation error when action a is taken on state y, where $y \in X$ and $a \in A$. $c(y, a)$ can be calculated as:

$$\begin{aligned} c(y,a) \quad &= \quad \sum_j P_{yj}^{(a)} \cdot e_{yj}^{(a)} \qquad (10) \\ &= \quad \sum_j P_{yj}^{(a)} \cdot \sum_{t=1}^{a-1} \Big[1 - \max_k \Big(\frac{P_{yk}^{(t)} \cdot P_{kj}^{(a-t)}}{P_{yj}^{(a)}}\Big)\Big] \end{aligned}$$

  where $e_{yj}^{(a)}$ is the aggregate state estimation error for a length-a observation interval starting at state y and ending at state j.
- **Expected Average Cost** $E'_u[R]$**.** under policy u, the expected average cost of infinite-horizon CMDP is defined as:

$$E'_u[R] = \lim_{n\to\infty} \frac{\sum_{d=1}^{n} E^u c(X_d, A_d)}{n} \tag{11}$$

  where n is the total number of decision epochs, and E^u is the corresponding expectation operator of the intermediate cost, under the policy u.
- **Intermediate Sampling Interval** $d(y, a)$**.** The intermediate sampling interval when action a is taken on state y, satisfies $d(y, a) = a$.
- **Expected Sampling Interval** $E_u[I]$**.** Similar to $E'_u[R]$, the expected sampling interval $E_u[I]$ is defined as:

$$E_u[I] = \lim_{n\to\infty} \frac{\sum_{d=1}^{n} E^u d(X_d, A_d)}{n} \tag{12}$$

- **Constraint** ξ**.** The maximum allowed expected energy cost. Therefore $E[C] \leq \xi$ or $E[I] \geq 1/\xi$.

4.2 Finding the optimal policy u^*

Let $\rho(y, a)$ denote the "occupation measure" of state y and action a, i.e., the probability that such state-action pair ever exists in the decision process. It is shown in [16, 14, 2] that the optimal policy of the CMDP with expected average cost criteria can be obtained by solving the corresponding LP. Inspired by these works, we rewrite the sensor duty cycle optimization problem defined above as the following LP (denoted as **LP1**):

$$\textbf{LP1: Find } \min \Big\{ \sum_{y\in X} \sum_{a\in A} \rho(y,a) c(y,a) \Big\} \tag{13}$$

subject to:

$$\sum_{y\in X} \sum_{a\in A} \rho(y,a)(\delta_x(y) - P_{yax}) = 0, \forall x \in X, \tag{14}$$

$$\sum_{y\in X} \sum_{a\in A} \rho(y,a) = 1, \tag{15}$$

$$\rho(y,a) \geq 0, \forall y, a, \textbf{ and} \tag{16}$$

$$\sum_{y\in X} \sum_{a\in A} \rho(y,a) d(y,a) \geq \frac{1}{\xi} \tag{17}$$

where $\delta_x(y)$ is the delta function of y concentrated on x. The constraint given in (14) emphasizes the property for ergodic processes and describes that the outgoing and incoming rate for a state need to be the same. The constraints (15) and (16) define $\rho(y,a)$ as a probability measure. The inequality constraint given in (17) guarantees that the expected energy usage is less than the energy constraint value ξ, by setting the expected idle interval greater than $1/\xi$.

Solving **LP1** yields the ideal occupation measure of each state/action pair that minimizes the quantity given in (13). The algorithm for selecting the optimal policy u^* is given as follows:

Algorithm 1 Pseudo code for selecting the Markov-optimal sampling policy u^* and calculating the corresponding expected user state estimation error $E_{u^*}[R]$

1: Input: ξ, P
2: Output: $u^*(\xi, P)$, $E_{u^*}[R]$
3: Initialize: Select a large enough $a^m \in \mathbb{N}^*$ such that the energy constraint can be sufficiently satisfied. Let $A = \{1, 2, ..., a^m\}$, $X = \{1, 2, ..., N\}$
4: Solve **LP1** for the optimal occupation measure $\rho^*(y,a), \forall y \in X, \forall a \in A$
5: Calculate $\rho^*_y = \sum_{a\in A} \rho^*(y,a), \forall y \in X$
6: Constructing u^*: Assign $\frac{\rho^*(y,a)}{\rho^*_y}$ as the probability of taking action a at state y, $\forall y \in X, \forall a \in A$
7: Calculate the expected user state estimation error: $E_{u^*}[R] = \frac{E'_{u^*}[R]}{1/\xi} = \frac{\sum_{y\in X}\sum_{a\in A}\rho^*(y,a)c(y,a)}{1/\xi}$

In Algorithm 1, the optimal occupation measure of each state-action pair can be obtained by solving **LP1** in step 4. Step 5 of Algorithm 1 calculates the overall probability of seeing a particular state y in the decision process under the optimal policy, and this quantity ρ^*_y is used later in step 6 as the normalization to the optimal occupation measure $\rho^*(y,a)$ in order to compute the probability of taking action a whenever state y is detected, in the optimal sampling policy u^*. This normalization step is needed to guarantee that

$$\sum_a \frac{\rho^*(y,a)}{\rho^*_y} = 1, \forall y \in X \tag{18}$$

In step 7, the optimal expected user state estimation error $E_{u^*}[R]$ can be calculated once the optimal expected average cost $E'_{u^*}[R]$ of the CMDP is obtained. Here we illustrate the relationship between $E[R]$ and $E'[R]$. Recall that $E[R]$ is defined as the long-term, average per-slot error, i.e., the ratio of incorrect estimations over total number of time slots; therefore, under policy u, it can be written as:

$$E_u[R] = \lim_{n\to\infty} \frac{\sum_{d=1}^n E^u c(X_d, A_d)}{\sum_{d=1}^n E^u d(X_d, A_d)} \tag{19}$$

$$= \lim_{n\to\infty} \frac{\frac{1}{n}\cdot\sum_{d=1}^n E^u c(X_d, A_d)}{\frac{1}{n}\cdot\sum_{d=1}^n E^u d(X_d, A_d)} \tag{20}$$

where n denotes the total number of decision epochs, whereas $E^u c(X_d, A_d)$ and $E^u d(X_d, A_d)$ denote the aggregated state estimation error and the sampling interval (action) size for the dth decision epoch under policy u, respectively. Considering the Law of Large Numbers, equation (20) can be further written as

$$E_u[R] = \frac{E'_u[R]}{E_u[I]} \tag{21}$$

where $E_u[I]$ is the expected sampling interval (action) size under policy u. Since the optimal policy u^* needs to be fully utilizing the energy budget, its expected sampling interval size satisfies:

$$E_{u^*}[I] = 1/\xi. \tag{22}$$

Algorithm 1 is able to return the Markov-optimal policy u^* in polynomial time for any number of states input. It can be seen that although step 4 is the most time-consuming procedure, it is able to obtain the optimal occupation measures in polynomial time.

4.3 A case study: Selecting u^* for two-state Markov chains

While Algorithm 1 returns the optimal policy u^* for any number of user state inputs, in this section, as a case study, we apply Algorithm 1 to two-state Markov chains and find the optimal policy u^* by solving the corresponding LP in MATLAB. We test six different user state transition matrices, namely:

$$\begin{bmatrix} 0.9 & 0.1 \\ 0.1 & 0.9 \end{bmatrix} \begin{bmatrix} 0.9 & 0.1 \\ 0.5 & 0.5 \end{bmatrix} \begin{bmatrix} 0.9 & 0.1 \\ 0.9 & 0.1 \end{bmatrix}$$

$$\begin{bmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \end{bmatrix} \begin{bmatrix} 0.5 & 0.5 \\ 0.9 & 0.1 \end{bmatrix} \begin{bmatrix} 0.1 & 0.9 \\ 0.9 & 0.1 \end{bmatrix}$$

Different energy budget constraint values ranging from 0 to 1 are used as different inputs to Algorithm 1.

The solution of the LP returns a randomization over all possible state-action pairs, which essentially constructs the stationary randomized optimal policy u^*. Since it is difficult to visualize the randomization of multiple actions, we compute the mean value of actions taken at each decision epoch for different user states, i.e., the expected average idle interval at each state according to the optimal policy u^*, and show the result of the average actions in figure 2.

It can be noticed that when $p_{12} = 0.1$ and $p_{21} = 0.9$, the Markov chain degenerates to an independently and identically distributed (i.i.d.) user state sequence, where the user state transition does not depend on any current or previous state information. In this case, the expected state estimation error $E_{u^*}[R]$ under the optimal policy u^* can be quantified in terms of user state transition probability matrix P and the energy budget ξ. The following theorem holds.

Theorem 1. *For two-state Markov chain that degenerates to an i.i.d. user state sequence, given its transition probabilities $p_{ij}(i,j \in \{1,2\})$ and the energy budget ξ, the following holds for optimal sampling policy u^*:*

$$E_{u^*}[R] = (1-\xi)\cdot \min\{p_{12}, p_{21}\} \tag{23}$$

i.e., $E_{u^*}[R]$ is linear in ξ.

PROOF. For i.i.d. transition probability matrix the following holds:

$$P = P^{(1)} = P^{(2)} = ... = P^{(I)}, \forall I \in \mathbb{N}^* \tag{24}$$

that is, the state transition probability matrix in I steps, denoted by $P^{(I)}$, is equal to the original state transition probability matrix P, for any positive integer I.

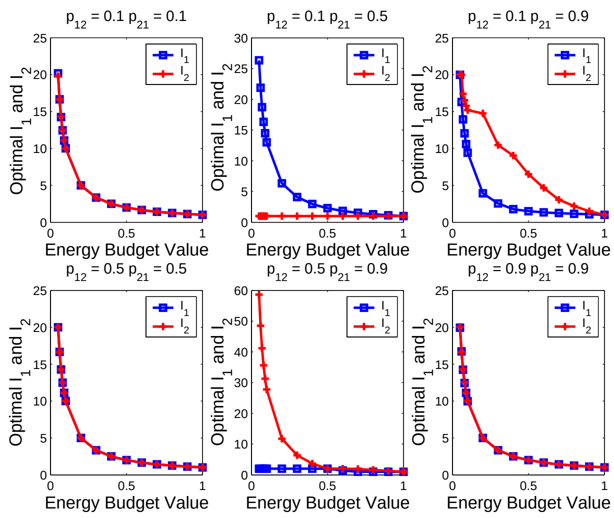


Figure 2: The average idle intervals in u^* for different energy budgets. I_1 and I_2 are the average idle interval lengths when state 1 and 2 is observed, respectively.

Let p, q be such that $p = p_{12} = 1 - p_{11} = p_{22} = 1 - p_{21} = 1 - q$. As equation (24) holds, the term e_t in equation (7) can be further written as:

$$\begin{aligned} e_t &= 1 - \max\left\{\frac{p^2}{p}, \frac{q^2}{q}, \frac{pq}{p}, \frac{pq}{q}\right\} && (25)\\ &= \min\{p, q\} && (26)\\ &= \min\{p_{12}, p_{21}\} && (27)\end{aligned}$$

i.e., e_t stays constant no matter what sample interval is used. This illustrates the fact that the estimation error for each time slot with missing observation is constant. Recall that $E[R]$ is defined as the expected per-slot estimation error, and that the optimal policy utilizes the full energy budget with expected sensor sampling interval $1/\xi$, therefore, $E_{u^*}[R]$ can be expressed as:

$$E_{u^*}[R] = \frac{1/\xi - 1}{1/\xi} \cdot e_t = (1 - \xi) \cdot \min\{p_{12}, p_{21}\} \qquad (28)$$

for optimal policy u^*. □

It can be easily concluded that for all Markov chains that degenerates to an i.i.d. user state sequence, there exist more than one optimal policy due to the fact that any randomization of actions that leads to the optimal sampling interval results in the same expected state estimation error.

Another observation from figure 2 is that, whenever the two-state Markov chain is symmetric, i.e., $p_{12} = p_{21}$, the average sampling intervals for both state 1 and 2 are equal. In fact, the following theorem describing the property of optimal policy holds for all symmetric two-sate Markov chain:

Theorem 2. *For two-state symmetric Markov chain where $p_{12} = p_{21}$, there exists an optimal sampling policy that makes the same decision, i.e., selects the same randomization of actions at each decision epoch.*

PROOF. Let $S = \{s_i, i = 1, 2, 3, ...\}$ be the user state sequence in the original decision process, where $s_i \in \{1, 2\}, \forall i$. Define T^* as the set of time slots where sensing is performed under the optimal policy u^*. We label the original process as $S^* = \{s_i^*, i = 1, 2, 3, ...\}$, in which s_i^* is defined as follows:

$$s_i^* = \begin{cases} s_i, & if\ i \in T^* \\ 0, & if\ i \notin T^* \end{cases}$$

S^* is a process that characterizes the sampled process based on the policy u^*, by retaining the original state sequence when observations are made, and labeling "0" for the rest time slots. Note that the numbers of consecutive zeros in all estimation intervals need not necessarily be the same, due to the fact that u^* adopts randomized decision at each decision epoch u^*.

We then define the process $S^{**} = \{s_i^{**}, i = 1, 2, 3, ...\}$ where

$$s_i^{**} = \begin{cases} s_i^{**} = 2, & if\ s_i^* = 1 \\ s_i^{**} = 1, & if\ s_i^* = 2 \\ s_i^{**} = 0, & if\ s_i^* = 0 \end{cases}$$

S^{**} is a state sequence containing the "flipped" state from S^* for all observed time slots, and zeros otherwise.

Since $p_{12} = p_{21}$, it immediately follows that $P_{12}^{(i)} = P_{21}^{(i)}, \forall i = 1, 2, 3....$ Recall equation (10) where the aggregated error for an observation interval with a certain length is calculated. It can be concluded that $e_{12}^{(a)} = e_{21}^{(a)}$ and $e_{22}^{(a)} = e_{11}^{(a)}$, since the following equalities hold:

$$\max_k\left\{\frac{P_{1k}^{(t)} \cdot P_{k2}^{(a-t)}}{P_{12}^{(a)}}\right\} = \max_k\left\{\frac{P_{2k}^{(t)} \cdot P_{k1}^{(a-t)}}{P_{21}^{(a)}}\right\} \qquad (29)$$

$$\max_k\left\{\frac{P_{1k}^{(t)} \cdot P_{k1}^{(a-t)}}{P_{12}^{(a)}}\right\} = \max_k\left\{\frac{P_{2k}^{(t)} \cdot P_{k2}^{(a-t)}}{P_{22}^{(a)}}\right\} \qquad (30)$$

where $k \in \{1, 2\}$. It follows that the relabeled process S^{**} produces the same expected error as S^*, which implies that by swapping all decisions made at state 1 with all decisions made at state 2 in the original decision process, the expected state estimation error remains optimal. Therefore, the optimal policy decision at state 1 is able to be applied to state 2, and vice versa, while maintaining the optimal error. This indicates that for symmetric two-state Markov chain, no matter what state is observed at each decision epoch, there exists an optimal policy that makes the same decision. □

5. PERFORMANCE COMPARISON: MARKOV-OPTIMAL VS. UNIFORM

Researchers have proposed many sophisticated sampling schemes such as [30] and [8], aiming at energy efficient event detection in mobile and wireless networks. However, in the context of mobile sensing for user state detection and estimation, there does not exist an established framework that aims to achieve the best tradeoff between energy consumption and state estimation error and select the best sampling intervals correspondingly. A baseline performance evaluation of the optimal policy u^*, therefore, is to compare it with a uniform policy $\bar{u}$ where the sensor simply performs periodic sampling.

In this section, we compare the expected user state estimation error, and visualize the gain (which is the ratio of the reduced amount of error over the original error of uniform sampling) of the Markov-optimal policy on two-state Markov chains with different transition probabilities. We then apply both policies to real user state traces, and identify the expected state estimation error by comparing the state estimation result against the ground truth.

5.1 Numerical comparison on Markov models

5.1.1 *Deriving $E_{\bar{u}}[R]$ for uniform sampling*

We first formally define the uniform policy $\bar{u}$ and derive its corresponding expected state estimation error $E_{\bar{u}}[R]$. Since time is discretized, a randomization of actions is required in the uniform policy such that the average idle interval length can achieve $1/\xi$, i.e., the energy budget can be fully utilized. Although the potential number of randomization choices could be infinite, we restrict the randomization to choose from two neighboring integer values as the sampling interval size. More strictly, the uniform sampling policy $\bar{u}$ is defined as follows: After each observation, the sensor waits for $\hat{I}$ time slots with probability μ, and $\hat{I}+1$ time slots with probability $1-\mu$, such that the following constraint holds:

$$\mu \cdot \hat{I} + (1-\mu) \cdot (\hat{I}+1) = \frac{1}{\xi} \tag{31}$$

where $\hat{I} \in \mathbb{N}^*$ and $0 \le \mu \le 1$. Equation (31) guarantees that the energy budget ξ is fully utilized by randomizing the action over two subsequent integer values. Given ξ, it is straightforward to obtain μ and $\hat{I}$. In particular, $\hat{I} = \lfloor \frac{1}{\xi} \rfloor$ and $\mu = \lceil \frac{1}{\xi} \rceil - \frac{1}{\xi}$ would satisfy equation (31).

We derive the expected state estimation error $E_{\bar{u}}[R]$ for uniform sampling policy with energy budget ξ. First, denote p_i as the steady state probability of detecting a particular state i in any observation. Since the state transition follows the Markovian rule, the current state observation result depends on the previous observed state, and the number of time slots being idle:

$$p_i = \sum_j p_j \cdot [\mu \cdot P_{ji}^{(\hat{I})} + (1-\mu) \cdot P_{ji}^{(\hat{I}+1)}] \tag{32}$$

Equation (32) accounts for all possible cases of last observation that may lead to state i in the current observation. It is obvious to see that:

$$\sum_i p_i = 1 \tag{33}$$

Therefore, the results of $p_1, p_2, ...,$ and p_N can be obtained by solving the $N+1$ simultaneous equations given in (32) and (33).

The expected state estimation error for uniform sampling policy with energy budget ξ can be expressed as the expected aggregate error per estimation interval divided by the average interval size:

$$E_{\bar{u}}[R] = \frac{\sum_{ij} p_i \cdot \{\mu \cdot P_{ij}^{(\hat{I})} \cdot e_{ij}^{(\hat{I})} + (1-\mu) \cdot P_{ij}^{(I\hat{+}1)} \cdot e_{ij}^{(I\hat{+}1)}\}}{1/\xi} \tag{34}$$

where $i, j \in \{1, 2, ..., N\}$, and $e_{ij}^{(\cdot)}$ is defined similarly as in equation (10).

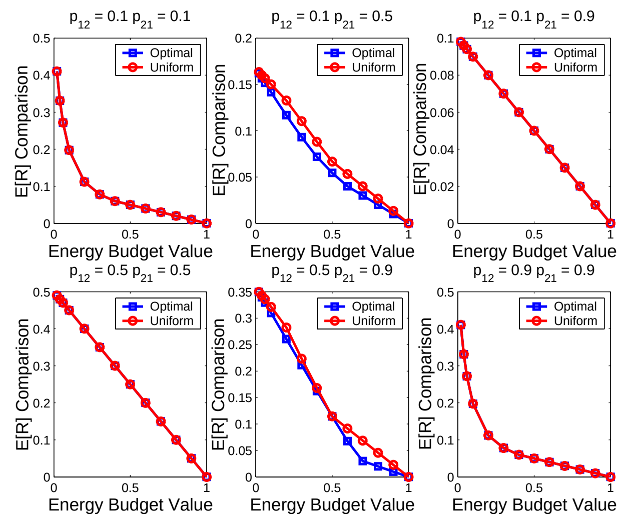


Figure 3: Policy comparison in terms of $E[R]$ for different energy budgets.

5.1.2 *Comparing u^* with $\bar{u}$ on 2-state Markov chains*

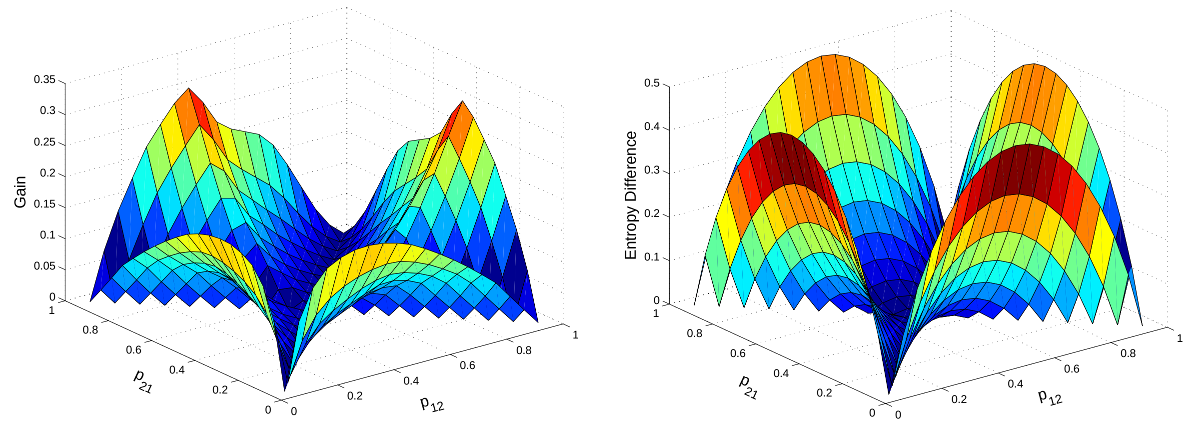
We compare the performance of u^* and $\bar{u}$ on two-state Markov chains. The results are summarized in figure 3 and 4 for different user state transitions and energy budget values. Figure 3 shows the policy comparison in terms of expected state estimation error with respect to different energy budgets. Figure 4 shows the average improvement of the optimal policy for different energy budgets, and the state entropy difference, on a matrix of user state transition probabilities ranging from 0.05 to 0.95, with interval 0.05.

It can be seen that uniform periodic sampling is optimal for both symmetric and i.i.d. two-state Markov chains, i.e., it leads to the same expected error as the optimal policy obtained by Algorithm 1. This is illustrated by both the overlapping curves in figure 3 and the zero performance difference on the diagonals of the matrix in figure 4. In fact, in Theorem 1 and 2 we have shown that there exists an uniform policy which is optimal for symmetric and i.i.d. chains. However, for Markov chains that are neither symmetric nor i.i.d., u^* leads to a positive gain except for $\xi = 1$, in which case the sensor is sampled in every time slot. For example, in figure 3, when $p_{12} = 0.1$ and $p_{21} = 0.5$, u^* produces 12.58% less error than the uniform policy on average.

We find that the improvement of the optimal policy increases as the difference of state entropy between the two states increases. Figure 5 illustrates the positive correlation between the two metrics. Recall that in information theory, the entropy of a state measures the uncertainty related to that state. As a result, as the difference of state entropy grows, more frequent sampling is required at the one with high entropy to provide lower estimation error. Unlike the uniform policy, the optimal policy is able to implement different sampling frequencies at different states to achieve better performance.

5.2 Policy comparison on real user state traces

The "Markovian user state transition" assumption enables us to provide a state estimation mechanism in case of missing observations, a way similar to the Forward-Backward



(a)The average optimal policy improvement. (b)Entropy difference between two states.

Figure 4: Given different state transition probabilities, left figure shows the average improvement over different energy budgets, by applying optimal policy as compared to periodic sampling, and right figure shows the difference of state entropy.

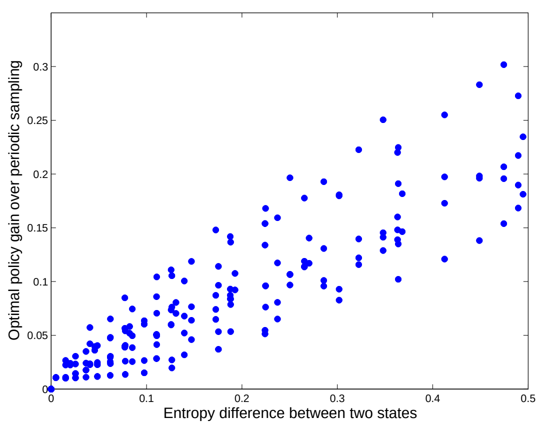


Figure 5: The gain of the optimal policy over uniform sampling (averaged over different energy budgets) vs. the state entropy difference.

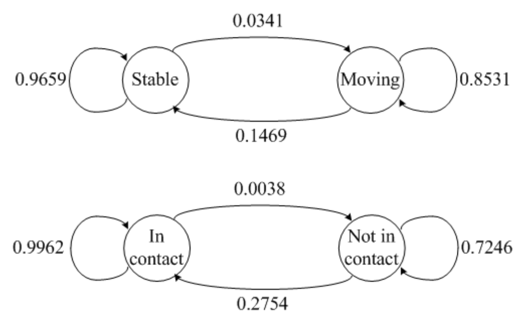


Figure 6: Top: Motion transition dynamics of a graduate student during the daytime of one weekday. Bottom: The transition dynamics of inter-user contact status for an undergraduate student carrying a mote over a weekly duration.

algorithm [24] that estimates hidden state sequence in traditional Hidden Markov Model (HMM) problems. Moreover, by assuming that the state transition is Markovian, the Markov-optimal sensor sampling policy can be obtained in polynomial time.

There certainly are some kinds of user state transitions that have been empirically shown previously to be Markovian. A classic example is speech and silence patterns within a monologue [15]. To further consolidate our study and evaluate the performance of Markov-optimal policy on real user data, we consider data traces that pertain to user motion change and status of inter-user contact, and answer the following questions: (a) Are these user state transitions strictly Markovian? and (b) If not Markovian, does the Markov-optimal policy still perform well? The data collection experiments[1] are explained as follows:

User motion: We conducted the user motion trace collection in fall 2009. We are particularly interested in the transition between "Stable" and "Moving", two motion states that characterize the basic user activity. During the experiment, one participant carried a Nokia N95 device with a python program running in background to automatically detect his activity, using the motion classification technique introduced in [33]. Approximately 40 hours of running data distributed in five different weekdays were collected. The mobile device recorded user motion every 12 seconds, in which, 10 seconds were consumed by the accelerometer for data collection, and the classification algorithm ran at the end of each sample duration.

Inter-user contact status: In fall 2006, twenty-five Tmotes [22] with wireless communication capabilities were handed out to an undergraduate class at USC for a week [31]. Each student carried the device during the whole experiment and each mote automatically logged the information about other devices within communication range. Specifically, the time, duration and node IDs of each contact were stored in the memory for off-line processing. Each node transmitted a contact packet every 0.1 second and the nearby nodes re-

[1]The data set from our experiments is available at the following website: http://anrg.usc.edu/www/downloads.

ceiving the contact packets recorded the contact information immediately. We view the user as in one of the following two states at any given time: "In contact" or "Not in contact", since the existence of neighboring devices is of importance in mobile P2P networking.

We use a standard method proposed in [3] to find the probabilities of the user state transition. Specifically, defining n_{ij} as the total frequency of state transition from i to j, the Markov transition probability matrix can be constructed, with

$$p_{ij} = n_{ij}/n_j, \tag{35}$$

where $n_j = \sum_i n_{ij}$. We illustrate the resulting Markov chains for two sample participants[2] in figure 6.

Both Markov chains illustrate that the user is more likely to be staying in one state than the other. We first explore the existence of Markovian property in real data trace, by examining whether the time user spent in a state is geometrically distributed. The state duration samples from the trace data are compared to a randomly generated geometrically distributed set of data, with the state transition probabilities shown in figure 6 being the success probabilities. Figure 7 compares the cumulative distribution function (cdf) of state duration in real data, to the corresponding geometric distribution. Moreover, table 1 shows the results from Kolmogorov-Smirnov (K-S) test [7], which compares the real data set with the corresponding geometrically distributed data sequence[3]. The results imply that the user data gathered from our current experiments does not strictly follow the Markovian property, as the duration of each state is not strictly geometrically distributed. The difference on both the median and the highest value between real data and geometric distributed data indicates the fact that the state duration in real case tends to show more concentration on both small and some extra-large values. In fact, in terms of inter-user contact, several previous studies such as [6, 30, 31] have shown that the inter-contact and contact time duration distribution may exhibit heavy-tails in certain time scale rather than memoryless decay.

Although the data we collected does not strictly follow the Markov property, as far as our present knowledge extends, there does not exist a framework that studies user state estimation accuracy while tracking the energy consumption using a "better-than-Markovian" model, for sophisticated user state transitions such as non-stationary or long range dependent processes. Moreover, we believe that the user data can be well divided into different "periods" such that in each period, different transition matrices can be utilized to better describe user state transition dynamics instead of trying to fit all the data into a single Markov chain. Different Markov-optimal policies can therefore be applied accordingly. For example, in case of the bottom chain shown in figure 6, it characterizes the inter-user contact state change over the duration of an entire week, whereas user behavior is normally different in day and night time. We leave the study of modeling user state sequence as a time-variant Markov chain and then applying different Markov-optimal policies for different periods to future work.

[2]The data from other participants and from different days shows similar transition dynamics.

[3]The Kolmogorov-Smirnov test is performed online at http://www.physics.csbsju.edu/stats/KS-test.html

We compare the Markov-optimal policy derived from the transition probabilities shown in figure 6 and the uniform policy by applying them to the collected user data, and the expected user state estimation error is measured as the percentage of incorrect state estimations as compared against the ground truth. The result can be found in figure 8, which shows the expected user state estimation error for both policies given different energy budgets, through both theoretical analysis and the results based on real traces.

It can be seen that by applying the Markov-optimal policy as compared with periodic sampling, the average gain in terms of expected state estimation error while satisfying the same energy budget is 18.00% and 27.86% for the two given user traces, whereas the numeric analysis suggests an improvement of 19.75% and 29.55%, respectively. This indicates that even though the real user state transition is not strictly Markovian, the Markov-optimal sensor sampling policy is still able to provide significant improvement over periodic sampling mechanism. The reason is that the Markov-optimal policy is able to reduce the expected estimation error by imposing more frequent samples whenever state transition is more uncertain (e.g., higher state entropy in Markov case), and on the other hand, increasing the length of the idle interval when state transition is more predictable.

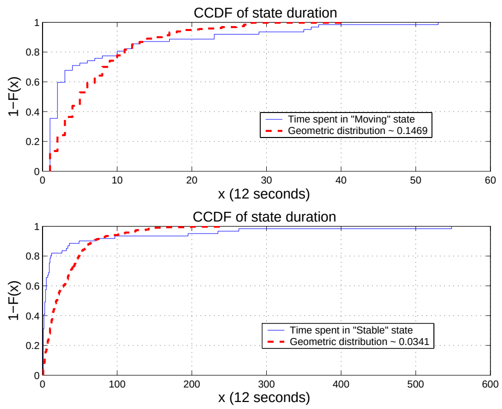
6. CONCLUSIONS

We study the problem of energy efficiently sampling of a discrete, Markovian user state process. While in our prior work the best stationary deterministic policy is found by exhaustively searching through all sensing intervals, in this paper, by formulating the constrained optimization problem as an infinite-horizon Constrained Markov Decision Process with expected average cost, the optimal sensor sampling policy for Markovian user state transitions can be obtained in a computationally efficient manner. The resulting Markov-optimal policy achieves the lowest expected user state estimation error, while maintaining the energy consumption below a given budget. The Markov-optimal policy is compared against uniform periodic sampling numerically and we find that the performance gain depends upon the user state transition probabilities. We also apply the Markov-optimal policy to real traces and it is shown to be capable of providing approximately 20% gain over periodic sampling, even the real user state transitions are not strictly Markovian.

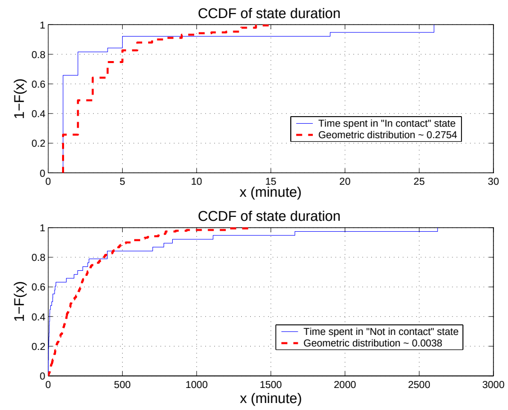
7. FUTURE WORK DIRECTIONS

In real scenarios, data distributions tend to show more sophisticated behaviors (arbitrary, non-stationary, or even unknown) as compared to simple Markov model. We plan to investigate models such as time-variant Markov chains (i.e., transition probabilities vary by time) and semi-Markov models that can be utilized to characterize user state transitions in a more realistic manner. Significantly more amount of data will be collected and studied and the performance of different models will compared.

In addition, since user state transition probabilities are not always known *a priori*, we plan to apply learning techniques (such as reinforcement learning) in order to obtain the optimal sensing policy without assuming prior knowledge of user state transition dynamics.



(a) State duration distribution for top chain in figure 6

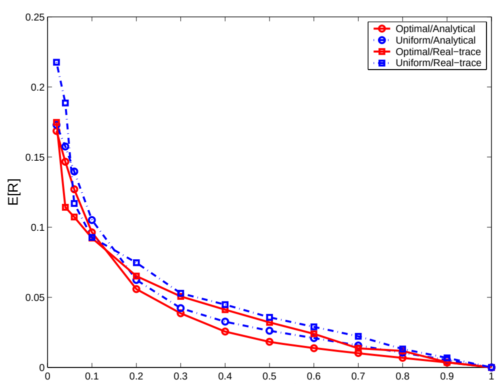


(b)State duration distribution for bottom chain in figure 6.

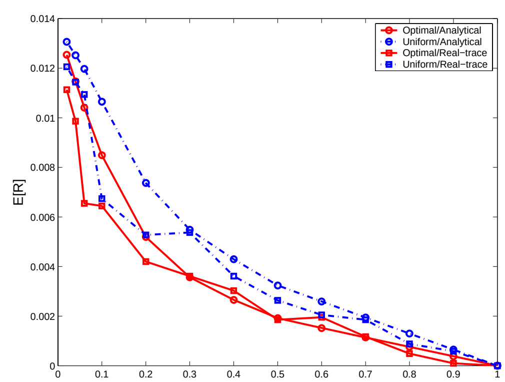
Figure 7: Comparing the cdf of state duration in real data to the corresponding geometric distribution generated with success probability indicated in figure 6.

	Stable		**Moving**		**Not In contact**		**In contact**	
	Real Data	Geometric	Real Data	Geometric	Real Data	Geometric	Real Data	Geometric
Mean	29.05	29.30	6.806	6.832	265.8	255.7	3.342	3.200
STDV	85.00	31.30	10.80	6.96	536.0	267.0	6.210	2.630
Median	4.000	18.00	2.000	5.000	26.50	175.0	1.00	2.00
Highest	548.0	192.0	53.00	63.00	2624	1705	2.00	17.0
Lowest	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
D	0.4852		0.3194		0.4474		0.3421	
P	0%		0%		0%		0.1%	

Table 1: K-S test results comparing the state duration distribution for "Stable", "Moving", "Not in contact", and "In contact", with their corresponding geometric distributed data. D: The maximum vertical deviation between two curves. P: Probability that two data sets have the same distribution.



(a) Policy comparison for the top chain in figure 6



(b) Policy comparison for the bottom chain in figure 6.

Figure 8: Comparing the Markov-optimal policy and uniform policy, through both numerical analysis and policy implementation on real traces. Different energy budgets are given as input.

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