Adaptive Regulation of Sampling Rates for Power Efficient Embedded Control System Design

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Abstract: In recent times adaptive regulation of sampling rates has gained significant attention in research community and researchers has demonstrated it’s effectiveness in embedded control applications from different perspectives. In low power embedded control systems, the sampling rate of the control tasks has a direct relationship with control performance and power consumption. In this paper, we present the possibility of improving the power efficiency of low power embedded control systems by regulating the sampling rate of the control tasks. On this regard, we present algorithmic approaches for on-line regulation of sampling rates of the control tasks under some power-performance trade-off. We present elaborative results which demonstrate the efficacy of our proposed approaches.

Keywords: Embedded Control Systems, Software Based Control, Sampling Rate, Power, Control Performance.

1. INTRODUCTION

Today majority of the embedded control applications are implemented using some digital platform, where the control tasks generally rely on periodic sampling and control. Traditionally the design of the control tasks are done using fixed and pre-defined sampling rate for the controller [1] and these sampling rate’s are chosen in such a way, that the controller can guarantee the desired level of control performance under all operating conditions. In recent times adaptive regulation of sampling rates of the control task [2–9] has gained significant attention in research community, where researchers has demonstrated the trade-off between computational resources and control performance using adaptive sampling in different contexts.

Moreover with the increasing popularity of low power cyber-physical systems, researchers have looked into various types of power related issues, specially in the field of wearable technology and wireless network control systems [10–12]. In many low power embedded control system applications, power efficiency is one of the major area of concern [13–16] as the sensors, actuators and electronic control units (ECU) can be battery powered with either individual or shared power supplies.

In [2, 3] researchers had demonstrated that one can achieve better utilization of shared computational resources by adaptively regulating the sampling rates in response to the disturbance level at the plant. In software based control, a higher sampling rate indicates a higher rate of sensing and actuation of the control tasks and thus have direct effect in power consumption. Thus, in scenarios where the system operates under high disturbance levels, a rise in sampling rate in response to a disturbance might affect the energy efficiency of the system and, in situations where the disturbances are rare, a slight rise in sampling rate in response to a disturbance does not have any significant affect on the systems power efficiency.

In a recent work [17], we had used this philosophy to study the trade-off between control performance and power under adaptive regulation of the sampling rate. The work presented in [17] considers the disturbance patterns generated from legacy data as an input to the problem and the control strategy adapts with different energy budget or energy efficiency levels. In [17], we considered the disturbance patterns in different forms and proposed a methodology for choosing the best possible multi-rate controller which guarantees optimal control performance under certain energy budget.

Although the methodology presented in [17] provides an optimal solution, but is computationally very expensive because of the underlying exhaustive search technique, which makes it practically hard to realize specially in cases where the computations are to be performed on-the-fly. In order to make the methodology computationally more efficient, some algorithmic improvement needs to be crafted such that it becomes feasible for cases where the computations are to be performed on-the-fly. In this paper, we extend the idea of the work presented in [17] and propose the following enabling contributions:

- We propose a framework for on-line adaptive regulation of sampling rates under power-performance trade-off.
- We propose algorithmic approaches to achieve our goal of efficient on-line adaptive regulation of sampling rates, under such power performance trade-off.

Further, we present elaborative results which demonstrate the efficiency of our proposed approach. Next, we outline the relevant background details.

2. BACKGROUND STUDY

In this paper, we consider the continuous-time linear systems (see [1–3]) which are described as:

\[ \dot{x}(t) = Ax(t) + Bu(t) + v_e(t) \]
\[ y(t) = Cx(t) + Du(t) + e(t) \]

(1)

here, \( x \) is the plant state, \( u \) is the input from the controller, \( y \) is the output of the plant. \( A, B, C, D \) are the
A multi-rate controller chooses a sampling rate for each disturbance level, thus the total possible choice of multi-rate controllers are given as $|H|^{|L|}$. Given the knowledge about the disturbance pattern and an energy budget $(E, T)$, the exhaustive/brute-force search approach finds the total control cost and the total energy consumption over the time window $T$ for all $|H|^{|L|}$ possible choice of multi-rate controllers and thereafter chooses the multi-rate option which promises the best control cost within the energy budget.

As the total possible choice of multi-rate options is given as $|H|^{|L|}$, thus with the increase in the elements in the sets $H$ and $L$, the total possible choice of multi-rate option and the computational overheads are expected to grow exponentially and therefore makes the approach [17] practically hard to realize or nearly infeasible specially in cases where the computations are to be performed on-the-fly.

3. METHODOLOGY OUTLINE

Our goal is to propose a computationally efficient power-aware strategy for regulating the sampling rates of the control tasks on-the-fly in response to different level of criticality. The proposed sampling rate regulation framework is outlined as,

- We consider that, initially the software based controller’s does not have any pre-specified disturbance pattern as an input.
- Therefore initially the system starts with the most frequent choice of sampling rate, from the given choice of sampling rate, $H$ and further decides it’s future actions by learning from the system’s behavior.
- In order to do so, it maintains a recent history of the disturbances encountered over a finite time window, $T_h$.
- For the sampling rate regulation, we propose some algorithmic approaches for finding the appropriate multi-rate controller, $M: L \rightarrow H$, here, the function specifies a sampling rate, $h \in H$, for each disturbance level, $l \in L$. 

In [17], we proposed a methodology for synthesizing multi-rate controllers which switches between a predefined set of sampling rates, considering the disturbance patterns in different forms as an input based on some disturbance levels and the overall systems is constrained under some given energy budget. The disturbance levels were discretized as a finite set, $L = \{1, 2, \ldots, k\}$.

Apart from the definition of the controller and the knowledge about the disturbance pattern the system has the information about an energy budget given as $(E, T)$, which specifies that the system can spend at most $E$ units of energy for a duration of next $T$ units of time. Estimate of battery life for determining the energy budget, can be calculated using existing well known methodologies [18].

In order to find the multi-rate controllers, a base line exhaustive search approach was proposed in [17], which in turn is used to find a solution for the different scenarios as per the knowledge about the disturbance levels.

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• The regulation of the sampling rate of the control tasks are decided using our proposed algorithmic mechanism (Approach-I and Approach-II), which is the heart of our work and are discussed in Section 3.2 and 3.3 in detail.
• Thus, given the knowledge about the disturbance pattern derived based on the past history of events and depending upon the energy budget or energy efficiency levels, our proposed methodology (Approach-I/Approach-II) regulates the sampling rate of the control tasks on-the-fly while achieving desired level of control performance.

3.1 Off-line Computations

To reduce the computational overhead during the online computations, we pre-compute the control cost and the power consumption for different choice of sampling rates, \( h_i \in H \) and different disturbance levels given as \( l_j \in L \) \( (1 \leq i \leq n, 1 \leq j \leq k) \). These values are calculated and stored in some tabular form, where a table, \( CT[H][L] \) stores the control costs (computed with the quadratic cost function) for each sampling rate \( h_i \in H \) and for each of the disturbance levels given as \( l_j \in L \), and a table, \( PT[H] \) stores the power consumption with respect to each sampling rate \( h_i \in H \).

3.2 Approach-I

For the set of sampling rates \( H = \{h_1, \ldots, h_n\} \) and disturbance levels \( L = \{1, \ldots, k\} \), each choice of multi-rate controller out of the all possible choice given as \(|H|^L\), can be characterized by the vector \( \langle M(1), \ldots, M(k) \rangle \) which maps the disturbance levels to a choice of sampling rates. Let \( S \) represent the set of all possible choice of multi-rate controllers given as \(|H|^L\).

We propose an intelligent pruning technique to reduce the search space. Using the notion of dominance, we introduce following pruning technique:

• If a choice of multi-rate controller \( \langle M(1), \ldots, M(k) \rangle \) exceeds the energy budget, then we can prune all options of the form \( \langle M'(1), \ldots, M'(k) \rangle \) such that \( M'(j) \leq M(j) \), for all \( 1 \leq j \leq k \), because all these options will also exceed the energy budget.
• If a choice of multi-rate controller \( \langle M(1), \ldots, M(k) \rangle \) satisfies the energy budget, then we can prune all distinct options of the form \( \langle M'(1), \ldots, M'(k) \rangle \) such that \( M(j) \leq M'(j) \), \( 1 \leq j \leq k \), because none of these options will improve the control performance over \( \langle M(1), \ldots, M(k) \rangle \).

Therefore, given the knowledge about the disturbance pattern derived based on the past history of events and an energy budget \( \langle E, T \rangle \), initially this approach computes the total control cost and the total energy requirement (using the precomputed datasets \( CT[H][L] \) and \( PT[H] \) as discussed in Section 3.1) for the different choice of multi-rate options. Further using the above mentioned pruning technique, it prunes out the irrelevant choices of multi-rate controllers to get a filtered set of multi-rate options \( S' \), such that \( S' \subset S \) and \( |S'| < |S| \).

Next, from this set of multi-rate options, \( S' \), we choose the switching function which promises the best control performance (lowest control cost) and also does not exceed the energy budget. This selected multi-rate controller is the one that optimizes control performance under the desired energy budget. In Section 4., we provide illustrative results which demonstrate the benefit of our proposed Approach-I in terms of computational efficiency and control performance.

3.3 Approach-II

Although, our proposed Approach-I reduces the search space to some extent and promises better computational efficiency compared to the exhaustive/brute-force search methodology presented in [17], still the reduced search space can be somewhat large and therefore may still be computationally expensive for larger data sets. Hence, in order to further optimize the computational efficiency, we propose another approach (inspired from fractional knapsack problem), the steps of which are discussed next.

Given an energy budget \( \langle E, T \rangle \) and knowledge about the disturbance pattern derived based on the past history of events, initially it computes the total control cost, \( CCTotal[h_i][l_j] \), and the total energy consumption, \( ECTotal[h_i] \), over the finite time interval \( T \), with the help of the pre-computed tables \( CT[H][L] \) and \( PT[H] \) as discussed in Section 3.1. Next, we define a function, \( B \) computed as \( B = 1/(CCTotal[h_i][l_j] \times ECTotal[h_i]) \), which defines the profit of using a particular sampling mode in terms of control performance (maximum performance) and energy (minimum power requirement). As, the nature of the quadratic cost function (Section 2.) is such that, a lower value of this cost function indicates a better level of control performance, hence we take an inverse of the control cost to represent maximum profit.

All these values are stored in some tabular form, where each table \( BTAB[H][l_j] \), will correspond to a specific disturbance levels, \( l_j \in L \) and store the control cost, the energy cost, and the profit function value, \( B \) corresponding to each choice of sampling rate \( h_i \in H, 1 \leq i \leq n \), as shown in Table 1.

| Table 1: \( BTAB[H][l_j] \) |
|--------------------------|
| \( h_i \in H \) | \( CCTotal[h_i][l_j] \) | \( ECTotal[h_i] \) | \( 1/(CCTotal[h_i][l_j] \times ECTotal[h_i]) \) |

A multi-rate controller, \( M : L \to H \), needs to choose a sampling rate for each disturbance level. As, the energy budget is a constraint on the energy consumption, thus we try to choose the multi-rate controller which guarantees maximum collective profit within the given energy budget. Therefore, we consider the elements of each of these tables, \( BTAB[H][l_j] \), and sort those elements in descending order in terms of the profit function, \( B \), and further store the rearranged elements associated with each of the profit function (e.g. sampling rate, total control cost and total energy cost) in tabular format in table \( STAB[H][l_j] \). Thus, we have \( k (= |L|) \), such sorted tables in terms of profit function for each of the disturbance levels and each of them will have \( n (= |H|) \), entries cor-
responding to sampling rates. Next, in order to find the appropriate choice of multi-rate controller, we search the possible combinations of multi-rate options in the following manner as given in Table 2.

Table 2: Selection of appropriate multi-rate controller following binary search pattern

| Choice | Mode-1 | Mode-2 | ... | Mode-(k-1) | Mode-k |
|--------|--------|--------|-----|-----------|--------|
| choice 1 | STAB[1][1] | STAB[1][2] | ... | STAB[1][k-1] | STAB[1][k] |
| choice 2 | STAB[2][1] | STAB[2][2] | ... | STAB[2][k-1] | STAB[2][k] |
| choice 3 | STAB[3][1] | STAB[3][2] | ... | STAB[3][k-1] | STAB[3][k] |
| ... | ... | ... | ... | ... | ... |
| choice | STAB[n][1] | STAB[n][2] | ... | STAB[n][k-1] | STAB[n][k] |

Table 2, depicts a binary table representation, where initially the choice of multi-rate option with maximum collective profit is selected and thereafter binary tabular search pattern is followed. The benefit of following such a binary tabular search pattern is that, for the next choice, the sampling rate of only one mode has to be varied and the succeeding choice always guarantees next possible maximum profit. Following this search technique, we finally select the multi-rate controller that satisfies the energy budget in first place. In Section 4., we present appropriate results which highlights the computational efficiency of this approach.

4. RESULTS AND DISCUSSION

In this section, we present experimental results in support of our proposed methodology. The experiments were carried out using MATLAB, TrueTime simulator [19] and Jitterbug Toolbox [20, 21]. We considered a test case from the TrueTime distribution, consisting of a DC servo motor controlled through a wireless sensor network. The linear plant dynamics is given by,

\[
\dot{x}(t) = \begin{bmatrix} -1 & 0 \\ 1 & 0 \end{bmatrix} x(t) + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u(t) + v_c(t) \\
y(t) = \begin{bmatrix} 0 & 1000 \end{bmatrix} x(t) + \begin{bmatrix} 0 \end{bmatrix} u(t) + e(t)
\] (3)

Further, we assume that the embedded platform admits the following sampling rates, \( H = \{10, 15, 20, \ldots, 90\} \) in milliseconds. The noise level is determined from the estimated (using residual variance estimator (RVE) [2]) value, \( \hat{r}(t) \) as follows, \( L = 1 : 0 < \hat{r}(t) \leq 10, L = 2 : 10 < \hat{r}(t) \leq 50, L = 3 : 50 < \hat{r}(t) \leq 100 \). The noise levels for \( L = 1, 2, 3 \) are referred to as low, medium and high respectively.

Initially, we compute \( CT[i][j], 1 \leq i \leq n, 1 \leq j \leq k \), following the steps of our methodology as described in Section 3.1. The calculations were done using Jitterbug Toolbox [20, 21] in MATLAB. Next, the entries of \( PT[i], 1 \leq i \leq n \), were computed using the following steps. In this example, the peak power consumption is considered as \( 100 \text{ mW} \), which corresponds to the shortest sampling rate, \( h_1 = 10\text{ ms} \), thus we have \( PT[1] = 100 \). Next, we compute the remaining entries of the table as, \( PT[i] = (100 * 10)/h_i, h_i \in H, 1 < i \leq n \).

We consider a scheduling hyper-period \( T_h \) as \( 100\text{ sec} \). As discussed in Section 3., our proposed methodology initially selects the most frequent sampling rate (\( 10\text{ms} \in H \)) for the first time window, \( T_h \) and thereafter regulates the sampling rate by learning from the system’s behavior. The knowledge about the disturbance pattern is derived based on the past history of events occurred during the past a scheduling hyper-period \( T_h \). Next, given the desired energy efficiency levels and knowledge of the disturbance pattern, our proposed methodology computes the multi-rate controllers (using Approach-I/Approach-II as described in Section 3.) for the next time window, \( T_h \) and thereafter follows the same steps.

Next, we provide elaborative results while considering one such scheduling hyper-period, \( T_h \), where the estimated noise level distribution is considered as \( \langle \text{low}=70\%, \text{medium}=10\%, \text{high}=20\% \rangle \). Assuming such operating scenario, the multi-rate controllers are synthesized using our proposed Approach-I (Section 3.2) and Approach-II (Section 3.3). The multi-rate controllers were also synthesized using the brute-force approach presented in [17]. In Figure 1, we present a comparative study between controllers using traditional fixed sampling strategy \( (h=50\text{ms}) \) and controllers using multi-rate sampling strategy for different energy budget options.

![Fig. 1: Comparative Study: Control Cost](image)

It is evident from the results presented in Figure 1, that multi-rate controllers promises better control performance (a lower value of control cost indicates a better level of control performance) compared to the fixed sampling strategy (Note that the y-axis has a scale factor of \( 10^5 \)). The multi-rate controller’s synthesized using our proposed Approach-I and the approach presented in [17] promises best control performance compared to the others. Whereas, the multi-rate controllers synthesized using Approach-II promises satisfactory level of control performance compared to the other approaches. Although our proposed Approach-II lags in terms of control performance, when compared with our proposed Approach-I.
and the exhaustive search approach presented in [17], but it is advantageous over them in terms of computational efficiency which is showcased next.

We present runtime comparison for synthesizing the multi-rate controllers using our proposed approaches (Approach-I and Approach-II) and the approach presented in [17]. The experiments were carried out using MATLAB, in a system with Intel Core i7-2600 processor clocked at 3.40 GHz with 8 cores, with a primary memory of 8 GB (DDR3), with disc space of 400 GB and with Ubuntu 14.04 LTS (64 bit) operating system. For demonstration purpose, the range of sampling rate is considered in between $H=\{10 \ldots 90\}$ ms and the total number of noise levels is taken as $|L|=3$. The finding are highlighted in Table 3.

It may be observed from the results presented in Table 3 that, both of our proposed approaches (Approach-I and Approach-II) are advantageous in terms of computational efficiency (less number of sampling combination explored to find a solution and therefore shorter runtime) compared to the exhaustive search approach [17]. Further, it is evident from the results showcased in Table 3, that our proposed Approach-II clearly has an edge over the exhaustive search approach [17] and our proposed Approach-I in terms of computational efficiency (significant runtime ratio, which is calculated by dividing the runtime achieved using other approach, with the runtime achieved using Approach-II, see Table 3).

The runtime efficiency of our approach is very advantageous considering the configuration of the ECUs [22, 23] used in embedded applications. It may be concluded that, our proposed Approach-I promises optimal result in terms of control performance but is computationally slightly expensive than our proposed Approach-II, whereas our proposed Approach-II is computationally very efficient and promises satisfactory level of control performance. So clearly there is a trade-off between the two proposed approaches (Approach-I and Approach-II) in terms of computational efficiency and control performance and any one of them can be used effectively based on the embedded control application requirements and overall system configuration.

Next, we showcase the power efficiency (possible extension in battery life) that can be achieved by using multi-rate controllers over fixed sampling strategy. We considered two different set of disturbance scenarios “Scenario-I” where high noise level is encountered more often and “Scenario-II” where low noise level is encountered more often. We employed our proposed methodology in these two different disturbance scenarios and calculated the power related benefits achieved compared to fixed sampling strategy and the findings are highlighted in Table 4. Further, the corresponding battery discharge results are shown in Figure 2a and 2b.

| Total choice of Sampling rates $|H|$ | Number of Sampling Combination Explored | Run Time (in second) | Run Time Ratio w.r.t. Approach-II |
|-----------------------------------|----------------------------------------|----------------------|----------------------------------|
|                                  | Exhaustive Search, [17] | Proposed Approach-I | Proposed Approach-II |
|                                  |                          |                      | Exhaustive Search, [17] | Proposed Approach-I | Proposed Approach-II | Exhaustive, [17] | Approach-I |
| 9                                 | 729                      | 438                  | 14                  | 0.122849 | 0.073819 | 0.002349 | 32.2984 | 31.4257 |
| 16                                | 4,096                    | 2436                  | 29                  | 0.184911 | 0.110068 | 0.003220 | 57.4257 | 34.1826 |
| 32                                | 32,768                   | 20,894                | 27                 | 0.476642 | 0.305212 | 0.004757 | 100.6184 | 64.1606 |
| 80                                | 5,12,000                 | 3,38,486              | 129                | 5.181520 | 3.425517 | 0.005768 | 789.3217 | 593.8829 |
| 160                               | 40,96,000                | 27,39,574             | 257                | 40.883443 | 27.344521 | 0.007158 | 5711.5734 | 3820.1342 |
| 800                               | 51,20,00,000             | 30,76,41,532          | 1281               | Out of Memory | Out of Memory | 0.031091 | - | - |

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Table 4: Comparative Study: Power Efficiency

| Test Pattern | Reduction in Power Requirements (in %) | Battery Life Enhanced (in %) | (∆ in months) |
|--------------|---------------------------------------|----------------------------|---------------|
| I            | 18.19                                 | 7.82                      | (nearly 5)    |
| II           | 50.18                                 | 27.55                     | 16.65         | (nearly 17) |

Fig. 2: Battery Life: Multi-rate v/s Fixed Periodic

Results presented in Table 4, Figure 2a and 2b, highlight that the multi-rate sampling strategy results in significant saving in power requirements and enhances the battery life time, therefore promising power efficiency.

5. CONCLUSION

This paper investigates the possibility of improving power efficiency of low power embedded control system by adaptive regulation of sampling rates of the control task. We present computationally efficient approaches for
on-line regulation of sampling rates under power performance trade-off. We report encouraging results in terms of control performance, power efficiency and computational efficiency. We believe that the framework proposed in this paper for adaptive regulation of sampling rates of the control task is novel in treatment of the problem and further motivates future research in these lines.

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