CyHOP: A Generic Framework for Real-Time Power-Performance Optimization in Networked Wearable Motion Sensors

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***Abstract*—Power consumption is a major obstacle in designing stringent resource constraint wearables. Several system-level design considerations contribute to energy consumption of these systems which must be taken into account while designing the system. We propose a power-performance optimization framework, namely CyHOP (Cyclic and Holistic Optimization framework), for connected wearable motion sensors. While existing work focus solely on one design parameter, our approach globally trades-off the performance of activity recognition and power consumption. CyHOP is capable of optimally adjusting the system to fulfill specific application needs. Using a smoothing technique, the initial multi-variate non-convex optimization problem is reduced to a convex problem and solved using our devised derivative-free optimization approach, namely, cyclic coordinate search. Our model performs a linear search by cycling through the system variables on each iteration until it converges to the global optimum. Using real-world data collected with wearable motion sensors during activity monitoring, we validate our approached with various performance thresholds ranging from 40% to 80%.**

I. Introduction

Internet of Things (IoT) is defined as a large set of connected application specific embedded devices that are in conjunction with and in service of people. Despite the recent interest in research community to further empower and grow the ecosystem, there remain important challenges regarding adaptive HW/SW design, integration capability, and user acceptance. Consistently, the demand for Network Wearable Systems (NWS), as a rapidly expanding component of IoT, has grown intensively in recent years. While different components of wearables such as sensors, transmission unit, and battery are shared with handheld devices (e.g., smart-phones), it is expected for wearables to function for days with a single charge [1]. In addition, for the purpose of pervasiveness and ease of use, we have witnessed significant form-factor reduction in wearables compared with traditional handheld devices. This has created a trade-off between size (in particular, the size of battery) and device lifetime where both of which are essential factors in user acceptability of the wearable technology and are directly associated with power consumption of the device.

NWS have been used for a variety of applications in particular in health and wellness. One of the main applications is activity monitoring. However, there still exist several obstacles in development of such systems. Two of these challenges are battery life-time and form factor. These systems are typically equipped with low-power micro electro-mechanical sensors (e.g., accelerometer, gyroscope, magnetometer), a micro-controller (e.g., ATmega328) and a low energy wireless transmitter (e.g., BLE). These are, respectively, in charge of sensing, processing, and communication in activity recognition (AR) wearable devices.

Several energy-performance optimization work aimed to reduce the power consumption while maintaining an acceptable performance [1]–[4]. A comprehensive system optimization platform can inherit the existing single variable optimization techniques and significantly lower the cost of system by finding the joint global optimum. To this end, we need a comprehensive multi-variant optimization technique that is not specific to an initial design of the node or its high level application. Brute-force approach is too complex to be used in real-time adaptation of resource-limited NWS when a possibly large number of variables are considered in the optimization problem (exponential complexity with respect to the number of optimization variables). Once the system is initially optimized and is employed, if a change is made in the network (e.g., a node is disconnected, there is a change in location of a node, etc.) or in the application level (e.g., change in desired performance of activity recognition), a low-cost multi-variant optimization approach (ideally with linear complexity) is needed to re-optimize the network for the new optimal energy-performance trade-off. It is essential with respect to the limited energy and computation resources of wearables.

While several rigid and isolated algorithms have been proposed for optimization of networked wearable systems, the need for a practical multi-variate optimization algorithm with low computational complexity is still unsatisfied.

The current wearable networks are highly dynamic. A low cost optimization algorithm capable of being implemented on wearable systems can further empower the dynamic nature of wearable applications. We propose an efficient approach for holistic optimization of NWS. The framework performs linear search and quickly converges to the global optimum configuration of the system. Therefore, it provides a practical solution to adaptivity requirement of NWS while guaranteeing optimal trade-off of performance and energy consumption. To the best of our knowledge, there has not been proposed a generic multi-variant optimization platform for wearables.

II. CyHOP Framework

We formulate the power-performance optimization problem in networked wearable systems given the set input system variables $V = \{v_1, v_2, \ldots, v_n\}$ as follows.

$$Minimize \quad Z : f(V) \tag{1}$$

Subject to

$$E(V) \leq \beta \tag{2}$$

where Z denotes the multivariate energy cost function on bounded region $S \subset R^n$ and V is the finite set of system variables of size n where $v_i \in V$ is on a discrete bounded domain of integer values. The parameter β is an upper-bound on activity recognition error of the system ($E = 1 - Performance$). This problem has two important properties: first, it is a constrained discrete multi-variant optimization problem meaning that it cannot be solved using derivative approaches (e.g., gradient descent); second, it has a non-convex hard constraint function turning the optimization problem into a non-convex problem that cannot be solved using local search solutions (e.g., coordinate descent). Local search approaches perform poorly on non-convex functions and do no guarantee the global optimum in presence of local minimum points. Generally, a non-convex multi-variate function introduces multiple local minima.

In general, a non-convex non-linear optimization problem is a computationally hard problem. As shown in [5], such discrete optimization is a reduction of Subset Sum Problem which is known to be NP-complete. However, if we restrain the size of V to a constant, a brute-force algorithm can solve it in pseudo-polynomial time. However, in practice, a brute-force approach is still expensive even for a moderate input size. An efficient alternative is to transform the initial non-convex optimization problem to a convex problem by finding a convex approximation of the non-convex part. Assume that function $E(.)$ has become convex by some smoothing function. As a result, the initial non-convex problem is now reduced to a multi-variate convex optimization. The new problem still preserves the remaining properties of the initial problem. However, given a smoothed convex constraint, it is now possible to solve the problem in linear time using the devised cyclic coordinate search algorithm. We further discuss the transformation of the optimization formulation and the devised linear search algorithm in Section II-A.

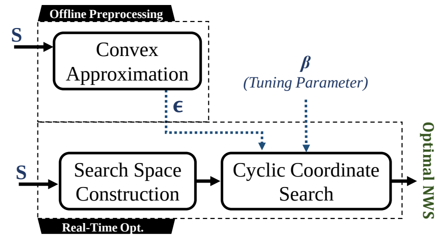

Fig. 1: An overview of the proposed real-time optimization framework.

A. Cyclic Coordinate Search

Linearity of our solution is crucial to CyHOP framework hence it enables the feasibility of real-time on-node execution. However, with such point-to-point linear optimization, we cannot directly access the smoothed $E(.)$ function, the reason is that the coordinate search will only execute the points that it visits along its search path. Alternatively, knowing the upper-bound on E distortion, we can efficiently approximate the constraint and relax the formulation to a weak constraint optimization problem.

$$Minimize \quad Z : f(V) \tag{3}$$

Subject to

$$E(V) - \beta \leq \epsilon \tag{4}$$

where ϵ represents the maximum distance of all points in $E-V$ subspace from the smoothed and convex approximation of $E(.)$. In other words, this convex optimization problem approximates the solution to the initial problem and is bounded by ϵ. In order to find the value of ϵ, given enough training data of NWS, we perform a convexity preserving piecewise linear interpolation. Using a piecewise linear interpolation is sufficient, considering the discreteness of the domain S. Such interpolation also needs to preserve the convexity of $E(.)$.

Fig. 1 illustrates an overview of the proposed generic multi-variate optimization framework (CyHOP). In the off-line preprocessing phase, a boundary on convex approximation of the initial non-convex problem is computed and fed into the main algorithm using the training data along with the bounded system variables considered in the optimization ($V \in S$). In the real-time holistic optimization phase, the discrete bounded system variables in S, construct a bounded multi-dimensional search space and using this virtual search space, the light-weight coordinate search algorithm will be performed to find the jointly optimal value for each variable with respect to its parameters: the upper-bound on error of classification (β) and the approximation boundary (ϵ).

The cyclic coordinate search algorithm comprises four main steps: (1) initialization, (2) local polling, (3) shrinking, and (4) stopping criteria. Fig. 2 illustrates an simple example of the algorithm finding the optimal solution for a bivariate problem. x_1 and x_2 axes are labeled with values of two variables of the optimization problem. The contour plot in the background

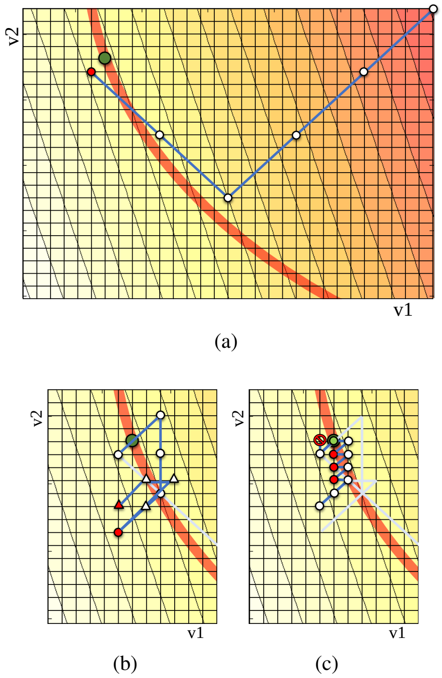

Fig. 2: The main steps in cyclic coordinate search algorithm, including initialization and local polling (2a), shrinking (2b), and stopping criteria (2c).

shows the values of Z for each $P \in (x_1, x_2)$. The optimal point in shown with a green dot that is the lowest cost point that satisfies the constraint in (4). Algorithm 1 describes the generic cyclic coordinate search solution.

Algorithm 1 Cyclic Coordinate Search Algorithm

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procedure MAIN(V)
    Result: The jointly optimal V, initially set to P^(0)
    Initialization:
    Construct the search space;
    Set the initial point and initial mesh size;
    Polling:
    While It has not converged:
     Move to the lowest cost neighbor that satisfies the constraint;
     If not found, shrink the mesh size;
     If reached the space boundary, break;
    return the current coordinates;
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III. Validation

A. Experimental Setup

To demonstrate the effectiveness of the proposed framework, we construct an activity recognition system using a wearable motion sensor placed on 'waist'. We used TelosB mote to measure acceleration and angular velocity of different body segments using a triaxial accelerometer and a biaxial gyroscope. Information on power consumption and specifications of the sensor nodes can be found in [6]. Three subjects were asked to perform 30 different daily activities such as 'sit to stand', 'sit to lie', 'bend and grasp', 'kneeling', 'step forward', 'step backward', etc. Each transitional movement was repeated 10 times by each subject. The sensor nodes were programmed to sample data at 100Hz and transmit the data wirelessly to a laptop computer.

The collected is segmented into windows of $1.5s$ of activity. We extracted 10 statistical features as well as 10 morphological features from each activity segment. We calculated instruction level energy consumption of MSP430 micro-controller, which is available on the TelosB mote used in our experiments. The details of energy calculations is based on an instruction level energy model provided in [7]. Morphological features were equally-spaced samples of the activity signal. Overall, we extracted 100 features per segment from the motion sensor.

B. Power Model

We define a power model for our activity recognition system. The power consumption of a wearable sensor node consists of three components: (1) data sampling (sensing cost); (2) feature extraction; and (3) machine learning algorithms (classification) and (4) and information transmission (communication). The sensing cost is given by:

$$Z^{(s)} = \lambda_s \times f \tag{5}$$

where f denotes the given sampling frequency and λ_s represents the sensing cost of one sample in one sensing node which is available on TelosB mote used in our experiments. The accelerometer consumes $2.64\ mW$ in active mode whereas the power consumption of gyroscope is $31.35\ mW$. The parameter $Z^{(p)}$ includes two processing modules: feature extraction and activity classification. It is formulated as follows:

$$Z^{(p)} = Z^{(feat.ext.)} + Z^{(class.)} = (\sum_{a_i \in A} \lambda_{a_i}) + \alpha \times \lambda_{class.} \tag{6}$$

where a_i represents a distinct feature from the set of selected features (denoted by A) and α and $\lambda_{class.}$ denote, respectively, the number of data segments generated in $1s$ and the classification cost of each data segments. a_i values are reported in Table II and $\lambda_{class.}$ is calculated using instruction level power numbers of MSP430 micro-controller. After a node performs activity classification, the predicted activity label will be ultimately transmitted to an access point. The communication cost of transmitting the labels is given by:

$$Z^{(c)} = \lambda_t \times B \tag{7}$$

where λ_t represents per-bit transmission cost of ZigBee transmitter used in TelosB mote and is extracted based on ZigBee protocol specifications [8]. The parameter B denotes the number of bits being transmitted. The power cost of transmitting a $5-bit$ class label in our experiment is equal to $929.5\ \mu J$.

C. Results

For the experimental proof of validity, we proceed this section with discussing the results of using CyHOP framework applied to a three-variate activity recognition syste, optimization. We utilize the proposed framework in order to perform joint optimization on (1) segmentation window size, (2) sampling frequency, and (3) feature selection with significantly low time cost.

As a benchmark for the proposed optimization solution, we first execute the brute force algorithm to find the ground truth solution to this optimization problem. The brute force algorithm examines all the possible configurations of the system to find the minimum cost sensing and processing pipeline which satisfies the accuracy constraint defined by user (β). Initially, the activity recognition algorithm achieves 0.83 accuracy (or equally $E(P^{(0)}) = 0.17$) which is a significant performance given the large number of classes. The machine learning algorithm chosen for our experiment is a j48 decision tree which is suitable for wearable sensors for its efficiency and low computation cost. The evaluation is performed off-line using Weka 3.6 machine learning toolkit with 10-fold cross validation scheme. We defined six activity recognition error constraints ranging from 0.2 to 0.6 (equal to classification accuracy of 0.8 to 0.4). We reported approximation boundary of $\epsilon = 0.02$ for constraint $E(.)$. The possible values of the input variables (v_i) are set to $v_1 = [0.2 : 1.5]$ second (equally spaced by 0.1), $v_2 = [1 : 100]$ Hz, and $v_3 = [1 : 100]$ for segment size, sampling frequency, and number of features, respectively. For the initial mesh size ($d_i^{(0)}$), we used one tenth of the range of input variables.

Table I shows the comparison of optimization results in terms of segmentation window size, sampling frequency, and the number of extracted features for various activity recognition error constraints. Comparing CyHOP with the brute-force solution, we confirm the convergence of our solution. However, since we are performing approximation on the initial optimization problem, the two results does not exactly match in several instances. For instance, when only 0.5 accuracy is desired, CyHOP converges to a slightly weaker configuration, violating the hard β threshold set for the initial problem. However, as discussed before, such violation is bounded by ϵ that is the upper-bound on the asymptotic smooth approximation of $E(.)$.

Table II lists the power consumption of the activity recognition node optimized using CyHOP and brute-force approaches. Since the idle power consumption of the node was shared in all comparisons, we did not consider it in our power computations. Moreover, power consumption of the node under CyHOP is 5% deviated from the optimal solution, that is essentially the asymptotic approximation factor of our solution for this optimization instance, given $\epsilon = 0.02$. One important observation from our results was that the computation cost of J48 classifier was significantly lower than other modules (less than few hundred μJ). Given the linear growth of the cyclic coordinate search algorithm, it roughly shows the minor power consumption overhead of the proposed real-time optimization framework, adding the fact that the optimization module will not be activated as frequent as the main activity recognition pipeline.

TABLE I: Optimized system variable using CyHOP vs brute-force approach: segmentation window size (s), sampling frequency (Hz), and the number of attributes.

-	beta →	0.2	0.3	0.4	0.5	0.6
Seg. size	CyHOP	1.3	1.1	1.3	1.3	1.3
	BF	1.3	1.2	1.3	1.4	1.5
Sampling Freq.	CyHOP	43	39	10	8	8
	BF	44	39	11	9	9
♯ of attr.	CyHOP	79	63	14	13	7
	BF	79	64	15	14	9

TABLE II: Power consumption (μJ) of the activity recognition system optimized for various thresholds using CyHOP versus exhaustive search.

beta →	0.2	0.3	0.4	0.5	0.6
CyHOP	16383.6	14843.2	4354.4	3652.6	3576
BF	16388.9	14844.6	4706.8	3972.1	3864.8

IV. Conclusion

In this article, we proposed an energy efficient holistic and real-time optimization framework, namely CyHOP. We approximated the initial hard optimization to a convex optimization problem and devised a coordinate search algorithm which functions on a multi-dimensional bound discrete domain. We showed that the proposed algorithm is capable of offering a practical NWS optimization solution in terms of multiple design variables. The linear time complexity of our algorithm provides the means for low cost deployment of a real-time optimization framework that can adaptively optimize the system based on the desired performance. Our real-world experiment showed that CyHOP can achieve a similar performance to brute-force approach.

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