Orchestrator: An Active Resource Orchestration Framework for Mobile Context Monitoring in Sensor-rich Mobile Environments

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Abstract— **In this paper, we present Orchestrator, an active resource orchestration framework for mobile context monitoring. Emerging pervasive environments will introduce a PAN-scale sensor-rich mobile platform consisting of a mobile device and many wearable and space-embedded sensors. In such environments, it is challenging to enable multiple context-aware applications requiring continuous context monitoring to simultaneously run and share highly scarce and dynamic resources. Orchestrator enables multiple applications to effectively share the resources while exploiting the full capacity of overall system resources and providing high-quality service to users. For effective orchestration, we propose an active resource use orchestration approach that actively finds appropriate resource uses for applications and flexibly utilizes them depending on dynamic system conditions. Orchestrator is built upon a prototype platform that consists of off-the-shelf mobile devices and sensor motes. We present the detailed design, implementation, and evaluation of Orchestrator. The evaluation results show that Orchestrator enables applications in a resource-efficient way.**

I. Introduction

Smart mobile devices have been the pivot for personal services. Many diverse sensors around the mobile device will enable highly proactive services with the help of a lot of *personal context-aware* applications, e.g., u-Trainer, dietary monitoring, and health monitoring. In such *PAN-scale sensor-rich* environments, mobile devices will serve as the common computing platform which accommodates diverse wearable sensors or nearby space-embedded sensors, e.g., e-watch, sensing garments, and textile electrodes in bed sheets. Then a mobile device will usually run multiple context-aware applications at a time which mainly focus on continuous monitoring of users' context with diverse sensors [19]. The context monitoring often requires multi-step and complex processing over multiple devices at the same time, e.g., for a 'running' context, sensing of body-worn accelerometers, filtering, FFT-based feature extraction, and classifying the features through a decision tree [20].

The challenge in this new environment is that the platform should simultaneously support a number of applications with highly scarce and dynamic resources. Greedy and injudicious resource use would significantly aggravate contention among multiple applications and accelerate skewed use of some specific devices. This can also lead to reduced overall system capacity. Especially, we note that most of the devices have highly constrained resources, often less than the capacity required for a context monitoring. More challenging, availability of such resources dynamically changes due to their wearable forms and mobility of users. Sensors join or leave the platform frequently as users may take off a sensor-equipped smart watch [21], or enter a new sensor-embedded smart office. Also, resource usage by running applications or environmental factors such as interference continuously affects the resource availability.

It is almost impossible for each application to address the challenges without system-level supports. First, context monitoring entails very complex processing, and often involves burdensome device-level exploration [19][20]. Second, it is more challenging to ensure applications' steady running under highly scarce and dynamic resource availability. To achieve this, each application should efficiently share the constrained resources with other applications. Without system-level support, however, each individual application has an extremely limited view of the existence or resource uses of other applications, and further cannot negotiate with the concurrent applications for coordinated and efficient resource utilization. Thus, system-level support is compelling for the effective and coordinated use of scarce computing resources among multiple applications.

In this paper, we propose a novel active resource orchestration system, *Orchestrator* for the PAN-scale sensor-rich mobile computing platform. Actively interplaying between context-aware applications and scarce dynamic resources, Orchestrator enables the mobile platform to host a number of applications stably, exploiting its full resource capacity in a holistic manner. More specifically, it helps applications efficiently share resources and processing as much as possible. It also seamlessly adapts the applications to dynamic resource availability by resolving resource contention between applications or selecting the best processing plan according to the resource availability at that time. In addition, Orchestrator can apply a system-level policy such as energy optimization with an integrated view of the total resource uses and status. With such system supports, applications become capable of providing mobile users with seamless, long-running high-quality service under dynamic circumstances with scarce resources.

To design effective resource orchestration, we take an active resource use orchestration approach that actively finds out the best combination of resources for requested context monitoring under the current status of resources and applications. This is substantially different from an existing approach, passive resource use management [3][4][7][10]. A key feature of the active approach is to decouple application's logical resource demand from physical resource allocation. It enables postponing resource selection and binding until resources' availability is sufficiently explored. Under this active approach, applications do nothing but turn in high-level context specifications to the system, and comply with the system's decision on resource allocation. Most of mobile and sensor systems, on the other hand, have taken passive resource use management approaches based on application-driven decision in resource selection and binding. In such approaches, applications should explicitly specify the type and amount of resources as in resource ticket [10] and resource descriptor [3]. A system simply allocates the requested resources if available. If not, applications would change their resource use plans according to predefined code blocks, e.g., by trading off data or functional fidelity. However, these approaches impose huge burdens on the programmer, and their flexibility cannot be fully utilized in practice since it is almost impossible for applications to estimate dynamic resource status and prepare well adapted code blocks for all the cases.

Orchestrator realizes the proposed approach as follows. First, it prepares multiple alternative resource use plans, each of which can process a high-level context from applications. Such alternatives result from the diversity of semantic translation. That is, a context can be derived by utilizing many different sensing modalities as well as feature extraction and classification methods. For instance, when a context quality required by an application is conditionally tolerable under a particular situation, a 'running' context is monitored with diverse methods, e.g., utilizing DC and energy features from acceleration data [20], or statistical features from GPS location data. Second, at runtime, it dynamically adapts a processing plan to reflect resource availability, running applications' requests, system-level policies in a holistic manner. Such flexibility and adaptation enable Orchestrator to support multiple context-aware applications, extending their running time while balancing their resource usage, in environments with highly limited and dynamic resources.

To the best of our knowledge, Orchestrator is an initial attempt to provide an active resource orchestration system, recognizing the PAN-scale sensor-rich mobile platform as a common underlying computing platform. Recently, many systems have been proposed for effective resource management of mobile devices [3][4][5][6][7] and sensors [8][9][10] comprising PAN. They are mostly designed to manage resources, especially battery in most cases, for applications on a single computing device. Such device-centric resource management, however, can hardly be utilized in our target environment, in which multiple sensors and a mobile device cooperatively serve multiple applications.

This paper is organized as follows. We discuss related work in Section II. Section III and IV describe the architecture and main functions of Orchestrator, respectively. Section V presents the implementation of Orchestrator prototype. We discuss experimental results in Section VI. Finally, we conclude the paper in Section VII.

II. Related Work

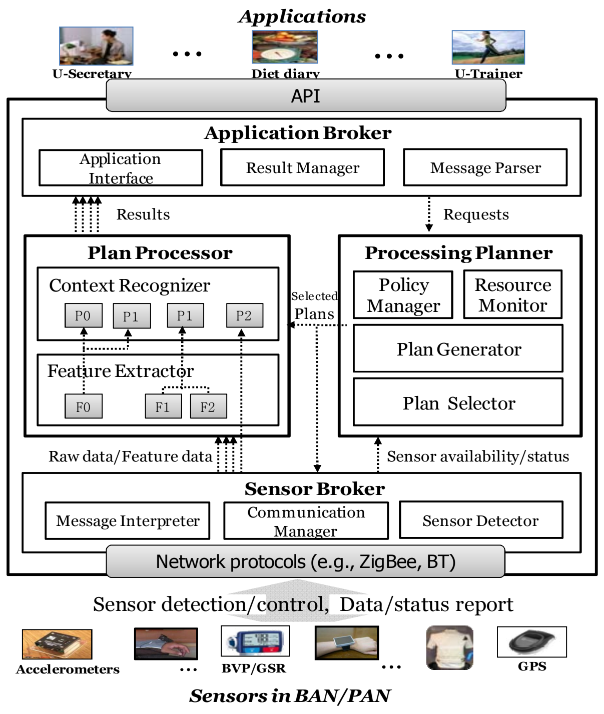
Recently, sensor-enabled mobile applications have been emerging in diverse application domains [1][2]. They provide useful mobile services based on the contexts of a user and her surroundings that are captured using diverse sensors such as accelerometers, microphones, and GPS. As many applications emerge to run on a mobile device with a variety of sensors, common underlying frameworks such as Orchestrator will be increasingly necessary to coordinate multiple applications and allow them to efficiently share resources in a systematic way.

There have been broad research efforts to effectively manage the use of limited resources in different environments. Some research proposed systems to manage the resources of a *mobile device*, to name a few, Odyssey [3][4][5], ECOSystem [6], and Chameleon [7]. Also, there have been ongoing research efforts to efficiently manage and utilize the limited resources of a *sensor node* such as Levels [8], Eon [9], and Pixie [10]. Some research has also been made to manage resource use in *sensor networks*. To increase the lifetime of the whole sensor network, algorithms for energy-efficient routing, filtering, and in-network processing have been proposed [11][12][13]. There has been, however, relatively little attention to develop a platform or to address issues for PAN-scale sensor-rich mobile environments. Orchestrator emphasizes a holistic view of resources of multiple devices as well as multiple applications that share the resources. Through the holistic approach, it effectively orchestrates the resource use of the applications.

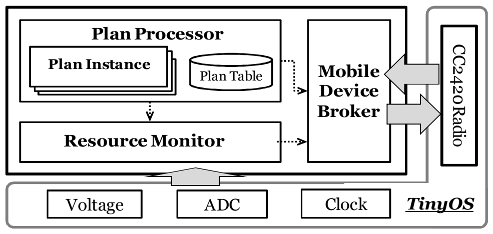
Several systems such as Pixie [10], Odyssey [3], and Chameleon [7] have taken an application-driven approach to resource management. They expose APIs for resource allocation to applications. Applications determine the types and amounts of resources required to execute program codes, and explicitly request the resources through the provided APIs. The systems play a rather simple role to bind and allocate the use of the requested resources.

We consider that a system-driven approach [8][9][6] is more suitable as the solution of the target environment as it gets too complex and dynamic for individual applications to deal with. This approach hides from applications the details of complex resource management. As such, they can focus on specifying their application logics. Instead, systems determine and allocate the required resources at runtime, reflecting resource status and system policies. However, many of the existing systems with this approach are still application-aided, e.g., Eon [9], Levels [8]. Applications provide multiple program code blocks, each mapped to highly abstracted resource levels.

There has also been research to support adaptive context data provision. Titan [14][15] supports context recognition in dynamic BAN environments. However, it allows only a single recognition algorithm to run at a time. Activity recognition techniques proposed in [16][17][18] allow performing recognition processes adaptively to improve



(a) Architecture on a mobile device



(b) Architecture on a sensor

Figure 1. Architecture of Orchestrator.

energy efficiency. Their focus was on reducing energy consumption only for activity recognition. None of the mentioned research tackles challenging issues arising when multiple applications run simultaneously and share dynamic and scarce resources over multiple devices.

SeeMon [19] was our early attempt at a context monitoring platform for a PAN-scale sensor-rich mobile environment. While it proposed important techniques, e.g., locality-aware context processing and ESS (essential sensor set)-based energy control, it did not address complicated issues of resource management. Thus, while the proposed orchestration framework can broadly be used as a platform for many context monitoring systems, it also forms the resource management stratum underneath the SeeMon framework.

Other than sensor-based context-aware applications, there have been research efforts for general middleware approaches to enable applications such as media streaming and instant messaging in dynamic pervasive environments [27][28][29][30]. They adaptively build and run applications by dynamically composing available components (e.g., RTP stream sources and sinks). Reflecting changing conditions, e.g., failure of components used, they reselect appropriate components to continue the execution of applications. However, they are not directly applicable to our target environments; they were developed and tested mainly in rather powerful desktop environments. Also, since their focus was on developing techniques to make a pervasive application adaptive to dynamic environments, they hardly consider problems due to scarce resources shared by multiple applications such as resolving resource contention and achieving high efficiency.

III. ORCHESTRATOR ARCHITECTURE

We design the architecture of Orchestrator to enable active resource use orchestration. The architecture spans a mobile device and multiple sensors (Fig. 1).

Plan generation and selection: The *processing planner* located in the mobile device plays a key role as a control center for resource use orchestration. It includes two major components: the *plan generator* and the *plan selector*. The plan generator dynamically creates a variety of applicable plans based on available sensors and their processing capability at runtime. Among the generated plans, the plan selector decides a set of plans to execute, which supports maximal application requests with available resources and best meets an orchestration policy enforced by the *policy manager*. The selection changes adaptively, reflecting dynamic resource status of sensors and the mobile device.

Plan execution: Orchestrator employs the *plan processors* in both the mobile device and sensors to execute the selected plans. They cooperatively process the plans, often involving sensing, feature extraction, and context recognition tasks. The plan processor in a sensor performs sensing tasks and optionally executes feature extraction tasks so that processing is offloaded onto the sensor. The plan processor in the mobile device executes the rest of the plan, i.e., feature extraction and context recognition tasks or the latter only, and completing plan execution. Note that we develop the plan processors to dynamically compose and share diverse processing modules for plan execution.

Resource monitoring: The *resource monitors* keep track of available resource status of sensors and a mobile device, respectively. They continuously monitor the status of CPU, memory, energy, and bandwidth. The status is periodically reported to the plan selector for runtime adaptation. The monitors are designed to minimize monitoring overhead while keeping reasonable level of accuracy.

Communication protocols: For effective cooperation between the mobile device and sensors, we develop a range of communication protocols. For example, a *sensor detection protocol* enables the mobile device to automatically detect available sensors. The detected sensors report heartbeat messages and resource status through a *status reporting protocol*. The mobile device sends diverse control messages based on a *control message protocol*

Application interface: The *application broker* in the mobile device interacts with applications through Orchestrator APIs. Fig. 2 shows the APIs. Using *registerCMQ()*, applications specify contexts of interests as a form of a query statement and register the query along with two callback functions to receive query results and status.

Context Monitoring APIs	*CMQ_ID* = registerCMQ (*CMQ_statement, query_result_handler, query_status_handler*)
	deregisterCMQ (*CMQ_ID*)
	updateCMQ (*CMQ_ID, CMQ_statement*)

Figure 2. Orchestrator APIs.

The query specification is extended from the Context Monitoring Query presented in our previous work [19]. For example, assume that an application wants to know if a user is running with more than 90% of accuracy. Then, the developer specifies the query as below.

registerCMQ("*CONTEXT Activity == running ACCURACY 90% DURATION 7 days*", *callback_for_result*, *callback_for_status*).

Applications are notified of query results via the specified callback functions. Also, they are provided with query evaluation status, e.g., "not activated" in case that the processing planner cannot find any available processing plan for query evaluation. Note that the APIs allow application developers to specify high-level contexts only without caring about low-level resource status.

IV. ACTIVE RESOURCE USE ORCHESTRATION

A. *Processing Plan Generation*

The plan generator creates a wide variety of processing plans regarding each context to monitor. The plans utilize different combinations of devices and their resources, and thus, serve as a basis for effective orchestration. A key idea to obtain diverse plans is to exploit the diversity of context recognition methods and sensing modalities. For example, Orchestrator detects a 'running' activity with frequency-domain features from acceleration data and a decision tree classifier [20]. Another method is possible with time-domain statistical features and a Naïve Bayes classifier [21]. Also, each method can utilize different combinations of accelerometers located on various body positions [16][17][21]. Moreover, there are alternative ways to derive affective state of individuals with different sensing modalities. It is possible to recognize the state using biomedical sensors such as BVP, GSR, and ECG and features such as heart rate, heart rate variability, and inter-beat interval [24]. The state can be also identified by voice-related features such as pitch [25].

To generate diverse processing plans, we develop a *two-phase translation method*, including a *logical translation* and a *physical translation*. First, the logical translation maps a context into multiple logical processing plans, *LPlans*. An LPlan represents a set of processing modules to derive the context. It often consists of sensing, feature extraction, and recognition modules, and optionally includes the accuracy of context recognition. Second, the physical translation associates an LPlan with different sensors and computing resources to run the modules of the LPlan, accordingly generating physical processing plans, *PPlans*. Together with logical translation, this second translation increases the possibility to prepare for a number of resource usage options.

Fig. 3 shows example LPlans. In the example, running activity and spine posture are monitored. There are two LPlans for the 'running' context. *LPlan$_1$* utilizes acceleration data from a left wrist, extracts two frequency-domain features, DC and energy, and runs a decision tree classifier. On the other hand, *LPlan$_2$* utilizes acceleration data from a left thigh and a left wrist, extracts two time-domain statistical features, RMS (root mean square) and MAD (mean absolute deviation), and finally recognizes the context through a Naïve Bayes classifier. For the 'spine posture' context, there is an LPlan, *LPlan$_3$*.

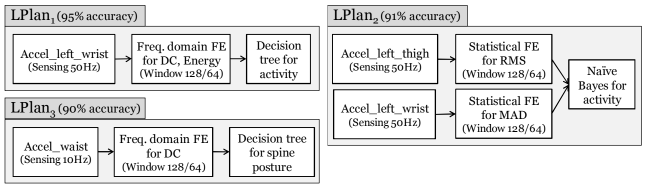

LPlan1 (95% accuracy)
Accel_left_wrist (Sensing 50Hz)
Freq. domain FE for DC, Energy (Window 128/64)
Decision tree for activity
LPlan3 (90% accuracy)
Accel_waist (Sensing 10Hz)
Freq. domain FE for DC (Window 128/64)
Decision tree for spine posture
LPlan2 (91% accuracy)
Accel_left_thigh (Sensing 50Hz)
Statistical FE for RMS (Window 128/64)
Accel_left_wrist (Sensing 50Hz)
Statistical FE for MAD (Window 128/64)
Naïve Bayes for activity

Figure 3. Examples of logical plans (LPlans).

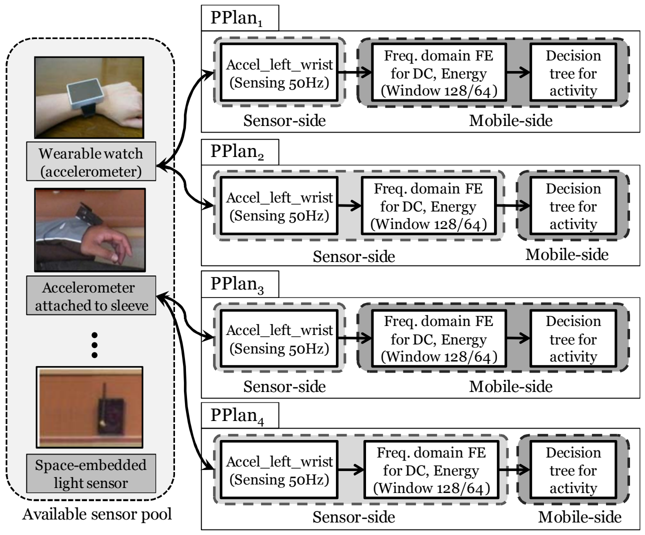

Wearable watch (accelerometer)
Accelerometer attached to sleeve
Space-embedded light sensor
Available sensor pool
PPlan1
PPlan2
PPlan3
PPlan4
Accel_left_wrist (Sensing 50Hz)
Freq. domain FE for DC, Energy (Window 128/64)
Decision tree for activity
Sensor-side
Mobile-side

Figure 4. Examples of physical plans (PPlans) for LPlan$_1$.

New LPlans can be easily incorporated in Orchestrator by specifying them with the relevant description and adding corresponding modules. The plan processor is designed to flexibly adopt and execute new modules, which will be required to support the new LPlans.

The plan generator dynamically performs the physical translation for available LPlans. It is necessary since available sensors and their resource status continuously change at runtime. When sensors are newly registered or deregistered, the plan generator updates available PPlans with the sensors. Orchestrator readjusts plan execution with the updated PPlans.

To increase the number of available PPlans, the plan generator maximally exploits the possibility of diverse hardware resource mapping through a sensor mapping and a distribution mapping. The sensor mapping contributes to the diversity by examining different sensors that are eligible to serve adequate sensor data and processing modules for an LPlan. The distribution mapping exploits the different distributions of modules into sensors and a mobile device.

Fig. 4 shows example PPlans for LPlan$_1$. The plan generator is aware of two available sensors, a watch-embedded accelerometer and a sleeve-attached one on a left wrist. It makes four different PPlans. PPlan$_1$ and PPlan$_2$ use an accelerometer on the watch, while PPlan$_3$ and PPlan$_4$ use a sleeve-attached one. PPlan$_1$ and PPlan$_3$ perform the feature extraction in the mobile device. PPlan$_2$ and PPlan$_4$ do in the sensor. PPlans for *LPlan$_2$* and *LPlan$_3$* cannot be generated since there is no available sensor on the left thigh and waist.

B. Holistic Resource-aware Plan Selection

The key of the effective orchestration is to properly select PPlans to execute among diverse alternatives. Through the plan selection, Orchestrator resolves contentions and maximizes sharing in resource use of multiple applications, and thus, supports application requests maximally with highly limited computing resources. At the same time, Orchestrator meets a system-wide policy for resource use in system operation, e.g., minimizing the total energy consumption.

For clear description of the plan selection, we define the selection problem as follows. Given $C=\{c_i \mid c_i$ is a context to monitor$\}$ and $P=\{p_{i,j} \mid p_{i,j}$ is a j^{th} PPlan for a context $c_i\}$, the plan selector determines P_e, a subset of P to execute. Among all possible subsets, P_e should support the most number of queries under given resources constraints while the cost of P_e, *Cost*(P_e) is minimized. Here, the cost function, *Cost*(), describes a system policy that should be satisfied to achieve desired system operation.

Fig. 5 shows overall plan selection process. It consists of two major processing steps, i.e. (1) detection of maximal PPlan sets, and (2) selection of the minimum cost set.

In the first step, the plan selector detects the maximal PPlan sets, each of which supports maximum number of queries with available resources. To obtain the sets, the plan selector computes the number of supportable queries for every possible PPlan set, $P_s \in 2^P$, and selects the ones supporting maximum queries. The computation involves three sub-steps as in the Fig. 5. In the first sub-step, the resource demand to execute P_s is calculated. Basically, it is computed by aggregating the resource demand of each plan. In the calculation, the module sharing among multiple plans are importantly considered; if more than two PPlans in P_s execute the same processing modules in the same device, t he resource demand to execute the module is taken into account only once. In the second sub-step, it is examined if the resource demand of P_s exceeds the available amount of system resources. Through the process, it filters out the PPlan sets that violate resource constraints. The last sub-step calculates the number of supportable queries for the plan sets that pass the constraint check. Here, the accuracy conditions are also checked for the queries specified with minimum accuracy requirement. Finally, the plan selector selects the ones that support maximum number of queries.

In the second step, the plan selector determines the minimum cost set among the candidate maximal PPlan sets. It is likely that there often exist multiple maximal PPlan sets. This step calculates the cost corresponding to each set and selects the one with minimum cost. Here, diverse cost functions can be employed from the policy pool. Note that the module sharing is also considered in the cost calculation.

Orchestrator provides a couple of system primitives that abstract the resource demand of applications and the real-time resource availability of the system. First, a function, *GetRDMatrix*(P_s), provides the resource demand to execute a set of PPlans, P_s, in the form of a matrix. Second, *GetRAMatrix*() returns the list of available devices and status of their resources such as CPU, memory and energy as a matrix. Fig. 6 shows examples of *RDMatrix* and *RAMatrix*. Note that the system primitives facilitate the specification of cost functions for various policies. For example, the policy to minimize total energy consumption can be easily specified as shown in Fig. 7.

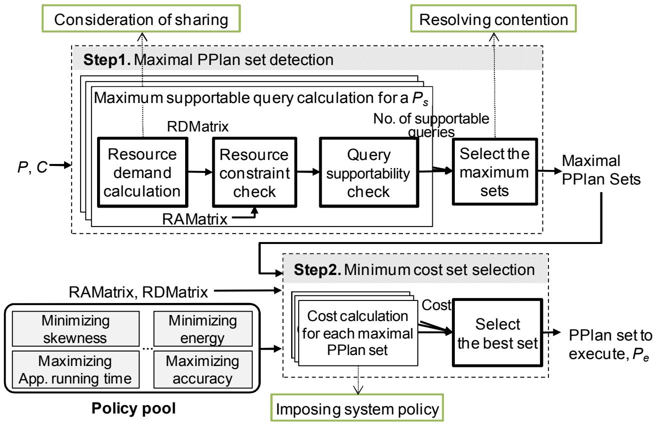
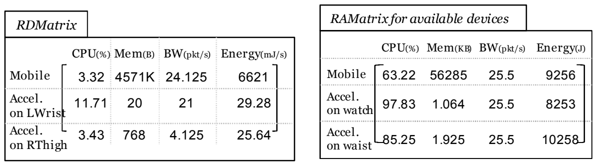

Consideration of sharing
Resolving contention
Step1. Maximal PPlan set detection
Maximum supportable query calculation for a P_s
RDMatrix
No. of supportable queries
P, C
Resource demand calculation
Resource constraint check
Query supportability check
Select the maximum sets
Maximal PPlan Sets
RAMatrix
Step2. Minimum cost set selection
RAMatrix, RDMatrix
Minimizing skewness
Minimizing energy
Maximizing App. running time
Maximizing accuracy
...
Policy pool
Cost calculation for each maximal PPlan set
Cost
Select the best set
PPlan set to execute, P_e
Imposing system policy

Figure 5. Plan selection process.



RDMatrix

	CPU(%)	Mem(B)	BW(pkt/s)	Energy(mJ/s)
Mobile	3.32	4571K	24.125	6621
Accel. on LWrist	11.71	20	21	29.28
Accel. on RThigh	3.43	768	4.125	25.64

RAMatrix for available devices

	CPU(%)	Mem(KB)	BW(pkt/s)	Energy(J)
Mobile	63.22	56285	25.5	9256
Accel. on watch	97.83	1.064	25.5	8253
Accel. on waist	85.25	1.925	25.5	10258

Figure 6. Examples of RDMatrix and RAMatrix.

```
Function: Cost(Ps)
Input: Ps, a candidate maximal plan set
Output: cost of Ps

1. RDMatrix ← GetRDMatrix(Ps)
2. totalEnergyConsumption ← 0
3. for ∀d_j where d_j is a device in RDMatrix
       totalEnergyConsumption ← totalEnergyConsumption +
               RDMatrix(d_j, ENERGY))
4. Return totalEnergyConsumption
```

Figure 7. A cost function to minimize total engergy consumption

C. Dynamic Plan Adaptation

Orchestrator adapts to changes in resource availability and application requests at runtime by continuously altering P_e, a set of PPlans to execute. The adaptation enables Orchestrator to support application requests seamlessly, to resolve newly occurring resource contentions, and to best meet the system policy continuously.

Orchestrator performs the plan selection process again when there are changes in a set of contexts to monitor, C, or in the set of corresponding PPlans, P. This is because the changes in C or P could disqualify the previously selected PPlan set from the best choice for execution. Also, changes in resource status could trigger the selection process regardless of changes in C or P. For example, the energy drain of devices periodically triggers the process when

TABLE I. ADAPTATION EVENT

Event	Inputs (C_{new}, P_{new}) for plan reselection
Registration of a query (regarding a context c_n)	$C_{new} = C_{old} \cup \{c_n\}$ $P_{new} = P_{old} \cup \{p_{n,j} \mid p_{n,j}$ is a jth PPlan for $c_n\}$
Deregistration of a query (regarding a context, c_d)	$C_{new} = C_{old} - \{c_d\}$ $P_{new} = P_{old} - \{p_{d,j} \mid p_{d,j}$ is a jth PPlan for $c_d\}$
Join of a sensor (s_n)	$P_{new} = P_{old} \cup \{p_{i,j} \mid p_{i,j}$ is a new jth PPlan for a context, c_i, enabled by the new sensor, $s_n\}$
Leave of a sensor (s_d)	$P_{new} = P_{old} - \{p_{i,j} \mid p_{i,j}$ is jth PPlan for a context, c_i, that utilizes the leaved sensor, $s_d\}$
Resource status changes, e.g., energy drain of devices	No changes in C and P

Orchestrator applies a policy to minimize skewness among remaining energy of devices.

Five types of events trigger the selection process of Orchestrator. When an event occurs, Orchestrator performs the plan selection described in Section IV.B with new inputs, C_{new} and P_{new}, changed by the event. Table I summarizes the event types and corresponding changes in the inputs of the plan selection. First, upon a registration of a query regarding a new context, c_n, the selection process is performed by adding c_n to C and corresponding PPlans to P. Deregistration of a context is handled similarly as shown in Table I. Second, the join or leave of a sensor triggers the selection process as it changes the available PPlan set, P; some queries might be newly supportable with the new PPlans, and other queries may not be supported anymore with old PPlans. Upon a join of a new sensor, the newly available PPlans are inserted in P and the plan selection is executed. On the other hand, upon a leave of a sensor, the PPlans enabled by the sensor are removed from P. Finally, in case of events by resource status changes, Orchestrator just reselects the PPlans with previous P and C once again.

For efficient adaptation, Orchestrator also adopts an incremental plan selection method. When there are a number of contexts to monitor and corresponding PPlans, it might be costly to reselect the whole P_e upon every event and redeploy new processing modules. To address the issue, the plan selector employs an incremental selection method as an effective heuristic solution. When the heuristic solution is used, Orchestrator periodically performs global selection to avoid errors that might accumulate due to repeated incremental selection.

The heuristic finds subset of contexts, $C_{sub} \subset C$, and corresponding PPlans, $P_{sub} \subset P$ that are directly affected by the triggering events. Then, it locally applies the selection process only for the subset. The selection is performed as follows upon each event. First, upon a query registration, Orchestrator performs the selection with only the requested context and corresponding PPlans. If the context has been already monitored, the executed PPlan is shared. Upon the query deregistration, Orchestrator simply stops executing the processing modules of the corresponding PPlans unless the modules are shared to support other queries; it does not perform plan selection again. Third, upon the sensor join, Orchestrator first generates new PPlans utilizing the sensor. In case that the new PPlans enable some of the queries that cannot be processed with the previously generated plans, Orchestrator executes the new PPlans. Also, if the new PPlans are more cost-effective than the currently executed PPlans, the new PPlans replace the current ones. Finally, when a sensor leaves, some of the running PPlans may be disabled. In this case, Orchestrator finds new PPlans for the affected queries and replaces the currently executing plans with new ones.

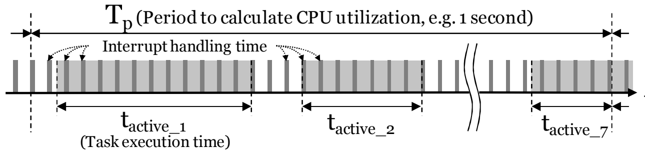


Figure 8. Example of CPU utilization.

D. Resource Detection, Monitoring and Demand Profiling

Orchestrator continuously updates RAMatrix and builds RDMatrix for resources orchestration. As a base to update RAMatrix, Orchestrator identifies sensors that become newly available or unavailable. Then, it updates RAMatrix by monitoring resource availability of the detected sensors and a mobile device in real-time. RDMatrix is generated through the off-line profiling. The following briefly describes the main ideas and methods implemented in Orchestrator.

Dynamic Sensor Detection Protocol: The protocol enables Orchestrator to dynamically detect available sensors in real-time. It is designed with a sensor-initiated approach, which achieves a high level of energy efficiency for energy-constrained sensors. The sensors need to turn on their radio transceivers only for a short period of time in order to send a heartbeat message and wait for corresponding ACK messages. We omit the protocol details.

Resource Status Monitoring: Resource monitors continuously track the availability of energy, CPU, memory, and bandwidth. For a mobile device, Orchestrator simply utilizes the resource information provided by resource monitoring tools in operating systems. For sensors, we develop our own monitors targeting MicaZ Motes.

For energy monitoring of sensors, Orchestrator adopts a voltage-based method [8]. It estimates remaining energy from voltage readings based on pre-built voltage-energy translation maps.

The CPU cycle is mostly occupied by two major operations: executing assigned tasks and handling timer interrupts for sensing, storing and transmission (See Fig. 8). Among them, the CPU monitor only considers the CPU cycle for task execution. More specifically, the monitor measures CPU utilization as ($\sum t_{active\_i} / T_p$). To measure t_{active_i}, we record timestamps right before and after a task execution.

The available memory size, M_{av}, is obtained as $M_{max} - \sum_i M_{used}(task_i)$, where M_{max} is the maximum available memory and $M_{used}(task_i)$ is memory used for a $task_i$. $\sum_i M_{used}(task_i)$ is computed as $\sum_i (M_F(task_i)) + Max(M_T(task_i))$, where $M_F(task_i)$ and $M_T(task_i)$ denote the size of *Fixed* and *Temporary Space* for a $task_i$, respectively. *Fixed Space* is continuously occupied by a task to store sensor readings and some internal states until the task is deregistered. *Temporary Space* is

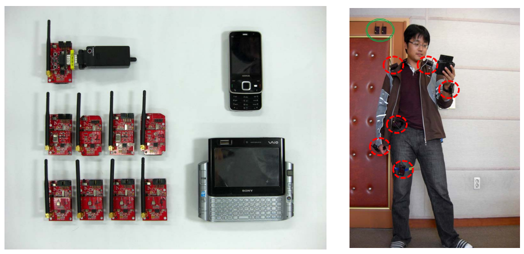


Figure 9. Hardware setup.

Sensor	Sensor location (sensor ID)	Sampling rate	Feature	Feature generation rate	Context type (# of possible values)	Context value examples
Four 2-axis accelerometer	Right(3) wrist, Right thigh(4), Left wrist(5), Waist (6)	50Hz x 8	DC, Energy, RMS, MAD, Percentile	0.78Hz x 8	Activity (4)	Run, Sit, Walk, Stand
Two light Sensors	Body(2), Space(102)	0.78Hz x 2	Illumination	0.78Hz x 2	Light (7)	Dark, Bright
Two temperature Sensors	Body(1), Space(101)	0.78Hz x 2	Temperature	0.78Hz x 2	Temperature(8)	Cool, Hot
Two humidity sensors	Body(1), Space(101)	0.78Hz x 2	Humidity	0.78Hz x 2	Humidity (6)	Dry, Humid

Figure 10. Sensor, feature, context profile used in the prototype.

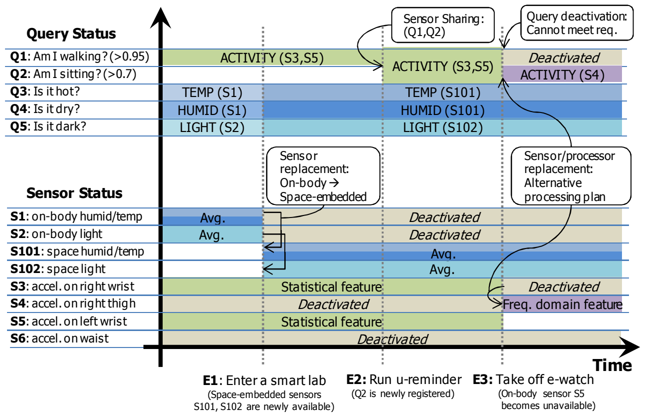


Figure 11. A short part of processing log.

allocated and used temporarily only when the task is scheduled to run.

Wireless network bandwidth is a shared resource for all sensors and a mobile device. The available bandwidth for all devices is measured and managed in the mobile device. An available bandwidth, B_{av} is measured as $B_{max} - B_{used}$, where B_{max} is the maximum available bandwidth and B_{used} is the bandwidth being currently utilized.

Resource Demand Profiling: We collect resource demand profiles of processing modules used for PPlans before runtime. The total demand is calculated by adding up the demands of all relevant modules to the baseline resource demand.

V. Implementation

We have implemented the Orchestrator architecture as a prototype system. First, we implemented the architecture of a mobile device in two platforms: (1) standard C/C++ over Linux, (2) Open C/C++ over S60 SDK and Symbian OS. Their total lines are about 13,000. Second, the sensor architecture is implemented in NesC on top of TinyOS 1.1.11. The total lines are about 2,300.

We deployed the prototype system on various types of mobile devices and sensors. Fig. 9 shows a snapshot of currently used hardware. First, we have deployed the prototype on two different mobile devices, (1) Ultra Mobile PC (UMPC), SONY VAIO UX27LN with Intel® U1500 1.33 GHz CPU and 1GB RAM, and (2) a smart phone, Nokia N96 with Dual ARM9 264MHz processor and 128MB RAM. Second, we have incorporated various wireless sensors that have been widely adopted for context-aware applications (See Fig. 10 for sensor details). Considering the wearability and controllability, we mainly use eight of USS-2400 sensor nodes (MicaZ clone), i.e., four 2-axis accelerometers, two light, and two temperature/humidity sensors. They are equipped with Atmega 128L MCU, CC2420 RF transceiver supporting 2.4GHz band ZigBee protocol, and TinyOS as an operating system. To provide communication between the mobile device and sensors, we attach one base sensor node to the mobile device. The node receives sensor data from other sensor nodes and forwards the data to a mobile device. Also, it transmits control messages to the sensor nodes on behalf of the mobile device.

Currently, the plan processor in the mobile-side architecture includes eight feature extraction modules (See Fig. 10 for feature details). We used kiss_fft [26], a Fast Fourier Transform library, to derive frequency-domain features. It also provides a recognition module implementing a decision tree algorithm. To generate diverse plans to monitor activity contexts, we combine diverse feature and sensor sets. As feature sets, we use frequency-domain features (e.g., DC, Energy) and time-domain statistical features (e.g., RMS, PRC, MAD). For sensor sets, we use all combinations of sensors on the left wrist, right wrist, right thigh, and waist. We trained the activity contexts via annotation-based learning [20]. The learning was done with C4.5 decision tree by Weka, a Java-based open source machine learning tool [22]. We implemented feature extractors on sensor nodes to offload feature extraction tasks. We used a highly optimized avr-fft library which is written in an assembly language for FFT computation on sensors.

A. Example Scenario and Operation of Orchestrator

We test and inspect the operations of Orchestrator under real situation. A student in our lab carried the UMPC and 6 sensors running an Orchestrator prototype while entering /leaving smart spaces or wearing/taking off wearable sensors on campus for 2 hours. Fig. 11 shows a short part of the processing log in his Orchestrator, describing query and sensor status according to changes in application requests and sensors. At 2:30 p.m., 6 sensors and 4 queries were registered. During 8 minutes, three events occurred; two sensor changes (E1 and E3) and an application request change (E2). Accordingly, processing plans were adaptively changed. For example, at 2:33 p.m., he entered a smart lab. Then, a processing plan using on-body sensors replaced the plan using space-embedded sensors for energy optimization.

VI. Evaluation

A. Experimental Setup

We demonstrate the effectiveness of Orchestrator under dynamic changes in resources and application requests. For

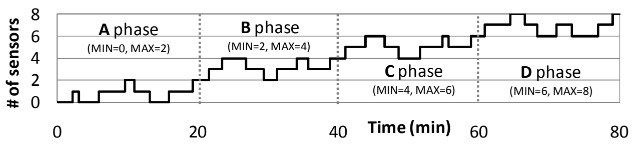


Figure 12. Dynamic sensor avaialblity.

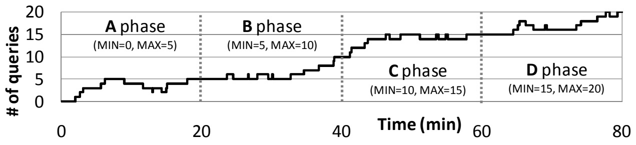


Figure 13. Dynamic query workload.

TABLE II. QUERY MODEL

Parameter	Default value
# of queries	20
# of context types per query	1
Distribution of context type	Activity (50%), Other Contexts (50%)
Distribution of context value	Uniform distribution
Distribution of Accuracy (only for activity)	Uniform distribution (min and max from training data)

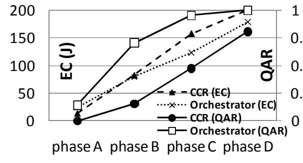
the experiments, we used the UMPC and the eight USS-2400 sensor nodes described in Section V.

Sensor availability: To make the environment dynamic for experiments, we continuously vary the number of available sensors as shown in Fig. 12. For the total 80min period, we randomly add or delete a sensor every 2.5 min in average among 8 sensors. To examine the effect of number of available sensors, we divide the total time into four 20 min phases such that each phase predefines different MIN/MAX sensor numbers. Note that sensor composition is diverse even with the same number of sensors.

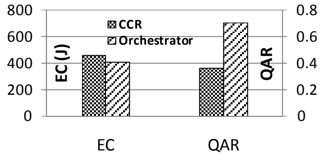
Query workloads: We also generate a dynamic query workload as shown in Fig. 13. We add or delete a query every 1.5 min in average. Also, we set the MIN/MAX numbers of queries for each phase. Note that the queries are generated by carefully reflecting our previous example scenario. Table II summarizes the parameters and default values used for the query generation.

Alternatives: We compare Orchestrator with Conventional Context Recognizer (CCR) which models existing context-aware systems [23] lacking of resource orchestration functionalities. CCR supports a query with a single and fixed recognition method that provides the best recognition accuracy with designated devices. All employed sensors are always turned on and send raw data. A mobile device extracts features from the sensor data and runs recognition modules. Note that CCR does not utilize newly joined sensors nor deals with sensor leaves. For Orchestrator, we use the orchestration policy that minimizes the total energy consumption of available sensors as a default policy.

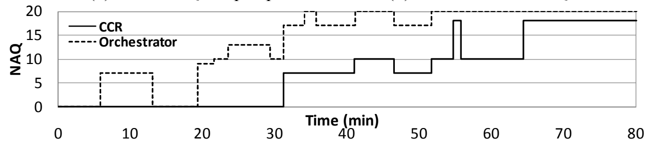
Metrics: We measure the effectiveness of Orchestrator in terms of application support and resource utilization. First, we measure the level of application support through *query activation*. We regard that a query is activated if a processing plan exists for the query and is executed with available resources. To quantify the query activation, we use Number of Activated Queries (NAQ) and Query Activation Ratio (QAR). QAR is formally defined as follows.



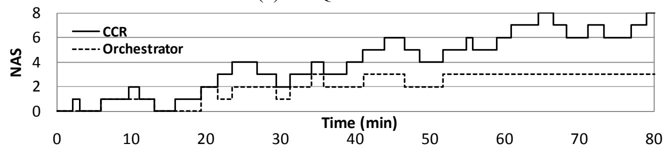
(a) EC and QAR per phase



(b) Overall EC and QAR



(c) NAQ over time



(d) NAS over time

Figure 14. Orchestration under dynamic sensor availablity.

$$QAR = \frac{\sum T_A(q_i)}{\sum T_R(q_i)}, \quad q_i \text{ is an } i^{th} \text{ query in a registered query set}, Q$$

$$T_A(q_i): \text{total activation time of } q_i$$

$$T_R(q_i): \text{total registration time of } q_i$$

As the metrics for resource utilization, we use Number of Activated Sensors (NAS) and the Energy Consumption (EC) of sensors in Joule (J). We regard that an *available sensor is activated* if the sensor executes certain tasks comprising any PPlan. In CCR, all available sensors are considered to be activated since CCR does not control the sensors. In general, higher NAS over time results in higher EC since the number of activated sensors is the dominant factor of energy consumption.

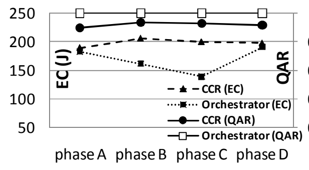
B. *Resource Orchestration under Dynamic Environments*

1) *Dynamic Sensor Availablity*

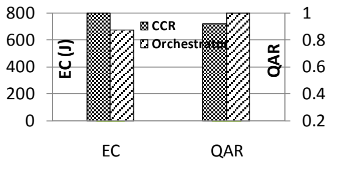
In this section, we evaluate Orchestrator under the dynamic sensor availability. The number of queries is fixed at 20.

Fig. 14 (a) shows QAR and EC per phase where more sensors are available as phase changes from A to D. In the graph, we can observe the key characteristics of Orchestrator. Under phase A and B where available sensors are scarce, Orchestrator activates more queries than CCR, while consuming almost the same amount of energy. It demonstrates that Orchestrator coordinates resource use well to support applications under resource-scarce environments. In contrast, under phase C and D where available sensors are plentiful, Orchestrator concentrates on energy optimization since the QAR of Orchestrator is already saturated to the maximum, 1. It shows that Orchestrator coordinates resource use well to maximize utilization under resource-abundant environments.

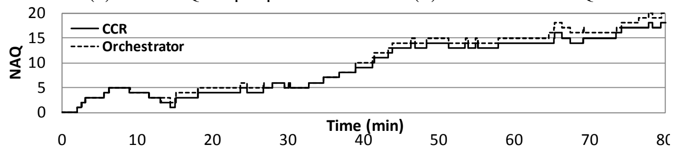
Fig. 14 (b) shows QAR and EC for total experiment time. To sum up, Orchestrator achieves better QAR (95% improvement) and less EC (10.7% reduction) than CCR. Fig. 14 (c) and (d) show NAQ and NAS over time, respectively. Most importantly, the NAQ of Orchestrator is always much higher than that of CCR, resulting in higher QAR. This is



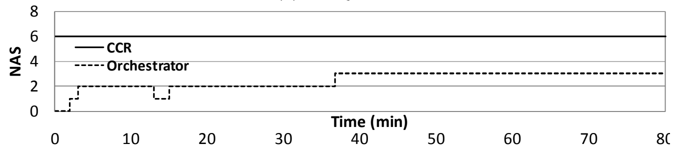
(a) EC and QAR per phase



(b) Overall EC and QAR



(c) NAQ over time



(d) NAS over time

Figure 15. Orchestration under dynamic query workload.

because Orchestrator prepares for and utilizes diverse PPlans such that it is highly likely to support application requests with diverse combinations of sensors. Also, the NAS of Orchestrator is lower than that of CCR. Orchestrator selects PPlans in a way to minimize the number of activated sensors applying the energy optimization policy. Specifically, we found that Orchestrator selects PPlans that run feature extraction tasks in sensors rather than those that send only raw data from sensors. Thus, sensor-based feature extraction significantly reduces the overall communication cost, which in turn reduces energy consumption.

2) Dynamic Query Workload

We examine the behavior of Orchestrator using the dynamic query workload. The number of sensors is fixed at 6 excluding the space-embedded sensors, S101 and S102.

Fig. 15 (a) shows EC and QAR per phase where more sensors are available as phase changes from A to D. Since sensor resources are abundant in all phases, the QAR of both Orchestrator and CCR are saturated to the maximum, 1. Meanwhile, the ECs of Orchestrator and CCR are kept high, i.e., about 200J. We look into EC per sensor, and discover that sensor 4 consumes more energy than other sensors. In our experimental setting, sensor 3, 4, 5, and 6 are accelerometers for activity recognition. Based on energy minimizing policy, Orchestrator tried to utilize sensor 4 rather than all sensors together since the accuracy requirements of most activity queries are satisfied only with sensor 4; sensor 4 is placed on the right thigh which is known as the most suitable position for recognizing activities such as running, walking, and standing [20].

Fig. 15 (b) shows EC and QAR for total experiment time. Orchestrator achieves better EC (15% reduction) along with slightly better QAR (8.5% improvement) than CCR. Also, Fig. 15 (c) and (d) show NAQ and NAS over time in detail. The NAQ of CCR is slightly lower than that of Orchestrator in most of time. Although the number of sensors is sufficient to activate all registered queries, some queries are deactivated in CCR. This is because it utilizes only a single

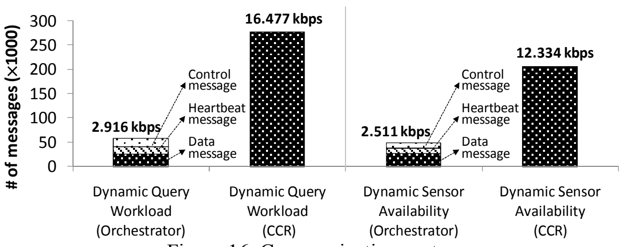


Figure 16. Communication costs.

recognition method. Thus, it does not meet the accuracy requirements of some queries. More important, the NAS of Orchestrator is always lower than that of CCR. This is because all available sensors are activated in CCR whereas Orchestrator selectively utilizes the sensors. It results in lower energy consumption, and better resource utilization eventually.

3) Orchestration Cost

We examine orchestration cost under the dynamic sensor and query workloads in terms of communication and memory cost.

First, we measure the number of messages exchanged during the total experiment time. To investigate the communication cost, we classify the messages into three types: control messages, heartbeat messages including sensor status information, and data reporting messages. Fig. 16 shows the number of messages for each message type. In Orchestrator, the control and heartbeat messages are additionally exchanged for active resource use orchestration, thereby incurring a slight communication cost, e.g., about 1.5 kbps for the dynamic query case. However, Orchestrator significantly reduces the number of data messages at the cost of those messages. Compared to CCR, it is decreased up to 10 times. Note that the number of control and heartbeat messages is controllable by configuring the heartbeat period.

Also, we measure the memory size consumed at runtime, which is averaged over time. The average memory sizes in the mobile device are 59.6KB under the dynamic sensor availability and 56.2KB under the dynamic query workload, respectively. The processing planner, a core component for orchestration in the mobile device, consumes 31.5KB and 30.6KB, respectively. Considering the memory capacity of the mobile device, they are negligible. In addition, each sensor consumes 276B of memory to maintain data structures storing executed tasks. The average sizes used in sensors vary from 278B to 769B depending on sensor type; the plan processor uses 512B in accelerometers and 4B in other sensors to buffer sensor data. Note that those values vary depending on executed tasks and runtime parameters such as window size. Considering the memory capacity of MicaZ, 4KB, and the memory taken by TinyOS, 329B, Orchestrator can offload multiple tasks such as feature extraction onto sensors.

C. Effects of Resource Orchestration Policies

We determine if Orchestrator can properly apply multiple orchestration policies. We consider two sample policies: (1) minimizing the total energy consumption of available sensors and (2) maximizing the average accuracy of registered queries. For the experiment, we use the dynamic query workload and fix the number of sensors to 6. Then, we measure the NAS and the average accuracy of activated queries over time for the two policies, respectively. We only consider the queries with activity contexts for accuracy measurement.

From the experiment, we could see Orchestrator supports the two policies well. We could observe that the NAS of the first policy is much lower than that of the second during the whole experiment time. Accordingly, the energy consumption is lower with the first policy, which shows the desired operation of Orchestrator. On the other hand, higher accuracy is achieved when the second policy is used, i.e., about 4% increases in average.

VII. Conclusion

In this paper, we described Orchestrator, a novel resource orchestration framework to support mobile context monitoring in a PAN-scale sensor-rich mobile platform. Orchestrator enables the platform to host multiple applications stably, exploiting its full resource capacity in a holistic manner. Thus, applications can provide users with seamless, long-running high-quality service under dynamic circumstances with limited resources. We present the design and implementation of Orchestrator running on off-the-shelf mobile devices and sensor motes, and also show its effectiveness in various system environments.

Acknowledgment

We thank our shepherd, David J. Yates, and the anonymous reviewers for their valuable comments to improve the quality of this paper. This work was partially supported by Defense Acquisition Program Administration and Agency for Defense Development, Korea under the contract.

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