Online Training Machine Learning based Runtime Decision Maker for Mobile Offloading Framework

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***Abstract*—OpenCL has emerged as the open standard for parallel programming for heterogeneous platforms enabling a uniform framework to discover, program, and distribute parallel workloads to the diverse set of compute units in the hardware. For that reason, there have been efforts exploring the advantages of parallelism from the OpenCL framework by offloading GPGPU workloads within an HPC cluster environment. In this paper, we present an OpenCL-based remote offloading framework designed for mobile platforms by shifting the motivation and advantages of using the OpenCL framework for the HPC cluster environment into mobile cloud computing where OpenCL workloads can be exported from a mobile node to the cloud. Furthermore, our offloading framework handles service discovery, access control, and data privacy by building the framework on top of a social peer-to-peer virtual private network, SocialVPN. We developed a prototype implementation and deployed it into local- and wide-area environments to evaluate the performance improvement and energy implications of the proposed offloading framework. Our results show that, depending on the complexity of the workload and the amount of data transfer, the proposed architecture can achieve more energy efficient performance by offloading than executing locally.**

***Keywords*-Mobile device, OpenCL, heterogeneity, parallelism, virtual private networks, energy consumption**

I. Introduction

Over the last decade, remote offloading techniques have emerged as intelligent means to overcome the constraints of the limited resouces from mobile platforms, smartphones and tabletPCs, so that these types of devices delegate computationally intensive computing tasks to more powerful external resources such as personal workstations or cloud servers. Initially, most of research interests on remote offloading techniques have focused on core mechanisms in which *what to offload* and *how to offload* have been primarily considered. The reseach community has studied various approaches to offload mobile computations such as application partitioning [1]–[3], thread migration [4], [5], and application migration [6].

However, benefits from offloading computation-intensive portions of mobile applications can be influenced by various internal and external factors such as application requirements, network condition, and computing capabilities of mobile or external devices. Thus, *whether to offload or execute locally* needs to be decided constantly by considering and monitoring abovementioned fynamic features on runtime. Otherwise, incorrect offloading decision may cause the performance degradation or worse energy consumption. For that reason, research focuses have been naturally shifted into dynamic scheduling or decision making problems for mobile offloading framework. For example, Kwon et al. [**?**] consider a simple rule-based decision maker in which the framework decides to offload the mobile computation only when the data transfer size is greater than the certain threashold. MAUI [2] utilizes a linear regression model among predefined features to make offloading decision. Even though these studies on making offloading decision take dynamic features such as data transfer size or network conditions into account to make offloading decisions, it is impractical to generalize these efforts for various mobile use case scenario, since they utilized application-dependent decision making models. Therefore, in practice, it is essential for decision maker to learn from self-observation of the previous decision correctness and to dynamically adapt the decision policy on runtime so that it can be *generally* applied to various mobile applications.

In this paper, we aim to build an online framework to train

The rest of the paper is organized as follows. In Section II, we overview previous studies on offloading decision problems in mobile offloading frameworks, as well as the use of machine learning techniques for various scheduling problems. Section III discusses the challenges in online training machine learing runtime scheduler for mobile offloading framework. In Section IV and V, we explain and evalute our implementation of the online training ML scheduler. Also, Section VI describes the current and potential applications for our work. Finally, we conclude the paper in Section VII.

II. Motivation

In this section, we describe a scenario that motivates our approach. Figure 1 gives a general idea of one example deployment scenario. Alice connects her smartphone to a virtual private network (VPN) consisting of her laptop, Bob's desktop, and her virtual machine running on Amazon EC2. Since each of these devices is running SocialVPN [7], they automatically join the same virtual private network creating a pool of trusted resources in a Social Device Network. With this secure IP layer consisting of trusted peers, our framework is able to use IP multicasting over the VPN to discover nodes that are available for computation offloading. During the discovery process, our system records the characteristics of each node in the network such as bandwidth, latency, and processing capabilities. When an application decides to offload some computation, our framework dynamically determines the best node to use as the remote offloading target. In many cases, for example, if the bandwidth or remote processing capabilities are not adequate, our framework may decide to simply run the workload locally.

By linking to our library, the developer can transparently access remote resources available via the SocialVPN, including GPUs running on computing resources which is more powerful than a mobile device. For example, if the mobile device is connected to a virtual network consisting of an Amazon EC2 GPU instance, and the workstation of the mobile user, our extensions to the OpenCL framework will automatically select the best candidate based on available device capabilities and network conditions as the target compute node for remote execution. Also, the use of SocialVPN ensures that the computation is offloaded securely to socially trusted nodes. This enhancement occurs transparently to the developer and the user requiring only code recompilation. We perform various experiments in our analysis to demonstrate the feasibility of this integration.

The goal of our design is to provide an intuitive offloading framework that developers can integrate into their application using well-adopted programming concepts. We aim to extend the umbrella of heterogeneous computing to include devices beyond the physical host platform. Currently, many software developers utilize the OpenCL framework to exploit on-board heterogeneous platforms. Popular software projects, such as OpenCV and OpenSSL, are re-implementing major portions of their functions to run on the OpenCL platform [8]. Mobile SoC platforms, based on processors such as ARM and Intel, are also starting to provide OpenCL support on their architecture. The latest version of the OpenCL specification allows for devices beyond CPUs and GPUs to be accessed through the API. There is also an industry momentum building up behind OpenCL with the formation of new industry foundations to foster fast adoption [9]. These considerations point to OpenCL API as the emerging de facto standard for heterogeneous computing.

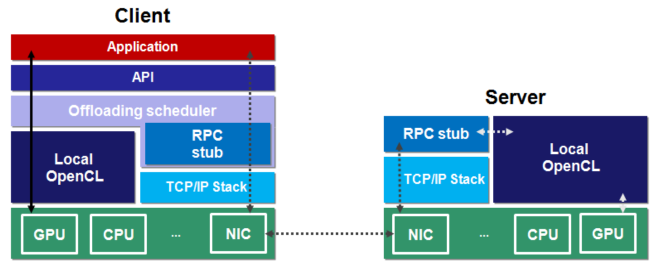


Figure 1. The overall system architecture.

III. Offloading Framework

Our overall architecture consists of five main modules: integration with the OpenCL API, RPC-based offloading mechanism, runtime scheduler, decentralized resource discovery feature, and trusted, private IP communication layer. The overall system architecture is shown in Figure 2.

A. Transparent OpenCL API Integration

Since OpenCL is an open standard currently supported by most of the major device manufacturers, we chose not to deviate from their API in order to minimize the learning curve for developers. Latest revisions of the OpenCL specification are extending the coverage to enable integration of a large pool of heterogeneous hardwares under the API. Because OpenCL is also a hardware level offloading framework, it provides various functions that we can leverage in our system. The OpenCL API possesses these set of features: device discovery and enumeration, device selection and customization, buffer management, job offload and status queries. With these features, the application developer has full control on the use of specific accelerators necessary to optimize their application performance. Here we explain how we extend each functionality to support remote offloading.

Discovery and Enumeration. In the initialization phase of the interface, the developer queries the platform for on-board OpenCL-capable accelerators. The OpenCL framework returns a list of accessible compute devices located on-board the device along with their capabilities (e.g. graphics cards, video decoders, cryptographic devices). We extend this portion of the API by allowing the developer to discover other OpenCL-enabled accelerators located on remote nodes over the network. Hence, when the developer performs this query on a mobile device, it may discover not just the mobile GPU but also another GPU running on the cloud, as long as they are part of the same virtual private network.

Selection and Configuration. In the standard OpenCL framework, once presented with a list of devices, the developer selects one or more targets for computation offloading. This selection is usually based on the characteristics of each particular device, (e.g. number of compute units of the accelerator, maximum number of work items, architecture, latency and so on). By extending the discovery process to include remote OpenCL devices over the network, this selection and configuration process can become cumbersome to the developer. Thus, our system can present just one virtual device handle which represents the best offloading node according to network conditions. Our analysis shows that bandwidth and latency have the most impact on the performance.

Workload State Transfer. Having selected a device, the next phase is the actual offloading of the data and code necessary to run remotely. The function to be executed (called a kernel) is first sent either as C99 source code or an LLVM-based intermediate language. Once transferred, the code is compiled for the target accelerator. In order to execute the kernel on the accelerator, the necessary state has to be transferred to the device regardless of whether it is local or remote. If the device resides on the host platform, the task of buffer management simply involves copying data from main memory to local storage accessible by the accelerator. However if the workload is being offloaded to a remote accelerator, then the buffers have to be managed slightly differently. First, the data has to be marshalled and copied into the networking stacks buffers then transported over the network to the appropriate remote host. The data is then copied from the remote hosts networking stack unto the accelerators own local storage. Upon completion, the output buffers are copied back from the GPUs local memory to the mobile devices memory over the network.

Resource and Failure Management. The final phase of the OpenCL API is the ability to discover errors and release its state and resources in a graceful manner. Each function has its error parameter which keeps the developer aware of the proper execution of the remote job. If an error occurs due to an issue with the source code, or the workload configuration, or any other hardware issues, an appropriate error code is returned to the developer. In return, the developer can release the various resources (e.g. buffers, device handles) that are associated with the job. Once again, we extend this functionality to support network failures as well. In case of a disconnection, the appropriate error code is returned to the developer who then performs the necessary actions to clean up the state belonging to the job. On the server, the necessary clean-up is taken as well by our framework. Our decision to utilize the OpenCL framework for computation offloading in mobile devices allows us to leverage all of the functionalities already in place for offloading computation locally from the CPU to an on-board hardware accelerator.

B. *RPC-based Computation Offloading*

In order to support offloading on the remote node, we create an RPC-based service which handles offloading requests received over the virtual private network. In our first attempt, we utilized SunRPC to provide the remote procedure calling interface, serialization, and networking capabilities. However, SunRPC provides many extra features that were not necessarily efficient (for example, the use of a portmapper daemon to discover the listening port of the RPC service). SunRPC also initiates a new TCP connection for each function call which incurs extra delay and poorer network performance. In contrast, our design uses a single TCP connection per offloading job thus achieving lower latencies. By running an RPC service which exposes the OpenCL API over the network, we provide a computation offloading design that is lightweight in terms of argument serialization and buffer management. Other approaches [10] rely on more sophisticated communication primitives such as MPI which require extra processing and memory resulting in poor battery performance.

C. *Runtime Scheduling*

As previously mentioned, our enhanced OpenCL framework provides developers with a list of accelerators (both local and remote) to select as offload targets. However, some applications developers may not want to bother with the task of figuring out which devices would make a good candidate for local versus remote offloading. Our framework includes a simple scheduler that can use latency to determine dynamically if a workload should be offloaded or run locally. The default behavior is to offload the computation to the node with the lowest latency. This is an overly simplistic model which can be extended to consider various different properties. In the future, we plan on supporting a more complex set of conditions along with heuristics which optimizes for better battery performance. The scope of this paper is to differentiate which scenario is ideal for our offloading framework; our analysis provides a base to develop a more sophisticated scheduler moving forward.

D. *Decentralized Resource Discovery*

Current mobile offloading solutions rely on a centralized service to provide this resource discovery capability. A key differentiation of our approach is our decentralized IP multicast-based service discovery subsystem. Because we deploy our system on top of SocialVPN which enables IP-multicasting over the Internet, we are able to leverage existing LAN-based service discovery techniques. The discovery process works in the following manner: the client periodically polls the network for eligible offloading nodes by sending a UDP datagram to the multicast IP address. The SocialVPN router distributes the IP packet to every node in the private network. The RPC-based service described earlier has a UDP listening thread that waits for service discovery request and responds to the request with its computing capabilities using the requests unicast IP address. The requester waits for a certain amount of time and accumulates all the replies that it receives within that time window. The requestor records their latency, bandwidth, and

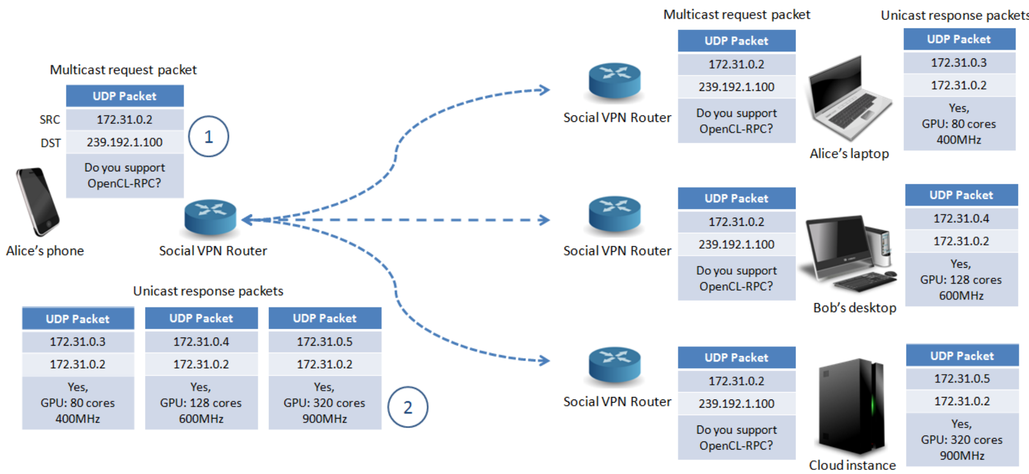


Figure 2. Decentralized multicast service discovery. 1) The mobile device sends on IP multicast packet to the SocialVPN software router running on the local device. The SocialVPN router forwards the multicast packet to each device in private network who are running the SocialVPN software router locally. 2) Each remote endpoint sends back a unicast UDP packet to the mobile device. Each response also contains the accelerator's computing capabilities. Our system records the latency and computing capabilities which allow the scheduler to determine the best offloading node.

processing capabilities and provides that to the scheduler. The scheduler then determines which node will provide the best performance and selects that node as the offloading candidate. Figure 3 depicts the decentralized multicast service discovery.

E. Trusted Communication via VPN

The virtual networking component addresses two key challenges of remote workload offloading – privacy and peer discovery – while supporting unmodified TCP/IP applications to offload computation to remote accelerators. In order to augment computing capabilities of the mobile platforms, it is important to find trusted nodes that are not just in the same local area network, but also geographically-dispersed peers, and to do so dynamically and transparently to the mobile application. SocialVPN ensures that peers anywhere on the Internet appear to be on the same virtual LAN and end-to-end encrypted peer-to-peer tunnels are abstracted as virtual IP links among peers. By leveraging SocialVPN as a trusted peer-to-peer messaging substrate, we are able to use the Berkeley sockets networking interface to offload our workload without any direct linking to SocialVPN itself. Most peer-to-peer systems require integration with a P2P library as well as a learning curve for learning its API. Because SocialVPN provides virtual private IP addresses to peers instead of P2P addresses, it supports unmodified applications.

IV. Evaluation

In this section, we evaluate the implementation of the OpenCL-based remote offloading framework for mobile platforms in terms of the performance improvement and energy consumption for mobile devices through real deployment over local- and wide-area environments. We first examine the overhead of adopting SocialVPN to the secure communication between the client and the server since SocialVPN utilizes its own encryption and IP tunneling. Then, we characterize the benefits and costs of our remote offloading framework through a series of experiments using various OpenCL workloads.

A. Experimental Setup

In order to evaluate our remote offloading framework under a variety of possible use case scenarios, we setup the experiment using various hardware and network configurations. First of all, our hardware setup consists of a client and three server types. For the mobile client, we utilized an Android tablet, Samsung GalaxyTab 10.1 equipped with 1GHz dual-core processor and 1GB RAM, and running Android 3.1. One of the servers is a workstation with an Intel 3.0 GHz Core2 Duo processor running Ubuntu 12.04 with 8GB RAM. Second server has same features as first server, but it is equipped with an Nvidia Geforce GT 640 GPU with 2GB RAM. Last configuration for the server is an Amazon EC2 GPU instance with 16 vCPUs, 22.5GB RAM, and two Nvidia Tesla GPUs running Ubuntu 12.04. We ran our experiments on the different networks: 1) a LAN within the lab with an average bandwidth of 6.5MB and 10ms latency, 2) the campus wireless network with an average bandwidth of 2.5MB and 15ms latency, 3) the Internet connection to Amazon EC2 with an average bandwidth of 0.17MB and 74ms latency.

We utilized OpenCL SDK code samples provided by AMD APP SDK [11] and Nvidia [12] as the offloaded workloads to measure the efficacy and the cost of our remote offloading framework. We selected four workloads each with different characteristics. *Sobelfilter* is an image

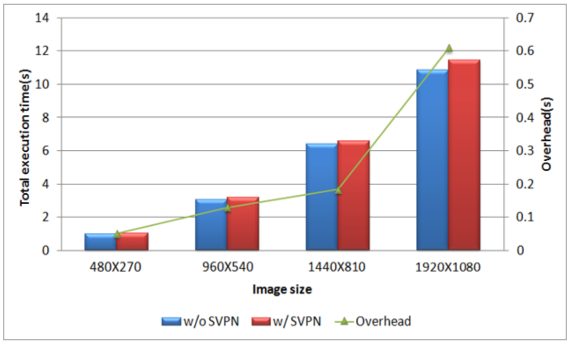


Figure 3. Execution time with and without SocialVPN.

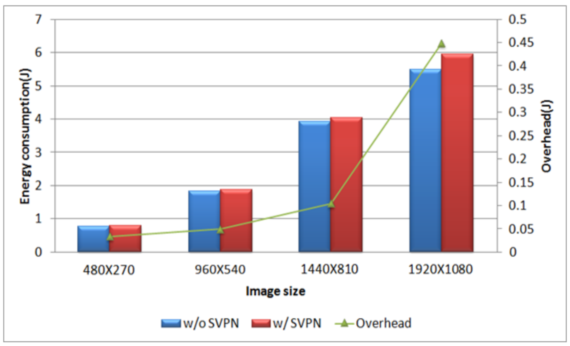


Figure 4. Energy consumption with and without SocialVPN.

processing workload for edge detection, we classify it as a high state transfer and low computation workload. The second workload is an *Hidden-Markov* model workload, a popular statistical tools for modeling sequences as well as machine learning; this represents a low state transfer and high computation workload. We also tested a *matrix multiplication* as one of the workloads because it is a common operation for scientific computing. Finally, an *N-body Physics* workload which is a common mathematical simulation method for modeling astronomical objects; this is considered a high state transfer and high computation workload. These workloads provide some insight into which use cases best fit our mobile cloud offloading scenario through our OpenCL-based offloading framework.

B. Overhead of SocialVPN

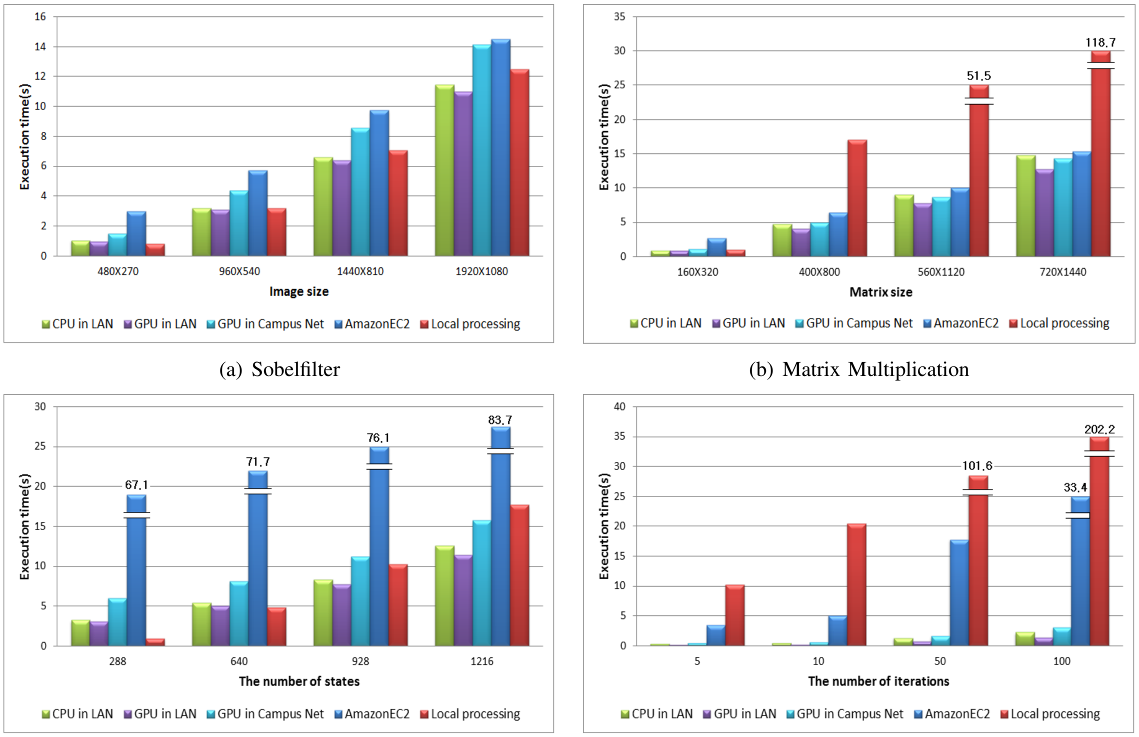
In our remote offloading framework, SocialVPN enables mobile devices and remote resources to securely communicate which incurs some overhead due to encryption and tunneling. In this section, we investigate the overhead of SocialVPN with respect to the performance and energy consumption. In order to measure the overhead of SocalVPN, we have conducted the LAN experiments in which the client offloads an OpenCL workload (Sobelfilter) to the server both with and without SocialVPN. As shown in Figure 4 and 5, as the image size increases, the execution time and energy consumption also increase. In the case of 480×270 of image, for instance, offloading with SocialVPN takes 0.05 seconds more than without SocialVPN while it takes 0.6s more to offload 1920×1080 image which means that the overhead ranges from 2.8% to 5.6%. In Figure 5, we also observed the overhead ranging from 2.6% to 8.1% in terms of energy consumption.

C. Performance and Energy Consumption Analysis

As mentioned above, we have utilized three types of servers for the different servers computing capabilities: CPU only-installed server, GPU-installed server and Amazon EC2 GPU cluster instance. For various network configurations, we used a local area network in which the client and the server directly connect via a wireless router, and a wide area network using campus network and traffic shaping. For Sobelfilter and matrix multiplication, we varied the image and matrix sizes to measure the impact of the amount of data transfer and computation. Also, Sobelfilter and matrix multiplication require 7 and 8 of one-time argument setups through the API called *clSetKernelArgs* which causes additional overhead to setup the extra arguments for kernel executions, respectively. For hidden Markov model, the different number of states is used to vary the size of input; however, the kernel execution is repeated 100 times each requiring 10 of argument setup calls (i.e. total 1000 of argument setup calls) which make the hidden Markov model workload most communication-intensive. In contrast with other workloads, however, N-body physics varies the number of the iterations that the kernel is executed on the server with a same data set processed for each iteration. Thus, regardless of the number of iterations, the size of input and output data is identical, but as the number of iterations increases, the number of argument setup calls proportionally increases.

Performance. We observed a few cases where offloading is faster than local processing for Sobelfilter as shown Figure 6(a). For image sizes with dimensions 1440×810 and 1920×1080, OpenCL-based offloading in a LAN environment has better performance than local processing, since the server has relatively low latency to the mobile client, and more powerful computing capabilities. On the other hand, when the workload is offloaded over the wide-area to Amazon EC2 GPU VM instance, the total execution time takes longer than local processing. In the wide-area scenario, the low bandwidth and high latency adversely impacts the execution for a low computation workload such as Sobelfilter. For smaller image sizes, however, 480×270 and 960×540, local processing is always faster than offloading because the small gain from offloading to more powerful compute node is easily offset by the data transfer overhead.

For matrix multiplication, in all the cases except for 160×320 of matrix size, it is evident that offloading is much faster than local processing showing the speed-up which ranges from 1.2X to 9.2X in Figure 6(b). In fact, the computation for matrix multiplication has higher complexity



(a) Sobelfilter

(b) Matrix Multiplication

(c) Hidden Markov Model

(d) N-body Physics

Figure 5. Execution time with various server setup

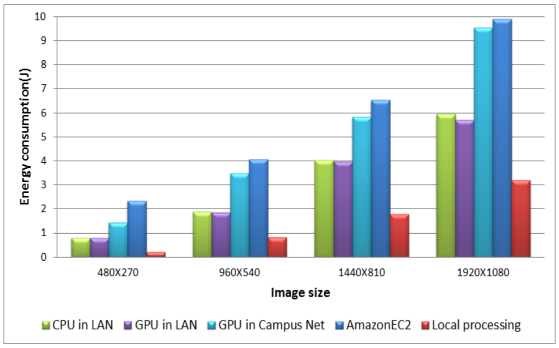
than Sobelfilter (the computation complexity for matrix multiplication is $O(n^3)$ while Sobelfilter is $O(n^2)$), which means that matrix multiplication is able to gain more from offloading to the remote server. Similarly as in the case of the small image size (i.e. 480×270) for Sobelfilter, offloading the small size of matrix multiplication (i.e. 160×320) is slower than local processing.

Interestingly, in the case of hidden Markov model in Figure 6(c), the worst performance is shown when the workload is offloaded to Amazon EC2. In order to execute hidden Markov model, the kernel is repeatedly executed requiring additional communication for each iteration. Consequently, offloading to Amazon EC2, which has the highest latency among our experimental setup, takes the longest time. In addition, N-body physics structured with the same programflow as hidden Markov model presents the similar pattern of the performance. Offloading to Amazon EC2 has worse performance than offloading to other server due to the high latency between the client and the server, but faster than local processing which means that it is still more beneficial to offloading to Amazon EC2 than local processing if no local peer is available.

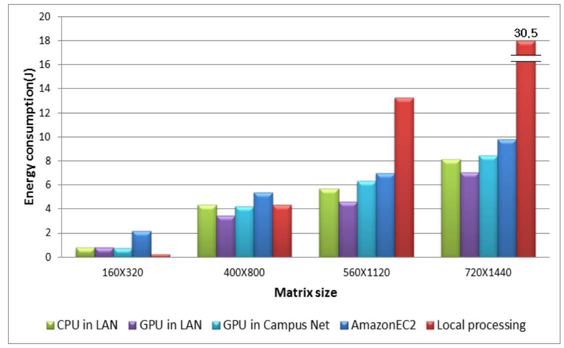
Energy Consumption. To profile energy consumption of the mobile device we used PowerTutor [13] which is an application for the variants of Android devices that displays the power consumed by major components such as CPU, network interface, LCD display, and GPS receiver. Every experiment is repeated 5 times and the results presented in the paper are the averaged values. Note that even though some cases for Sobelfilter showed the benefits from offloading in terms of the total execution time, offloading consumes more energy than local processing as shown in Figure 7(a). This different result comes from the discrepancy in the amount of power consumed by CPU and the Wi-Fi networking card. According to our measurement data profiled by PowerTutor, while CPU consumes 200∼220mW per second in active mode, the Wi-Fi networking card consumes about 710∼720mW per second in high power mode. For that reason, it is possible that offloading consumes more energy than local processing, even though offloading is faster than local processing. However, in matrix multiplication and N-body physics which result in high speed-up by offloading, it is also observed that offloading also saves energy consumption as shown in Figure 7(b) and (d).

V. Related Works

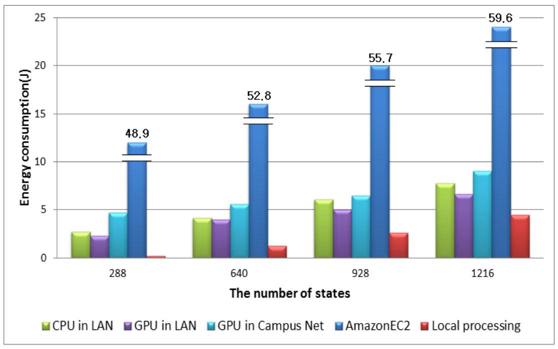
The research community has been investigating different methods to offload computation for decades; however, remote execution to the cloud has created new opportunities to explore novel offloading solutions. In this section, we discuss the most recent proposals for mobile computation offloading.



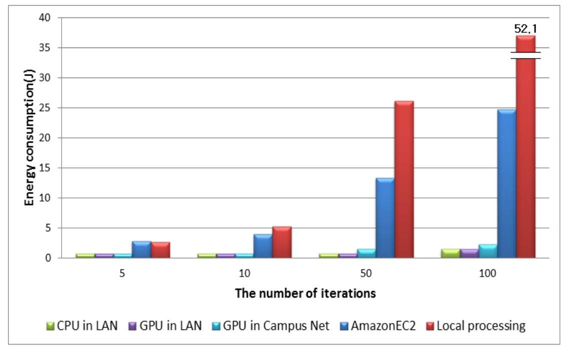
(a) Sobelfilter



(b) Matrix Multiplication



(c) Hidden Markov Model



(d) N-body Physics

Figure 6. Energy consumption with various server setup

Application Partitioning. This approach involves selecting portions of an application to execute remotely through the use of a static or dynamic scheduler. In Spectra [1], developers identify functions in the application that can be offloaded to a remote server over RPC. By monitoring the CPU, file I/O, and bandwidth, Spectra decides at runtime which portions of the application should run locally or remotely. MAUI [2] takes a similar approach but alleviates the process by using many of the programming features in the .NET platform such as method attributes, and the Reflection API. Through the .NET Framework's virtual machine, MAUI is able to dynamically serialize and ship *remotable* methods and data to a server proxy, thus leveraging the server's superior processing capabilities while saving energy on the mobile device. Cuckoo [3] takes a slightly modified approach by focusing more on integrating with the Eclipse IDE; however, it requires developers to implement both local and remote versions of their functionality, whereas MAUI only requires annotations from developers. Our approach may be classified as application partitioning similar to Cuckoo because developers are required to re-implement portions of their code for the OpenCL runtime environment; however, the developer does not have to worry about the complications of shipping the workload to the remote device.

Thread Migration. The source code modification required for most partitioning schemes can preclude adoption by many applications; thread and process migration, on the other hand, can be achieved without any source code modification. CloneCloud [4] achieves this by employing thread migration in the Dalvik Java Virtual Machine (JVM) by transferring all of the thread state (thread stack, necessary heap objects and registers) to the remote virtual machine. When the remote thread completes, the results are merged back with the local Dalvik JVM memory stack. The authors of COMET [5] developed a similar thread migration technique by doing application VM synchronization through a distributed shared memory (DSM) model. Our proposed solution does not require any thread stack or heap synchronization because the OpenCL framework requires explicit declaration of input and output buffers for remote kernel execution.

Application Migration. While the previous thread migration techniques can be technically challenging to implement since they require memory synchronization between the remote thread and other threads running locally, Application migration does not have such requirements. Hung et al. [6] describes an application migration design that leverages the *onResume* and *onPause* events of an Android application as the markers for process migration. The *onPause* event occurs when a user switches to another application. The Android system requires that application states are stored on persistent storage in case the operating system decides to shutdown in the case of low memory situation. Hence, Hung et al. creates a solution which uses the *onPause* event to force the application to save its state. The state is then copied to a cloned VM running on the cloud and resumed there until completion, then transferred back. Our design automatically handles the state transfers between the local and remote devices without relying on specific Android-based events.

Distributed Offloading Framework. Various recent approaches have focused on a totally different model requiring more effort from the developers. Proposals such as Mobile MapReduce (MMR) [14], Sonora [15], and Serendipity [16] all expose a distributed offloading framework for developers to adopt. For example, MMR is a MapReduce system optimized for the constrained networking conditions of mobile devices by taking into account bandwidth and latency for efficient mobile device performance. Sonora exposes a distributed stream-based programming model which handles workload distribution and failures in a mobile network. Serendipity provides an offloading framework for intermittently connected mobile devices and does not rely on cloud services. Our approach can also be classified as a distributed offloading framework; however, instead of defining the system from scratch, we reuse the workload offloading paradigms of the OpenCL framework which provides more familiar and widely supported interfaces for developers.

VI. Conclusion

In this paper, we proposed the OpenCL-based remote offloading framework for mobile platforms through SocialVPN. We implemented the prototype of our remote offloading framework on the mobile platforms running Android OS and built the dynamic resource discovery mechanism in which the mobile user is allowed to dynamically and transparently discover the resources through IP multicasting on top of SocialVPN. Also, we characterized the benefits and the costs of our framework in terms of total execution time and energy consumption through real deployment of the prototype in local- and wide-area networks. According to our evaluation, depending on the complexity of the workload and the amount of data transfer, the proposed architecture can achieve more energy efficient performance by offloading than executing locally. In fact, in the case of matrix multiplication which is the computation-intensive workload, offloading shows up to 9.2X speedup depending on the matrix size, server's computing capabilities and network conditions while it saves energy consumption up to 76.8%.

We currently seek to real mobile applications suitable to obtain the benefits from our remote workload offloading framework such as face or voice recognition. With fault tolerant design, it is also possible that mobile devices switch offloading to other available resources in the case of computing node failure.

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