

A Source-level Energy Optimization Framework for Mobile Applications

Xueliang Li* John P. Gallagher*[†]

*Roskilde University, Roskilde, Denmark

[†]IMDEA Software Institute, Madrid, Spain

Email: {xueliang, jpg}@ruc.dk

Abstract—Energy efficiency can have a significant influence on user experience of mobile devices such as smartphones and tablets. Although energy is consumed by hardware, software optimization plays an important role in saving energy, and thus software developers have to participate in the optimization process. The source code is the interface between the developer and hardware resources. In this paper, we propose an energy-optimization framework guided by a source code energy model that allows developers to be aware of energy usage induced by the code and to apply very targeted source-level refactoring strategies. The framework also lays a foundation for the code optimization by automatic tools. To the best of our knowledge, our work is the first that achieves this for a high-level language such as Java. In a case study, the experimental evaluation shows that our approach is able to save from 6.4% to 50.2% of the CPU energy consumption in various application scenarios.

I. INTRODUCTION

Smartphones have become widespread in modern society, with a market penetration of about 75% of mobile subscribers in the U.S in February 2015 [3], a figure that is still growing. With the improvement of hardware processing capability and software development environments, the smartphone is no longer just a handset to make phone calls, but also lets the user play entertaining games, watch movies, browse web pages, and so on. However, users are often frustrated by limited battery capacity – applications running in parallel could easily drain a fully-charged battery within 24 hours – and therefore energy optimization of applications is of increasing importance.

Although energy is ultimately consumed by hardware, it is the software that controls the hardware and is often responsible for significant waste of energy. Software optimization by current compilers achieves very little energy saving for mobile devices, since besides energy efficiency, the compiler for the mobile device has to consider many other important factors, such as limited memory usage and fast response to user interactions. The Android platform, for instance, employs the Just-In-Time (JIT) compiler [7], also known as the dynamic compiler. Its optimization window is generally as small as one or two basic blocks in order to use less memory and speed up delivery of performance boost. However, the small window restricts the space of energy-saving strategies. Recently, researchers have proposed tools to systematically automate software improvement [9], [22], but it is hard for developers to guide such optimizations. Powerful code refactoring is needed, but this is beyond the scope of compilers and present tools, relying more on developers' knowledge of the code.

Unfortunately, current software development is performed in an energy-oblivious manner and few developers and designers have any awareness of the energy usage of code written by themselves. However, energy-aware programming techniques are in high demand among software developers. In the most popular software development forum STACK-OVERFLOW [33], energy-related questions are marked as favorites 3.89 more often than the average questions [25]. Furthermore, among energy-related questions, code-design-related ones are prominent. Source code is the interface between the developer and hardware resources; only if developers understand the energy characteristics of the source code can they perform more targeted refactoring to reduce energy use. To realize this goal, the first step is to analyze the source code at different levels of granularity and from different points of view.

We construct a source-level energy model based on "energy operations", which is fine-grained and gives valuable information for code optimization. By "source-level" we mean that the energy costs of running a program are all attributed to source code constructs, despite the fact that much of the energy consumed is actually accounted for by things outside the source code such as the operating system. Thus the model is bound to be an approximation, yet as our results show, it is precise enough to give useful information and guide energy optimization.

Compared with coarse-grained techniques [14], [18], [37], [40] at the level of source-lines, methods, applications or even the system, there are some advantages of the operation-based model in guiding energy-aware programming techniques:

- The energy operations are atomic units that comprise the entire energy consumption of the application. Thus using the energy estimate of operations, developers can quantitatively assess the effects of code changes on the energy consumption of code.
- It provides more valuable information for selecting strategies. For example, the experiment shows that method invocation is one of the most expensive operations, suggesting that in some cases we may inline some thin methods, at the cost of losing the integrity of the structure of code.

In this paper, we propose a generic energy optimization framework: 1) understanding the energy features of the source code and 2) optimizing the source code. We then implement one instantiation of the framework, which is guided by an operation-based energy model. Briefly, the steps are:

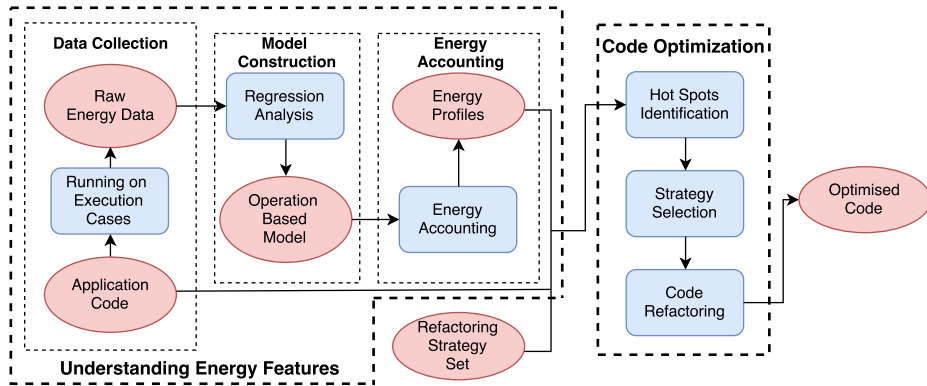


Fig. 1: A Framework for Source-Level Energy Optimization

1) we build an operation-based source-level energy model, which is achieved by analyzing the data produced in a range of well-designed execution cases; 2) we perform energy accounting based on the model, at operation and block level to capture the key energy characteristics of the code; 3) we focus efforts on the most costly blocks, where we refactor the code to remove, reduce or replace the expensive operations, while maintaining its logical consistency with the original code.

The contributions of this paper are the following:

- An energy optimization framework, which is driven by the understanding of energy features of the source code, while the current systematic solutions do not analyze the energy features of the source code before optimizing it.
- An instantiation of the framework, which builds the infrastructure for software optimization by both automatic tools and developers.
- An instantiation of the framework guided by an operation-based model. The model can map the energy use to the basic operations at source-level, which is critical to guide optimization. In contrast, traditional profile-based code-optimization techniques [36] cannot easily yield operation-related information.
- The evaluation is implemented on a physical device and a real-world game engine. The experimental result shows that the improved code can save the CPU energy consumption by up to 50.2%.

In the rest of this paper, we start with the description of the energy optimization framework in Section II, then introduce the identification of source-level energy operations in Section III. In Sections IV and V, we demonstrate the setup and construction of the energy model. Based on the model we are able to capture energy characteristics and optimize the source code in a case study of three different scenarios, as seen in Sections VI, VII and VIII respectively.

II. FRAMEWORK

The generic framework of our approach begins with *Understanding Energy Features* of the source code, based on which we perform the *Code Optimization*. Even though it is simple to state, it is a novel approach since the state-of-the-art solutions [9], [22] for systematic code optimization usually treat the code as a black box (i.e., without an

analysis of energy features of the code as the first step). Furthermore, realizing the connections between understanding and optimization of code is not trivial.

In this section, we firstly propose a generic framework for source-level energy-optimization, and secondly present an instantiation of the framework to show one way to associate energy features with effective code optimization.

Figure 1 shows an overview of the framework. In the rest of this section, we will present and discuss the details.

A. Understanding Energy Features

There are various ways to analyze and understand the energy characteristics of the source code, and produce a diversity of energy information forming the basis for code optimization. For instance, static analysis for cost upper-bound [5] and computational complexity [30] can give an indication of how good or bad the code is, which may inspire the developers to improve the code. But this high-level information can hardly give clear guidance to developers on how to refactor the code, neither can it facilitate the automation of code optimization.

Our instantiation of the framework uses an operation-based technique (the explanation of "operation" is in Section III) to analyze the code and provide energy information at a wide range of levels. As shown in Figure 1, *Understanding Energy Features* includes three components: *Data Collection*, *Model Construction* and *Energy Accounting*.

The *Raw Energy Data* is produced during *Data Collection* by running the application code on a set of well-designed execution cases. *Model Construction* utilizes the *Raw Energy Data* as input to build the operation-based model, powered by which *Energy Accounting* generates energy profiles to capture the key features of the source code. Lastly, the profiles are applied as one crucial input to the *Code Optimization* component.

B. Code Optimization

Code Optimization has three main inputs: application code, energy profiles and a set of refactoring strategies. Our instantiation is given by the procedure *Code Optimization* described by the pseudo code in Algorithm 1.

Input: *Application Code* ρ is the source code that developers want to improve.

Algorithm 1: The Algorithm of Code Optimization

Input : Application Code: ρ
Energy Profiles (for each code block id):
 $Blocks = \{(id, cost, OpCosts)\}$
Set of Refactoring Strategies:
 $Strategies = \{strategy_i\}$
Output: Optimized Code: ρ'

```
// Hot Spots Identification (HSI)
1 HotBlocks = findCostlyBlocks(Blocks);
2 foreach block in HotBlocks do
  // Strategy Selection (SS)
3 StrategiesToUse =
  selectStrategies(Strategies,  $\rho$ , block);
  // Code Refactoring (CR)
4  $\rho' =$ 
  applyStrategiesToCode( $\rho$ , block, StrategiesToUse)
5 end
```

TABLE I: Examples of Code Refactoring Strategies

Category	Examples
Control Flow	<i>Loop unrolling, Loop unswitching</i> <i>If combination, Method inline</i>
Data Flow	<i>Common sub-expression elimination</i> <i>Constant folding and propagation</i> <i>Loop-invariant code motion</i> <i>Induction variable elimination</i>
Other	<i>Replacement by library function</i>

Energy Profiles are the connection between understanding and optimization of source code, and presented in the data structure $Blocks = \{(id, cost, OpCosts)\}$; $Blocks$ is a set of triples where id is the identity of the block, $cost$ is the energy consumption of the block, $OpCosts$ is a set containing the energy usage of individual operations in the block.

The *Set of Refactoring Strategies* represents the available optimization strategies to apply to the code. Table I lists examples of code refactoring strategies applied in our case study. Usually, one strategy is targeted to reduce one category of operations, which facilitates automatic selection of strategies. For example, if arithmetic operations are the major energy consumers, the data-flow strategies are likely to be chosen; if method invocations are costly, then method inlining is selected. Additionally, replacement of a source-level function by a library function reduces energy consumption for both data and control related operations since the latter is already compiled into native code which does not incur costly run-time compilation.

The *Code Optimization* algorithm consists of *Hot Spots Identification (HSI)*, *Strategy Selection (SS)* and *Code Refactoring (CR)*.

HSI is a component that shows clearly which parts are the most energy-consuming and suggests to the optimization tools or developers where to focus efforts, rather than examining the whole application code. As seen in Algorithm 1, *HSI* is implemented by $findCostlyBlocks()$ which identifies the costly blocks (*HotBlocks*) by comparing the $cost$ element in their triples. There are several possible im-

plementations of $findCostlyBlocks()$. For instance it could compute all the blocks in order of energy cost, choosing the most costly as the *HotBlocks*. Another approach is to return blocks that consume more than say 10% of the overall energy usage as the *HotBlocks*.

Thereafter, the algorithm traverses the *HotBlocks* and for each block, the *SS* component chooses the refactoring strategies according to several criteria: the energy breakdown on operations (referring to $OpCosts$ in each *block*), the structural characteristics of the code around and within that *block*. For example, if control-flow operations are the most costly and the `for` loop is the syntax structure around the block, *SS* will adopt loop unrolling for refactoring.

Finally, *CR* applies the selected strategies to improve the code. The scope in which the code is refactored is not limited within a block; i.e. some code outside the block may be changed to reduce the costly operations in the block. The example strategy for this case is loop unrolling. ρ' is the *Optimized Code* resulting from the refactoring. In summary, this algorithm presents a systematic approach to optimizing the source code, providing a framework for optimization by both automatic tools and developers.

For simple strategies, like loop unrolling and method inlining, refactoring can be automated. Even though some of these simple strategies could be done by other tools such as the compiler, focusing on *HotBlocks* can be crucial. For instance, method inlining or loop unrolling are important energy-saving techniques, but if applied indiscriminately, the size of code can explode.

For algorithm and design level strategies, such as replacement of a source-level function by a library function, the refactoring relies more on the developers because it is very difficult for automatic tools to identify which pieces of code can be replaced by library functions. In fact, *Energy profiles* are completely human-readable, and *HSI* reduces the effort needed for manual code improvement, which is shown in the case study in Section VI, VII and VIII.

III. BASIC ENERGY OPERATIONS

The operational semantics of a language specifies the effect of each language construct on the behavior of a program. Guided by the semantics of the source code, we select a set of *energy operations*, which are basic constructs such as statements and functions that cause evaluation or state changes. We assume that the energy consumed during program execution can be attributed to these, and only these operations. The choice of energy operations is thus an informed guess; operations not appearing in the source code that consume energy will not be directly reflected in the energy model (examples could be garbage collection or operating system tasks); their energy will be absorbed into the source code operations. On the other hand, if we select operations that have little or no energy effect, this will not cause problems as they will automatically be identified by the regression analysis in the later stage of the analysis.

Our experiment focuses on the Java language for which an operational semantics is available [8] to inspire the selection of Java source-code energy operations. Table II lists 14 representative operations out of a total of 120 in the experiment, giving them names that correspond to their function

TABLE II: Examples of Energy Operations

Operation	Identified where:
Method Invocation	<i>one method is called</i>
Parameter_Object	<i>Object is one parameter of the method</i>
Return_Object	<i>the method returns an Object</i>
Addition_int_int	<i>addition's operands are integers</i>
Multi_float_float	<i>multiplication's operands are floats</i>
Increment	<i>symbol "++" appears in code</i>
And	<i>symbol "&&" appears in code</i>
Less_int_float	<i>"<"s operands are integer and float</i>
Equal_Object_null	<i>"=="s operands are Object and null</i>
Declaration_int	<i>one integer is declared</i>
Assign_Object_null	<i>assign operands are Object and null</i>
Assign_char[]_char[]	<i>assign operands are arrays of chars</i>
Array Reference	<i>one array element is referred</i>
Block Goto	<i>the code execution goes to a new block</i>

and argument types. They include arithmetic calculations like *Multi_float_float*, *Addition_int_int*, in which operands types are explicit, as well as *Increment* whose operand is implicitly an integer. Boolean operations and comparisons, such as *And*, *Less_int_float* and *Equal_Object_null* also form a major category. *Method Invocation* and *Block Goto* are important for the control flow which plays a key role in the execution of the code. Assignments and *Array Reference* are expensive, as will be shown in Section VI-A.

Applications often employ a diversity of library functions, some of which are frequently called (graphics functions, for example). Unlike normal code which is interpreted by a virtual machine at run-time, key parts of library code has been compiled into native code before execution and some part may be already written in different languages and at lower levels of the software stack. Thus we include library functions as energy operations.

IV. EXPERIMENTAL SETUP

In this section and the next, we summarize the construction of the energy model for a generic class of Android applications based on a game engine, including the setup of the target device and the design principles of the execution cases. Further details on these can be found in [19]. Note that, this setup is also applied to the evaluations of the code refactoring, as seen in Section VI-C, VII-B and VIII-B.

A. Experimental Targets

Device. We employ an Odroid-XU+E development board [23] as the target device. It possesses two ARM quad-core CPUs, which are Cortex-A15 with 2.0 GHz clock rate and Cortex-A7 with 1.5 GHz. Odroid-XU+E has built-in sensors to measure the voltage and current of CPUs. These sensors are supposed to be integrated into the future architecture of mobile devices since they provide the ground truth for run-time energy modeling and optimization.

In our experiment, we turn off the small cores (because in several execution cases, small cores cannot afford the workload) and run workload on big cores at a fixed clock frequency of 1.1 GHz. We do this also in order to control the influence of voltage, clock rate and CPU performance on energy usage because we are only concerned about the effects of basic operations.

Application Source Code. The target source code is the Cocos2d-Android [2] game engine, a framework for building games, demos and other interactive applications such as virtual reality. It also implements a fully-featured physics engine. Games are increasingly popular on mobile phones and include more and more fancy and energy-consuming features, requiring high CPU performance. Our instantiation of the framework demonstrates the energy modeling, accounting and improvement for the source code of the game engine, and evaluates the improvement in three game scenarios.

B. Design of Execution Cases

The execution cases whose energy usage is measured and analyzed represent typical sequences of actions during game, including user inputs. We focus on three scenarios which are *Click & Move*, *Orbit* and *Waves*.

In the *Click & Move* scenario, the sprite (the character in the game) moves to the position where the tap occurs. In the *Orbit* scenario, the sprite together with the grid background spins in the three-dimension space. In the *Waves* scenario, the sprite scales up and down, meanwhile the grid background waves like flow. In both the *Orbit* and *Waves* scenarios, the animation will restart from the starting point whenever and wherever the tap occurs.

To simulate the game scenarios under different sequences of user inputs, we script with the Android Debug Bridge [1] (ADB), a command line tool connecting the target device to the host, to automatically feed the input sequences to the target device.

An execution case is made up of one user input sequence and one set of basic blocks. In order to obtain a more varied set of execution cases and thus a more precise model, we vary the executions of individual basic blocks in the code. This is achieved by systematically removing a set of blocks for each execution case, using the control flow graph extracted using the Soot tool [31]. We ensure that each block could be removed in some execution case and thus execution sequences are not restricted to "normal" behavior but contain some randomness.

C. Energy Consumption from Power samples

Power is equal to voltage times current (voltage and current are obtained from the sensors); we approximate energy consumption by calculating Equation (1): $p = power(t)$ is the power trace, that is, the continuous power-vs-time function; $power(t_i)$ is the power sample at time-stamp t_i ; Δ_i equals to $t_i - t_{i-1}$, which is the interval between two consecutive samples.

$$E = \int_{t_0}^{t_n} power(t) dt \approx \sum_{i=1}^n power(t_i) \cdot \Delta_i \quad (1)$$

$$where \quad t_0 \leq t_1 \leq t_2 \cdots \leq t_{n-1} \leq t_n$$

Control of Measurement Variability. We run each execution case 10 times (when the cooling fan keeps the CPU temperature stable at 51°C) to obtain 10 records of the energy consumption computed by Equation 1. We use the coefficient of variation (C_v) to represent the variability

of the records. C_v is computed by $C_v = \frac{\sigma}{\mu}$, where σ , μ are the standard deviation and mean of the 10 records for each execution case. The experimental results show that the mean of C_v s of all the execution cases is about 1.6%, indicating that the variability is very limited. We employ the mean of 10 records as the "real" energy consumption of the execution case, which makes the variability as small as 0.5%.

V. MODEL CONSTRUCTION

The entire energy use is composed of three parts: the cost of energy operations, the cost of library functions and the idle cost. The model is formalized in Equation (2):

$$E = \sum_{op_i \in EnergyOps} Cost_{op_i} \cdot N_e(op_i) + \sum_{func_i \in LibFuncs} Cost_{func_i} \cdot N_e(func_i) + Idle Cost \quad (2)$$

The cost of energy operations is the sum of $Cost_{op_i} \cdot N_e(op_i)$ (the cost of one operation multiplied by the number of its executions), where $op_i \in EnergyOps$, the set containing all the operations. The cost of library functions is the sum of $Cost_{func_i} \cdot N_e(func_i)$ (the cost of one library function multiplied by the number of its executions), where $func_i \in LibFuncs$; $LibFuncs$ is the set of library functions. The *Idle Cost* is the energy consumption of the device when running no application, but simply the Android system.

Model construction is based on regression analysis. Each execution case produces one example for training the model, whose purpose is to capture the correlation between energy operations and their costs from the examples produced by all the execution cases. To validate the model, we apply a four-fold cross validation procedure: the set of execution cases is randomly evenly divided into four subsets; in each one of four rounds in all, one of the subsets is chosen to be the validation set and the others together to be the training set. We utilize two statistical criteria to assess our model. The first one is the correlation coefficient (r) that represents the strength and direction of the linear relationship between estimated and measured values. The result shows r in the training sets is from 0.81 to 0.84, and the validation sets from 0.88 to 0.91 which means the estimated value has a positive and strong relationship with its corresponding measured value.

The other criterion is the Normalized Mean Absolute Error (NMAE). The NMAE is a well-known statistical criterion that indicates how well the estimated value matches the measured one. It is computed by Equation (3), the mean value of normalized difference between the predicted energy cost \hat{e} and the measured cost e . The lower the ratio the better the result. The NMAE in training sets ranges from 14.1% to 16.3%, and in validation sets from 9.3% to 15.7%.

$$NMAE = \frac{1}{n} \sum_{i=1}^n \left| \frac{\hat{e}^{(i)} - e^{(i)}}{e^{(i)}} \right| \quad (3)$$

We choose the model that performs well (accuracy above 85%) both in training and validation sets for the later energy accounting and code optimization stage.

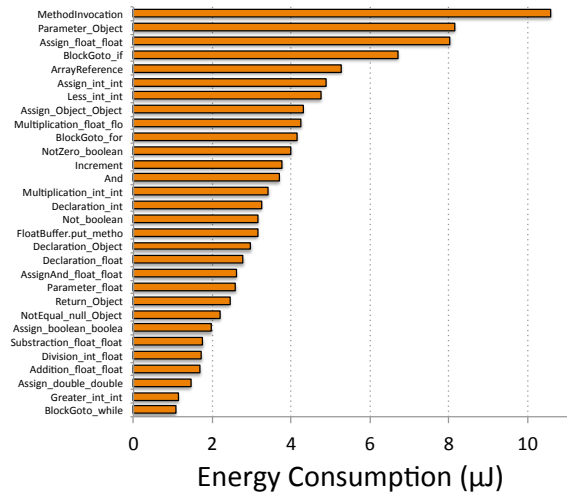


Fig. 2: The top 30 energy consuming operations in Click & Move scenario.

Next we present three instances of the code optimization procedure based on the energy model, applying it to code for performing three typical game scenarios: Click & Move, Orbit and Waves. The description of the scenarios is shown in Section IV-B.

VI. THE CLICK & MOVE SCENARIO

In this section, we first discuss the operation costs computed by the energy model, after which we apply the energy optimization procedure from Algorithm 1, consisting of hot spot identification, strategy selection and code refactoring. Lastly, we present an evaluation of the refactoring strategies.

A. Operation Costs

Figure 2 shows the top 30 energy consuming operations in the model, ranked by their single-execution energy costs. It might be supposed that the sophisticated arithmetic operations, such as multiplications and divisions, should be the most costly. However, the result shows that *Method Invocation* ranks the highest. This is due to a sequence of complex processes to fulfill *Method Invocation*, for example, most of the method calls in Java are virtual invocations which are dispatched on the type of the object at runtime and implicitly passed a "this" reference as their first parameter, not to mention other operations such as storing the return address and managing the stack frame.

This suggests a trade-off between code structure and energy saving when writing the code. That means, in certain cases, we could inline some thin and highly-invoked methods in the code, at the cost of losing the integrity of the structure of the code to some extent.

Block Goto operations are expensive as well. Based on the types of conditionals and loops where "Block Goto" occurs, they are classified into *BlockGoto_if*, *BlockGoto_for* and *BlockGoto_while*. The result shows that they cost different amounts of energy as operations themselves, respectively 6.7 μ J, 4.1 μ J and 1.1 μ J. Together with *Method Invocation*, they take up 37.6% of the total application energy consumption.

TABLE III: The top 10 most costly blocks in Click & Move.

Block ID	Energy Cost (mJ)
CCNode.visit()	2128.6
CCNode.transform()	1648.4
CCTextureAtlas.putVertex()	1494.4
CCNode.visit().if_4.for_1	1426.8
CCNode.transform().if_1	1426.3
CCTextureAtlas.putTexCoords()	1107.8
CCAtlas.updateValues().for_1	1018.7
CCNode.visit().if_3.for_1	915.7
CCSprite.draw()	766.9
CCTexture2D.name()	537.5

To facilitate the discussion on operations in the reminder of this paper, we classify a number of operations into groups. Specifically, the "Block Goto" operations, *Method Invocation* and field references are gathered in *Control Ops*; the parameter passing and the value returns of methods are in *Function Ops*; the comparisons and Booleans are in *Boolean Ops*; all the arithmetic computations are in *Arithmetic Ops*; all the library functions are in *Lib Functions*.

B. Code Optimization

1) *Hot Spot Identification*: In practice, a hot spot is the size of a block. Using the energy profiles ($Blocks = \{(id, cost, OpCosts)\}$), we identify the 10 most costly blocks when Click & Move runs without removing any block (see Table III). For example, *CCNode.visit()* is the entrance block of the *visit()* function; *CCNode.visit().if_4.for_1* is the body block of the *for* loop. These 10 blocks are distributed in seven methods, so the code review is straightforward.

2) *Strategy Selection & Code Refactoring*: We find four easy opportunities to improve energy efficiency of some blocks: *CCNode.visit()*, *CCNode.visit().if_4.for_1* and *CCTexture2D.name()*. There are also other opportunities in other blocks supposed possible to save energy, but requiring more efforts and gaining little. For example, *CCAtlas.updateValues().for_1* has several busy arithmetic expressions. Usually it is assumed that replacing the busy expression with a variable would reduce energy, however in this case the overhead of variable declaration counteracts the saved energy.

Program 1 Simplified parts of **original** code in *CCNode.visit()*

```

if (children_ != null) {
    if_body1;
}
draw(gl);
if (children_ != null) {
    if_body2;
}

```

Program 2 The changed Program 1

```

if (children_ != null) {
    if_body1;
    draw(gl);
    if_body2;
} else {draw(gl);}

```

(i) *If Combination*: This change is made in the most costly block *CCNode.visit()*, which has two comparisons, two Boolean operations, one *Method Invocation* and one parameter passing. In fact, the two *if* headers make the same comparison, as shown in Program 1. We change the code to Program 2, which combines the two *if* statements and meanwhile keep it logically consistent with Program 1. By these means each execution of the block can remove one comparison, and when the condition is false, it can additionally remove one *BlockGoto_if*.

(ii) *Inner-Class Method Inline*: When Click & Move runs with full set of blocks, the *transform()* function is invoked 18903 times and mostly by the *visit()* function. We switch the body of *transform()* to the function call of *transform()* in *visit()*, meanwhile retaining the original definition of *transform()* in case that other parts of the code call it. This change can greatly decrease the number of calls to *transform()*s and thus *Method Invocations* that are costly. However, it may be at the cost of losing readability of the code (which might be partly compensated by adding explanatory comments).

(iii) *Loop-Invariant Code Motion*: *CCNode.visit().if_3.for_1* and *CCNode.visit().if_4.for_1* are entrance blocks of the two *for* loops. These two loops share a quantity, *children_size()*, which is computed in each iteration but actually constant. We thus hoist it outside the loop, which saves the energy of invoking and executing the *size()* function during every iteration. Meantime, we move the declaration of the *child* outside the loop, considering the cost of *Declaration_Object* is about 2.97 μ J and also among the top 30 most costly operations.

(iv) *Inter-Class Method Inline*: *CCTexture2D.name()* is the 10th most costly block and costs 537.5 mJ when Click & Move runs with full set of blocks. However, its job is to simply get the value of the private member variable, *_name*, of the class *CCTexture2D*. This method has only two callers in the code. So we consider to make this variable public and let the two callers directly get access to the variable, which avoids the cost of *Method Invocation*. This change may harm the encapsulation of data, however, only one member of one class is changed. The trade-off between energy saving and data encapsulation will in the end be decided by developers.

C. Evaluation

Figure 3 illustrates the energy dissipation of the software without and with the changes introduced in the previous section. From left to right, the bars indicate cumulative effects of the changes. For example, "+ *If Comb*" is the energy consumption of the original code with the change of "If Combination"; "+ *Inner-Class MI*" is the energy consumption of the code with the changes of both "If Combination" and "Inner-Class Method Inline". In total, these four simple changes save 6.4% of the entire energy consumption without influencing the functionality of code. These changes are made in the basic part of the game engine, which most applications will be bases on, so any gain here can have fundamental impact. Furthermore, these changes are made with little knowledge about the algorithm of the code, the developers who designed the code are surely

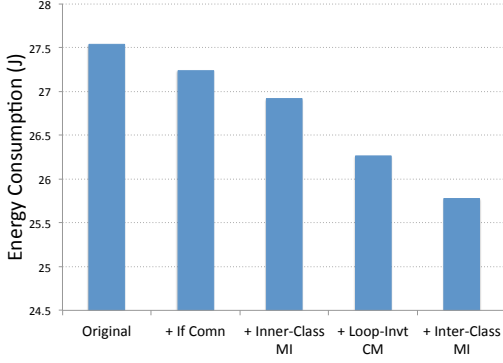


Fig. 3: Energy consumption of the code without and with the changes in Click & Move.

able to improve the code much more and achieve far more energy saving, if the energy model was available to them.

VII. THE ORBIT SCENARIO

In this section, we evaluate our approach in the Orbit scenario, where we again refactor the most costly block according to the expensive operations. The experimental result shows that the improvement saves 50.2% of the CPU energy consumption.

A. Code Optimization

1) *Hot Spot Identification*: In the Orbit scenario, the block `CCGrid3d.blit().for_1` dominates the overall energy consumption. 80.9% of the entire cost is consumed by this block. The second most costly block consumes only 1.3%. We thus focus attention completely on this single block.

Program 3 The original code of `CCGrid3D.blit().for_1`

```
for (int i = 0; i < vertices.limit(); i=i+3) {
    mVertexBuffer.put(vertices.get(i));
    mVertexBuffer.put(vertices.get(i+1));
    mVertexBuffer.put(vertices.get(i+2));
}
```

Program 4 The changed Program 3

```
int limit = vertices.limit(); //added
for (int i = 0; i < limit; i=i+24) { //changed
    mVertexBuffer.put(vertices.get(i));
    mVertexBuffer.put(vertices.get(i+1));
    mVertexBuffer.put(vertices.get(i+2));
    ...
    mVertexBuffer.put(vertices.get(i+23)); //added
}
```

2) *Strategy Selection & Code Refactoring*: Program 3 shows the original code of `CCGrid3D.blit().for_1`. In this block, the *Control Ops* (`BlockGoto_for` and *Field Reference*) use up 35.6% of the energy; *Boolean Ops* use up 20.5%; the assignments use up 16.7%; *Arithmetic Ops* use up 14.0%; *Lib Functions* use up 13.3%. We find three easy changes to reduce or replace the pricey operations.

(i) *Loop-Invariant Code Motion*: In this block, the value of `vertices.limit()` is the constant 2112; we therefore hoist it outside the loop and replace it with the variable `limit`, as shown in Program 4. This change avoids invocations and

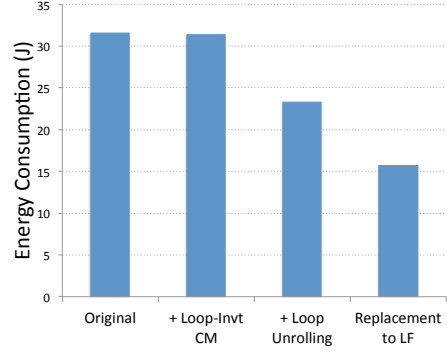


Fig. 4: Energy consumption of the code without and with the changes in Orbit.

executions of `vertices.limit()` and at the same time decreases a small amount of *Field Reference*.

(ii) *Loop Unrolling*: Also as shown in Program 4, we duplicate the loop body eight times, reducing the times of comparisons, `BlockGoto_for`s, assignments and additions. Note that we set the value of the increment as 24 since 24 is a factor of the `limit`, 2112.

(iii) *Replacement by Library Function*: The job of Program 3 or Program 4 is to get all the elements in `vertices` one by one and put them one by one into `mVertexBuffer`. Program 3 can be simply replaced by one line: `mVertexBuffer.put(vertices.asReadOnlyBuffer())`. This puts all the elements of `vertices` into `mVertexBuffer`. This change realizes the same functionality using the existing library function, which is one of the key library functions already compiled into native code.

B. Evaluation

Figure 4 shows the cumulative effects of the code changes on energy consumption. In contrast to the other columns, "Replacement by LF" does not take previous changes into account and means only replacing Program 3 with the built-in library function as stated above. The figure shows that loop-invariant code motion does not gain much energy saving because `vertices.limit()` is a library function and in addition uses a very small percentage of energy consumption. On the other hand, loop unrolling achieves 25.8% energy saving due to the reduction of the amount of *Control Ops*, comparisons and assignments, which occupy most of the cost. The most effective change is the replacement by the library function, avoiding the waste of 50.2% energy use because this library function has been compiled into native code before execution; by contrast the Java source code need run-time interpretation which of course incurs an energy cost. The result implies that it is a good idea for developers to make an appropriate use of library functions rather than implementing the same function with Java source code.

VIII. THE WAVES SCENARIO

In this section, similarly, we first analyze the energy features of the blocks in the Waves scenario, based on which we modify the code and then evaluate the effects of changes on energy consumption.

TABLE IV: Top 10 most costly blocks "In Application" in the Waves scenario and the energy percentages of different kinds of operations in each block.

Block ID	#Executions	Energy Cost (mJ)	Assign	Decl.	Cont.	Func.	Bool.	Arit.	Libr.
CCGrid3D.blit().for_1	112193	8094.1	16.7%	0%	35.6%	0%	20.5%	14.0%	13.3%
CCVertex3D.CCVertex3D()	40219	5232.0	27.2%	0%	10.0%	62.8%	0%	0%	0%
CCWaves3D.update().for_1.for_1	34604	4088.7	10.7%	0%	32.1%	0%	14.7%	39.0%	2.2%
ccGridSize.ccg()	42275	3769.1	0%	0%	32.1%	67.9%	0%	0%	0%
CCGrid3DAction.setVertex()	31856	3285.4	14.6%	7.8%	30.9%	46.7%	0%	0%	0%
CCGrid3DAction.originalVertex()	36566	2891.3	19.1%	10.2%	40.3%	30.4%	0%	0%	0%
CCNode.getGrid()	49119	2145.1	0%	0%	58.1%	41.9%	0%	0%	0%
ccGridSize.ccGridSize()	10570	1173.8	30.3%	0%	31.6%	38.0%	0%	0%	0%
CCGrid3D.setVertex()	3944	657.2	10.1%	1.6%	32.8%	28.9%	0%	26.4%	0.2%
CCGrid3D.originalVertex()	2785	374.2	14.0%	1.9%	33.4%	17.9%	0%	32.8%	0%

A. Code Optimization

1) *Hot Spot Identification*: Unlike the Orbit scenario where only one block dominates energy cost, in the Waves scenario the costs of the top eight blocks are at the same order of magnitude of Joule, as listed in Table IV. The *CCGrid3D.blit().for_1* is also employed in this scenario and is the most costly as well among all the blocks.

Program 5 The original code in *CCWaves3D.update()*

```
int i, j;
for( i = 0; i < (gridSize.x+1); i++ ) {
  for( j = 0; j < (gridSize.y+1); j++ ) {
    CCVertex3D v=originalVertex(ccGridSize.ccg(i, j));
    ...
    setVertex(ccGridSize.ccg(i, j), v);
  }
}
```

Program 6 Program 5 after Method Inline & Code Motion

```
ccGridSize ccgridsize = new ccGridSize(0,0); //added
CCGrid3DAction ccgrid3d =
  (CCGrid3DAction) target.getGrid(); //added
CCVertex3D v = new CCVertex3D(0,0,0); //added
int i, j;
for( i = 0; i < (gridSize.x+1); i++ ) {
  for( j = 0; j < (gridSize.y+1); j++ ) {
    ccgridsize.x=i;ccgridsize.y=j; //added
    v =ccgrid3d.originalVertex(ccgridsize); //changed
    ...
    ccgrid3d.setVertex(ccgridsize, v); //changed
  }
}
```

2) *Strategy Selection & Code Refactoring*: The majority of blocks in Table IV are directly or indirectly invoked by *CCWaves3D.update().for_1.for_1*, as shown in Program 5. The purpose of these methods is mainly to set or get the values of member variables, so a large part of energy consumption goes to assignments, *Function Ops* and *Control Ops*. It was not expected that the code spends such a large amount of energy on simple set and get functions.

(i) *Replacement by Library Function*: We mentioned previously in Section VII the optimization for *CCGrid3D.blit().for_1* where we replace the entire Program 3 with one line of code making use of library functions. We keep this change in this scenario. For other blocks, we come up with a package of modifications as below.

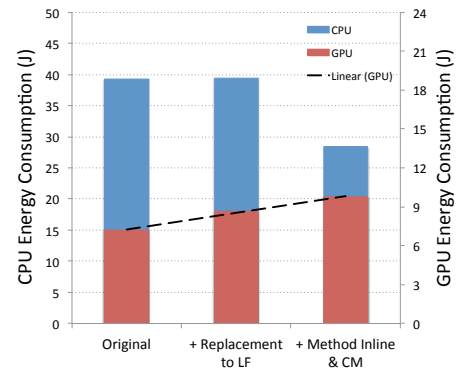


Fig. 5: CPU and GPU Energy consumption of the code without and with the changes in Waves.

(ii) *Method Inline & Code Motion*: As shown in Program 5, the three functions called in the inner loop body are *CCGrid3DAction.originalVertex()*, *ccGridSize.ccg()* and *CCGrid3DAction.setVertex()*, which respectively cost 2891.3 mJ, 3769.1 mJ and 3285.4 mJ when Waves executes with all the blocks. Note that, *CCGrid3DAction* is the parent class of *CCWaves3D*, so in Program 5 *originalVertex()* and *setVertex()* can be directly called without referring to their class names. As seen in Program 6, we unpack these three methods in this block: the first and fourth "added" lines are unpacked *ccGridSize.ccg()*; the second "added" and first "changed" lines are unpacked *CCGrid3DAction.originalVertex()*; the second "added" and second "changed" lines are unpacked *CCGrid3DAction.setVertex()*. This change removes all the *Method Invocations*, parameter passing and value returns related to these three functions invoked by this block. Note that the first three "added" lines are located outside the loop in order to reduce energy consumption of initializing objects and calling *CCNode.getGrid()*.

B. Evaluation

Figure 5 shows the cumulative effects of changes on energy consumption of CPU and GPU (note that previous figures only showed the CPU energy consumption because the GPU energy consumption did not vary noticeably), and the dashed line indicates the linear trend of the GPU energy consumption. In the case of games, the aimed frame rate is usually 60 Hz; when the game overloads the CPU, the

rate will decrease, and when the workload is light, even very light, the rate is generally fixed to 60 Hz. The rate in "*Original*" is around 36 Hz; that in "+ *Full-Use LF*" is around 50 Hz; that in "+ *Method Inline & CM*" is around 60 Hz. The change of *Full-Use LF* (full use of library function) does not save energy for CPU because the original *Waves* actually overloads the CPU capacity, so the improvement of code enables the device to generate more frames every second. Consequently, the CPU does the same volume of work and consumes the same amount of energy, while the GPU does more work and consumes more energy, as seen in Figure 5. After this change, when we apply the method inline and code motion, 27.7% of the overall CPU energy is saved, and for the same reason GPU consumes slightly more. This result indicates that our approach not only saves energy but also potentially boosts performance.

IX. DISCUSSION

The experiment was targeted successfully at applications using a game engine, which represents one important class of mobile applications, namely games. Further experiment is required to see the extent to which the framework can produce good results on other applications. For instance, in some applications, energy consumption is distributed more evenly among the blocks, and so the code would not contain such obvious hot spots amenable to optimization.

Energy modeling is limited to the CPU because the source-level operations identified are CPU-bound. It is another challenge to identify and model source-level operations for GPU, network interface, display and such like.

Optimization with regard to execution time may result in similar refactorings, if energy use has a strong correlation with execution time as is often the case. However, this observation does not weaken the effectiveness of our approach for saving energy. The novelty of this work is utilizing source-level operation-based information to guide code optimization. The correlation between execution time and energy consumption is beyond the topic of this paper.

X. RELATED WORK

A large amount of research effort on energy saving for mobile devices has been focused on the main hardware components, such as the CPU, display and network interface. The CPU-related techniques involve dynamic voltage and frequency scaling [11] and heterogeneous architecture [15], [20]. Techniques regarding the display include dynamic back-light dimming [12], [24] and tone-mapping based back light scaling [6], [16]. Network-related techniques try to exploit idle and deep sleep opportunities [21], [32], shape the traffic patterns [13], [26], and etc. Such work attempts to reduce energy dissipation by optimizing the hardware usage at a level below the source code. Besides, several pieces of work aim at designing new hardware and devices [34], [38].

On the other hand, there is a significant research engaged in source-level optimization for saving energy. The basic work seeks to understand how the different methods, algorithms and design patterns of software influence the energy consumption. For example, [28], [29], [39] propose new routing techniques and protocols that are aware of energy

consumption, which are evaluated by comparing with traditional techniques. For another example, [10] investigates the affects of different sorting algorithms on the energy use with respect to the algorithm's input size.

Considering design patterns, Litke et al. [4] conduct an experiment showing how big the difference of energy consumption is, before and after the application of design patterns, such as *factory method pattern*, *observer pattern*, and etc. The result reveals that except for one example the use of design patterns does not increase the energy use obviously. Comparable work to [4] is done by [27]; they explore more design patterns and arrive at the conclusion that applying design patterns can both increase and decrease energy consumption, so design-level artifacts cannot be used to estimate the effect of design patterns on energy use.

Vetrò et al. [35] define the concept of "energy code smells" that are the code patterns (such as self assignment, repeated conditionals and useless control flow) that suggest energy inefficiency. However, the code patterns selected in [35] have little influence (less than 1.0%) on energy usage.

Regarding code refactoring for energy saving, Ding et al. [17] perform a small scale evaluation of several commonly suggested programming practices that may reduce energy. Its result shows that reading array length, accessing class field and method invocation all cost remarkable energy. However, this work only provides a small number of tips to developers on how to make the code more energy-efficient.

Two pieces of work [9], [22] provide systematic approaches to optimizing code. In the former, Boddy et al. attempt to decrease the energy-consumption of software by handling code as if it were genetic material so as to evolve to be more energy-efficient. In the latter, Irene et al. propose a framework to optimize Java application by iteratively searching for more energy-saving implementations in the design space. In summary, these two pieces of work treat the code as a black box, i.e., the optimization is achieved without an analysis on the energy features of the code. In comparison, our approach views the code as a white box since the optimization is guided by the understanding of energy characteristics of source code.

Apart from the energy modeling, our instantiation of the framework is literally profile-guided, however, employs the Operation-Based information (the standard profile technique [36] can not access) to connect the understanding of code features with very Targeted refactoring strategy for such a high-level source code as Java. By comparison, the standard profile-based technique can only tell the hot spots at a size as smallest as methods or functions and hardly indicate the very targeted solution.

XI. CONCLUSION

This paper presents a source-level energy-optimization framework, guided by the understanding of energy features of source code. The framework constructs the infrastructure for code optimization by both automatic tools and developers. We also implement an instantiation of the framework driven by a source-level operation-based energy model.

We evaluate the instantiation on a physical Android development board with two ARM quad-core CPUs and on

a real-world game engine. In the case study our approach has a significantly impact on energy saving. In different scenarios, this approach saves CPU energy consumption up to 50.2%.

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