

# Dependence-based Multi-level Tracing and Replay for Wireless Sensor Networks Debugging<sup>\*</sup>

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## Abstract

Due to resource constraints and unreliable communication, wireless sensor network (WSN) programming and debugging remain to be a challenging task. Runtime errors must be constantly monitored, often by checking for violations of certain invariants. Once an error is detected, diagnosis must be performed to identify the origin of the error. Deterministic replay is an error diagnosis method which has long been proposed for distributed systems. However, one of the significant hurdles for applying deterministic replay on WSN is posed by the small program memory on typical sensor nodes. This paper proposes a dependence-based multi-level method for memory-efficient tracing and replay. In the interest of portability across different hardware platforms, the method is implemented as a source-level tracing and replaying tool. To further reduce the code size after tracing instrumentation, a cost model is used for making the decision on which functions to in-line. A prototype for the tool targets C programs is developed on top of the Open64 compiler and is tested using several TinyOS applications running on TelosB motes. Preliminary experimental results show that the test programs, which do not fit the program memory after straightforward instrumentation, can be successfully accommodated in memory using the new method such that the injected errors can be found.

**Categories and Subject Descriptors** D.2.5 [Testing and Debugging]: Debugging aids

**General Terms** Algorithms, Reliability.

**Keywords** Wireless sensor network; program debugging; invariants; dependence analysis; resource constraints.

## 1. Introduction

Wireless sensor networks (WSN) are gaining increased attention for possible use in applications such as structural health monitoring, environmental surveillance, scientific observation,

and others [27,28]. A wireless sensor network typically consists of a large number of unattended wireless sensor nodes. Despite the increasing efforts [6,20] made to ease the development and simulation of WSN applications, sensor network programming and debugging is still a difficult task in view of resource constraints and unreliable communications on wireless sensor nodes.

Deterministic replay (or record-replay) is an error diagnosis method which has long been proposed for distributed systems. Under this method, nondeterministic events are recorded throughout the system operation. When an error is reported, the program can be re-run, with the recorded events restaged to allow the programmer to inspect the executed statements and the state change they cause such that the source of the error, namely the incorrectly written statements or unexpected events causing the error, can be located. The replay method significantly reduces the amount of information to record at run time.

In this paper, we make two main contributions to replay-based diagnosis on WSN. Firstly, we present a dependence-based multi-level tracing and replay scheme to significantly reduce the required program memory for record and replay in WSN applications. The severely limited program memory on WSN motes (48 KB on the popular TelosB motes, for example) has forced most existing schemes for run-time logging on WSN to record only coarse information which is far from sufficient for deterministic replay. This makes it difficult to pin-point the source of the errors which are detected at run time. Our scheme, lends an effective solution for the memory size problem. Secondly, based on our multi-level scheme, we develop a source-level tracing and replaying tool which is independent of the hardware platforms and the cross compiler (except for a system library call to make certain memory accesses atomic). The source-level tracing, compared to assembly-level tracing, offers high portability of the tool. It also enables the user to take advantage of many existing source-level debuggers, such as GNU's gdb, when replaying on a desktop machine.

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The rest of the paper is organized as follows. Section 2 defines the problem addressed by this paper and gives an overview of our solution. Section 3 discusses how to reduce instrumentation based on dependence information and proves its effectiveness under a number of assumptions. Section 4 discusses multi-level tracing in case such assumptions are not satisfied. Implementation and experimental results are presented in Section 5. Section 6 summarizes related works on WSN debugging and deterministic replay, and we conclude in Section 7.

## 2. An Overview

### 2.1 Error detection

The types of errors targeted by our scheme go beyond system crash. The application programmer may specify a set of correctness properties, e.g. sensor data must be reported from each mote to the base station within a certain time limit. Such properties are specified using predicates defined over a list of program variables under a certain system of logic, e.g. temporal logic [21,22]. (The exact system of logic used is not of particular concern for this paper.) The program is required to satisfy this set of predicates within a specified program scope, e.g. the entire program (as long as all variables in the predicate are global), individual functions, individual program segments, or any point between two specific program statements.

In general, a distributed system reacts to events whose timing is difficult to predict or specify at the time of program development. Also, the developers may not have verified the correctness of the program thoroughly under deployment conditions, which can be significantly different from the test conditions in the lab. Errors, therefore, often exist in WSN programs after deployment. However, by inserting assertions to the program, violations of certain predicates, i.e. errors, can be detected at run time.

### 2.2 Record-and-replay

Assuming that the predicates themselves are composed correctly, when a predicate gets violated, we know at least one of its variables has obtained an incorrect value through some point in the program where the variable was updated. That value may be the result of earlier operations using incorrect operands, and so on. Eventually the error must be traced back to its source through a chain of data dependences and control dependences. *For the purpose of this paper, we consider two possibilities:* (a) one or more program statements are written incorrectly, and (b) certain unexpected events occur, e.g. messages are received with incorrect contents.

If the entire sequence of executed instructions and operands were recorded, then one could follow the dynamic use-def chain backward and inspect the program statements along the way until the origin of the error is found. The cost of such complete recording is prohibitive in both time and space. Under the record-and-replay scheme, however, we only need to record all nondeterministic events on each mote, which includes all external messages, task scheduling decisions, and internal interrupts. On current WSNs, all these can be captured by inserting logging operations in high-level languages such as C.

After an error is found, we still leave the instrumented code in the program. This is because the program may still have other hidden errors. Moreover, removing instrumentation may cause certain timing-dependent errors to resurface while we lose the means to record the trace.

### 2.3 Main assumptions

Since the program on each node in a distributed system such as a WSN may run indefinitely, the length of the trace is unbounded. With limited storage for the trace, in general one retrieves only a tail of the full trace. Replay is therefore often partial in practice. In order to enable deterministic replay corresponding to the retrieved trace tail, we require the program being considered to satisfy the following assumptions:

- **Assumption 1:** The infinite running of the program is controlled by one or more infinite loops which are recognized at compile time.

Under this assumption, we insert in each infinite loop an *anchor checkpoint* at which we record the values of all variables needed to enable replaying the program starting from this program point. The function containing an anchor point is called its *boundary function*. Local variables of the callers of a boundary function are not recorded at the anchor point. In order for the replay tool to capture the source of the error, the following assumption must also be satisfied:

- **Assumptions 2:** The trace storage is sufficiently large such that, when an error is detected, the stored trace will contain at least one anchor point prior to the source of the error.

If the above assumption is unsatisfied, then either the trace cannot be replayed (because of the lack of any anchor point) or the replay will not lead to the source of the error (because the error source falls off the trace). In such an unfortunate case, we will resort to multi-level tracing which instruments a subset of the functions but yet permit the trace to be replayed. That is, we will utilize multi-level approach to recompile and re-run the program. One of the main goals of this paper is to reduce the storage overhead for tracing, thus increasing the chance of capturing the source of the error in the stored trace. This is in addition to the objectives to minimize the instrumented code size and the increased processing time.

### 2.4 Framework of the tool

Given the error conditions to be detected at runtime, we use a compiler (the Open64 C compiler [13]) to compute the program slice [19], using the error conditions as the slicing criteria. We then partition the program slice into multiple levels such that initially lower-level tracing is performed, targeting only the functions close to where error conditions are checked. The tracing level increases as farther away functions must be traced in order to find the error source. Tracing operations, which record run-time events for diagnosis, are inserted in the given C program before the cross compiler converts it to the machine code. In addition, our tool generates another C program for later replaying on a desktop machine.

We use TinyOS [12], which is written in nesC [20], as our current testing environment for the developed tool. TinyOS is one of the most popular operating systems for sensor network applications. It has been used by more than 100 research groups worldwide. Typically, a TinyOS application consists of a group of wired components. The nesC compiler first converts the application into a C program which is then compiled by the cross compiler into machine code executable on the specific hardware. We use the same cross compiler to compile the C program instrumented by our Open64-based tool before loading it on the sensor mote for normal execution with tracing. When an error is detected, we retrieve the trace and feed it to our replaying C program which is executed on a desktop machine where many

well developed debugging tools, e.g. the GNU gdb, can be used to isolate the source of the error. To replay the interaction between different nodes, we simply start multiple processes, one for each node, feeding each with its own retrieved logging information. We can use one of various existing methods [37] such as using a different radio on the same node, storing logged information on a nearby node, etc. The details of how to retrieve the logged information from a node is out of scope of this paper.

The information logged must include the execution context for each invocation of an interrupt handler so that the replay program can restage the invocation of the interrupt handler accurately. The type of information to be recorded at run time will be discussed in the next section. Since interrupt handlers will be treated differently from the other functions, we identify interrupt handlers by annotations before applying our instrumentation tool. Furthermore, those interrupt routines which take external inputs such as radio communication messages are explicitly marked. The external inputs can then be recorded at run time, allowing the interrupt routine to be replayed.

Although our experiments are performed on TinyOS-based WSN applications, the proposed methodology and the developed tools can be applied to other distributed embedded platforms as long as *the program is single threaded and the assumptions made above are satisfied*. Our current toolset also relies on an intermediate C code generated from the original program.

In the next section, we first discuss how to use dependence information to exclude functions irrelevant to the invariants from the run-time logging so as to reduce the size of the instrumented program. This is followed by a presentation of the instrumentation algorithm with relevant guarantees.

### 3. Using Dependence Information to Reduce Runtime Logging

The benefit of reducing runtime logging is two-fold. First, a longer execution history can be replayed with the same amount of data storage for the trace. The time to execute the annotated program that is being traced is reduced. Second, the number of instrumented operations to perform tracing is reduced, which leads to a smaller code size.

If a function never has any effect on the kind of errors we monitor, i.e. on any of the variables appearing in the predicates (also called the *invariants*) which specify the correctness properties, then such a function does not need to be traced at runtime. To exclude such functions from tracing, we first compute the backward slice [19] using the given set of invariants as the slicing criteria. The result of this computation is a set of control/data dependence chains which include all operations (such as assignments, branching decisions and function calls) having an effect on the set of invariants. Each function that contains any of these operations will be instrumented to obtain the runtime execution log. Obviously, the main function of the program is always instrumented.

This set of functions, however, does not yet include those interrupt handlers which may have an effect on the invariants. In microcontroller execution, interrupts are the basic source of non-determinism. For example, TinyOS adopts an event-driven execution model. Until interrupts occur, the scheduler sequentially schedules the tasks from a FIFO queue for execution. As soon as an interrupt occurs, the current task is preempted until the interrupt handler is finished and no other pending interrupts exist. If any variables which have an effect on the invariants are modified by the interrupt handler, then obviously the interrupt handler may have an effect on the invariants as well. Since it is infeasible to predict when a particular interrupt may happen, we

instrument all those interrupt handlers whose execution may modify global variables on which the invariants depend.

#### 3.1 What to log

After we determine the set of functions to instrument, we insert operations into the source code of these functions to record the following pieces of information. We shall prove in this section that this set of information is sufficient for accurate replay.

LOG type 1 (Function entry/return) -- A function always has a single entry but may have multiple return points. We use  $N\_RET_i$ , where  $i$  is an integer, to indicate which return statement is executed. If this is a function entry, it marks whether it is an interrupt handler and, if so, the name of the function. This type of information is needed for efficiently replaying the correct instance of execution of the function, which will be explained later.

LOG type 2 (Global variable update count) – In order to prepare for replaying interrupt routines, when an interrupt routine is invoked at run time, a global-variable reference counter, denoted by  $\#gv\_reference$ , is written to the log, after which the count is reset to zero. For any other functions,  $\#gv\_reference$  is reset to zero both at the entry and at the exit. Every reference (read or write) to a global variable is followed by an increment of  $\#gv\_reference$ . This count will be used during the replay to help determine where in the program to replay specific interrupt routines. The reference to the global variable and the increment of  $\#gv\_reference$  are made a single atomic operation by calling a system library function to disable and re-enable interrupts. Without atomicity, it would be impossible to exactly determine whether an interrupt happens right before the global variable reference or between the reference and the increment of  $\#gv\_reference$ .

LOG type 3 (Task scheduling) – If task scheduling order is random, then we need to record the task that is scheduled to next. However, TinyOS uses a FIFO task queue. Hence, as long as the invocations of the interrupt routines are replayed accurately, this type of information does not need to be recorded.

LOG type 4 (Anchor points) – As discussed previously, at each anchor point, we record all variable values which are needed in order for the program to replay from here.

LOG type 5 (non-deterministic inputs) – It is necessary to record non-deterministic input for future replay. In TinyOS, the messages received from radio communication and the sensor data arriving from the bus belong to this type. Note that the interrupt handlers export such input by writing it to a global variable. Since the interrupt handlers which take external input are explicitly marked, we add operations in such handlers to save their global variables to the trace.

#### 3.2 How to replay

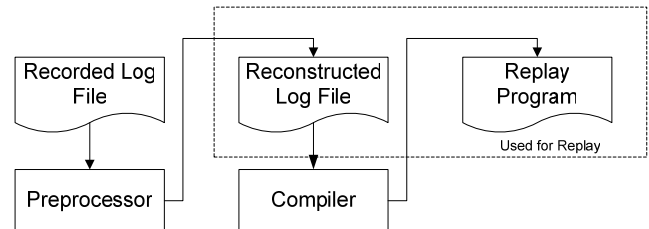


Figure 1. The Replay Scheme

Most existing replay schemes either simulate the machine code or interpret an intermediate code, taking the run-time log as input. Our replay scheme is unique in that it instruments the source code

by adding log-reading operations based on the run-time log, which makes it possible to recompile it for direct execution on any desktop machines, instead of interpretation or simulation. This approach makes the replay tool more portable since it does not depend on the existence of a simulator for the motes hardware and it is not tied to any intermediate code design. Moreover, direct execution is well known to be faster than interpretation or simulation by at least an order of magnitude.

Figure 1 shows a diagram for our replay scheme. The Preprocessor reorganizes Recorded Log File, which contains the raw log information recorded from the motes, into Reconstructed Log File. The latter file consists of a *data section*, which is to be fed to the replay program later, and an *interrupt table*, which is used for the creation of the replay program. The data section simply lists all the  $\langle \text{variable, type, value} \rangle$  tuples and the task scheduling log (LOG type 3) recorded by the motes program, all kept in the same order as they were recorded. The  $\langle \text{variable, type, value} \rangle$  tuples may either be from the anchor points or from the nondeterministic inputs. The interrupt table is composed by examining the interrupts recorded and the associated  $\#gv\_reference$  values. If an interrupt, say  $\text{interrupt}_x$  with  $\#gv\_reference = y$  occurs in the  $m$ -th instance of function $_n$ , then a tuple of the form  $\langle \text{function}_n, m, \text{interrupt}_x, y \rangle$  is added to the interrupt table.

The replay program is generated at the source level automatically by the compiler based on both the interrupt table and the code instrumented for mote execution. In conventional replaying, after every instruction (or some intermediate-level statement) is simulated or interpreted, the tool checks to see whether an interrupt handler should be replayed at this point (based on the logged information such as the PC, iteration count and recursive call depth). For our source-level replay, which is directly executed on a desktop after compilation, the replay of an interrupt is triggered by the match between the  $\#gv\_ref$  value observed during replay and that recorded by the interrupt handler. According to each item  $\langle \text{function}_n, m, \text{interrupt}_x, y \rangle$  in the interrupt table, we need to instrument a matching operation only in function $_n$  to check whether  $\text{interrupt}_x$  must be triggered, instead of checking for every interrupt in every function. Although function calls are deterministic, without Type 1 log, every update to  $\#gv\_ref$  will trigger a matching operation, which is obviously much more time consuming.

The main program is transformed such that it starts by calling *processLOG(type4)*, which searches the data section for the earliest anchor point recorded. (The original beginning of the program is an anchor point by default which, however, may have been pushed off the log at run time.) The main program reads all the  $\langle \text{variable, type, value} \rangle$  tuples for the anchor point before executing from the anchor point. After this, the replay program simply executes the original C program statements until it meets the next *processLOG* library calls. If Recorded Log File shows that, for some reason, the execution returns from the boundary function containing the anchor point, then the execution goes back to the main function which looks for the next anchor point. For each operation inserted to the instrumented mote program which writes LOG type  $i$  to the trace, the compiler inserts a corresponding operation, *processLOG(type i)* in the replay program. For each log type, the *processLOG* function executes according to the following description.

- *processLOG(type1)* – This is encountered either at the beginning of a function or right before a return. The routine resets  $\#gv\_reference$  to 0. If it is encountered at the function entry, it also keeps a counter to indicate which instance of the function is being executed. This counter will be used in

*processLOG(type2)* to check the conditions that trigger interrupt handlers.

- *processLOG(type2)* – The replay program updates  $\#gv\_reference$  just like in the mote-executed program except that the atomicity control is no longer necessary because we have sufficient information about when interrupts occur. The current function ID is passed as another parameter to *processLOG(type2)* which, at each time  $\#gv\_reference$  is increased during replay, checks to see whether the current instance and  $\#gv\_reference$  value meet the interrupt triggering condition. If so, the corresponding interrupt handler is called. The interrupt handler may not be invoked at exactly the same program point as in the original run, but its effect on the control and data dependences will be exactly the same and therefore does not alter how the error may be propagated.
- *processLOG(type3)* – If the tasks are scheduled randomly, unlike in TinyOS, then the replay program reads LOG type 3 in order to determine which task to execute.
- *processLOG(type4)* – A flag indicates whether this is the first anchor point encountered. If so, according to the pre-determined format, this *processLOG* routine reads in all variable values before starting to execute the first statement at the anchor point.
- *processLOG(type5)* – This *processLOG* routine reads in the external input from the log at the same program point as in the mote-executed code which records the information.

We have two alternatives for handling hardware-dependent code, the operations to hardware registers, to be specific. Our first option is to remove all hardware dependent code for replay. The impact of interrupts will be on the values of certain global variables. (Similar handling is performed in certain TinyOS simulators [6,24].) This however misses the opportunity to trace the error source further when a message containing wrong contents is received and saved to a hardware register by a low-level interrupt handler. Only when the second interrupt handler, posted by the first one, copies the wrong contents from a hardware register to a global variable will the error be located by backward tracking from a violated invariant. A remedy for this omission is to write a preprocessor customized for the hardware platform which converts references to hardware registers to global variables.

Statements which do not affect the invariants are deleted from the replayed program as described in the literature [10]. After these treatments, the resulting code for replay is compiled and executed on an ordinary desktop machine.

Note that the bookkeeping on  $\#gv\_reference$  to enable source-level tracing and replay does not cost much more than the operations to save the loop counts in the assembly code in order for the replay program to be able to continue correct execution after an interrupt handler exits. Recording the return address in the trace alone is insufficient. As a matter of fact, if the function contains irreducible cycles in its control flow graph, it is not obvious how to count loop iterations so the replay can continue correctly after returning from an interrupt handler.

The correctness of our replay scheme is formally stated by the following theorem.

**THEOREM 3.1.** Suppose an incorrect program statement causes an invariant to be violated at run time. Under the record-replay scheme described above, the same incorrect program statement will cause the same invariant to be violated in the replayed program. □

Due to space limitation, we omit the formal proof to the above theorem. Nonetheless the main idea is quite intuitive. For each

violated invariant, the error eventually must be traced back to a wrong value which is propagated through a use-def chain to the invariant. In the absence of nondeterministic events at run time such as interrupts, it would be a trivial matter to show that the use-def chains observed during replay is identical to that exhibited by the mote program. The impact of the nondeterministic events can be analyzed by considering different possibilities for an interrupt handler to modify or to use a global variable's value and thus may alter the use-def relationship. It can be demonstrated that, under all circumstances, the use-def relationship exhibited by the replay program will be identical to that of the motes-executed program.

#### 4. Multi-level Tracing

Theorem 3.1 uses Assumption 2 made in Section 2. If that assumption is not satisfied, then when an error is detected, we either cannot find an anchor point to replay the program or cannot find the error source during replay. This can happen if the storage for logging is small or the error happens long time before it is detected (through the violation of a predicate). To enable replay under such a circumstance, we present multi-level tracing in this section. Rather than instrumenting the whole program, we divide the program functions into different levels based on how "far away" (as defined bellow) they are from the invariants being checked. Naturally, another benefit of multi-level tracing is the relaxed requirement on program memory size. Nonetheless, with multi-level tracing, we no longer have the guarantee that the error source will be found, but at least we have partial traces to narrow the search.

Multi-level tracing follows an iterative procedure described below.

##### 4.1 An Iterative Tracing and Replay Procedure

For the purpose of defining the levels of tracing, we build a graph based on the dependence information computed previously. For convenience of implementation, we wrap each invariant-checking operation in an *invariant-checking function* and insert a call to this function wherever the invariant must be checked.

DEFINITION 4.1 Given a set of invariants, the *invariant-based Program Function Dependence Graph (PFDG)* for a program is a set of nodes, each representing a function whose execution directly or indirectly affects whether the invariants holds, and a set of edges of two kinds, namely the *calling edges* and the *dependence edges*. A calling edge  $\langle f1, f2 \rangle$  is drawn if  $f1$  is directly called by  $f2$ . Dependence edges are drawn according the construction rule below.

##### Construction Rule for Dependence Edges:

Suppose operation  $u$  in function  $f1$  has a direct control/data dependence on another operation  $d$  in function  $f2$  and this dependence is a link in a dependence chain originating from an invariant. We draw a directed dependence edge from  $f1$  to  $f2$ , denoted by  $f1 \rightarrow f2$  if one of the following is true:

- Function  $f1$  calls  $f2$  ( $u$  takes place after  $f2$  returns to  $f1$ )
- Function  $f2$  calls  $f1$  ( $d$  takes place before  $f1$  is called)
- Both  $f1$  and  $f2$  are directly called by a third function  $g$ .

However, if none of the above is true, then  $f1$ 's dependence on  $f2$  is passed through a number of function calls and returns. For the purpose of our tracing algorithm, we draw a chain of dependences to make it clear how this dependence is propagated through a call chain. This is described below.

If there is a call chain,  $C1$ , from  $g$  to  $f1$  and another,  $C2$ , from  $g$  to  $f2$  such that no other node belongs to both call chains, we say  $g$  is a *closest common ancestor* of  $f1$  and  $f2$ . We find all *closest common ancestors* of  $f1$  and  $f2$  in the call graph.

Next, for each closest common ancestor of  $f1$  and  $f2$ , say  $g$ , we find two of its immediate callees,  $g1$  and  $g2$ , one in the path from  $g$  to  $f1$  the other in the path from  $g$  to  $f2$ . We draw a chain of dependence edges connecting  $f1$  all the way to  $g1$  following  $C1$ . Next we draw another chain of dependence from  $g2$  to  $f2$ , following  $C2$  in its opposite direction. Finally, we connect these two chains of dependences by the edge  $g1 \rightarrow g2$ . □

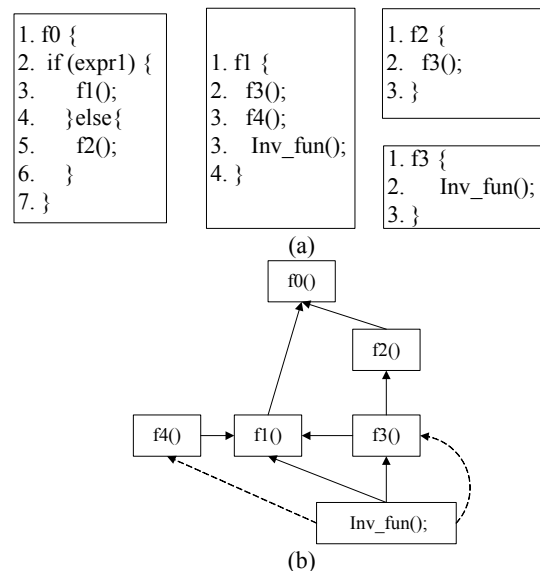
By following call edges and dependence edges, all dependences can be found in this graph by transitivity. Unless specified otherwise, functions mentioned in the rest of the paper refer to those in the invariant-based PFDG, and all variables mentioned will be those used in the invariants or those affecting the variables in the invariants.

##### Example:

```
f {
  f1(); //
  inv(); //use x
}
f1 {
  f2(); //define x
```

In the example above,  $inv()$  is assumed to be an invariant-checking function. We have call edges  $\langle inv, f \rangle$ ,  $\langle f2, f1 \rangle$  and dependence edges  $f1 \rightarrow f2$ , and  $inv \rightarrow f1$ .

Figure 2(a) shows another piece of program and its invariant-based PFDG (Figure 2(b)). Here the function  $Inv\_fun()$  is an invariant-checking function and function  $f3()$  and  $f4()$  both modify some variables used in the invariants.



**Figure 2.** An Example of invariant-based PFDG (Solid arcs represent call edges and dotted arcs represent dependence edges. In this example, an operation within  $Inv\_fun()$  uses a value passed from the caller  $f4()$  and another value passed from the caller  $f3()$ .)

DEFINITION 4.2 In an invariant-based PFDG, a sequence of connecting edges is called a *canonical path* if the sequence

originates from an invariant-checking function  $inv$  and is composed by a prefix  $\langle inv, f_1 \rangle, \langle f_1, f_2 \rangle, \dots, \langle f_{m-1}, f_m \rangle$ , with calling edges only, and a postfix  $f_m \rightarrow g_1, g_1 \rightarrow g_2, \dots, g_{n-1} \rightarrow g_n$ , with dependence edges only. The prefix or the postfix may be empty, but not both.

**DEFINITION 4.3** In an invariant-based PFDG, a function  $f$  is said to be at the level  $n(n \geq 1)$  if, among all canonical paths ending with  $f$ , the shortest path has the length  $n$ .

With the prefix and postfix clearly separated for each canonical path, we can define set of functions in which variable values are recorded for replaying. In order to make replay possible, in addition to the five types of logs discussed in the previous section, we need to record additional information for boundary functions defined below.

**DEFINITION 4.4** In an invariant-based PFDG, a function  $f$  is said to be a *boundary function* for level- $n$  tracing if there exist an  $n$ -long canonical path ending with  $f$  which consists of call edges only.

In our iterative debugging procedure, what to be included in level- $n$  tracing depends on the result of tracing and replay at the lower levels. Our iterative procedure can start with any level  $m$ , as long as all functions at levels  $m$  or lower are all included for instrumentation. Without loss of generality, we assume the procedure starts at level 1. The functions to be instrumented include all level-1 functions and all interrupt handlers which may modify any global variables used by any level-1 functions.

Obviously, for level-1 tracing, all immediate callers of an invariant-checking function are boundary functions. At the entry of each boundary function we record the entire calling context at run time, i.e. all global variable values and the arguments passed to the function. For all non-boundary level-1 functions, i.e. those non-interrupt functions connected by dependence edges from an invariant-checking function only, logs of types 1-3 are recorded but not the entire calling context. For all interrupt functions that receive external inputs, logs of type 5 are also recorded.

If an instrumented function calls a higher-level function  $g$  (which is not instrumented),  $g$ 's return value (if any) and the global variables written during  $g$ 's execution are recorded right before  $g$  returns. This allows the instrumented function to continue the execution correctly. Nothing else in  $g$  is recorded no matter what non-instrumented routines are called within  $g$ . At replay, the program statements in  $g$  are not replayed, but its return value and modified global variables are used to continue the execution of  $g$ 's caller. This way, we limit the size of the instrumented code and the recorded trace. This multi-level tracing is different from existing partial-replay schemes which either replay all callees of any replayed function or estimate the call effect bases on certain statistic assumptions.

Note that, during replay, the level-1 functions may be executed multiple times while the program statements belonging to higher-level functions are skipped in between.

Since the invariant-checking functions are always replayed, violation of invariants will always be detected. The programmer, using debugging tools such as GNU's gdb, can follow the program execution and produce a replayed execution trace. The statements along the trace leading to the error can be examined, which will have one of the two outcomes: the faulty statements (or the unexpected events) which cause the error are found, or such statements (or events) lie outside the level-1 trace. In the former case, debugging is done. In the latter case, the execution path extends beyond the level-1 trace. Mapping this non-ending

path back to the invariant-based PFDG, we obtain a subset of canonical paths which are called *error-hiding paths* from level-1 tracing.

Next, we inductively assume that level- $(n-1)$  tracing has not led to the discovery of the source of the error but has marked all parts of error-propagation paths that are found during all level- $m$  tracing ( $m < n$ ). We present the following algorithm for level- $n$  tracing.

#### ALGORITHM 4.1 Determine which functions should be instrumented for level- $n$ tracing

Steps:

1. Let  $S$  be the set of functions to be instrumented.
2. Add all functions in the error-propagation paths found in level- $m$  tracing ( $m < n$ ) to  $S$ .
3. Add every level- $n$  function which is immediately reachable from any error-propagation path (i.e. can be connected by a single edge from a node in the path) to  $S$ .
4. Add all invariant-checking functions to  $S$ . □

Among all functions in  $S$ , we find the boundary functions for level- $n$  tracing according to the invariant-based PFDG. We add recording operations in these functions to record the entire calling context. The rest of the instrumentation follows the same discussion in the case of level-1 tracing. In practice, one can be flexible when using our iterative tracing procedure. If the original program size is too large for even level-1 tracing described above, one can a subset of level-1 functions as long as the side-effect of their callees are recorded to allow replay to continue. The invariant-checking functions must always be executed for tracing, so that the error can at least be detected. If the subset chosen for level-1 tracing does not lead to the discovery of the error source, another subset is chosen, and so on. On the other hand, if the size of the original program is small, one can start with level- $m$  tracing for some  $m > 1$ . The relationship between the original code size, the available program memory and the choice of  $m$  is not explored further in this paper.

#### 4.2 Termination of the Iterative Tracing Procedure

If the replay for the level- $n$  tracing does not lead to the discovery of the error source and neither does it repeat any of the previous execution paths, then the execution paths used for the next level tracing will accumulate further. The tracing may also lead to the violation of a different invariant. The level-1 tracing for the new violation will then be mixed with tracing for the previous violations. All these may theoretically cause the instrumented code size to exceed the available program memory.

However, if we assume that the error-hiding path found in level- $m$  tracing always repeats itself in level  $m+1$  tracing, then, obviously, the iterative tracing and replay will eventually expose the error source by replay, as long as the instrumentation of all functions in the error-hiding paths always fit in the program memory. Note that the program memory required in this case will usually be significantly less than full instrumentation, because we instrument along a single path. Also note that, even though under nondeterministic external inputs the program may take different execution paths in each deployment or each tracing, the *function call/dependence paths* leading to the violation of the invariant, i.e. the error-hiding path, may still be the same. Our assumption here, therefore, accommodates nondeterministic behavior to a certain degree, even though it is not ideal.

### 4.3 Decision on Whether to Inline a Function

To further reduce the code size after tracing instrumentation, we notice that we can reduce the number of logs of type 1 if we inline function calls. (Of course, interrupt handlers cannot be inlined.) However, if a function is called in more than one place in the program, then inlining may increase the program size due to duplication of the function body. Fortunately, the inlining decisions for different functions are independent and the cost model is simple. For each function, let  $S_{original}$  be the code size

before instrumentation and  $S_{Instr\_func}$  be the increased code size due to inserted operations to write LOG types 2, 3 and 4. (Type 5 is recorded in interrupt handlers only, which are never in-lined.)

Further, let  $S_{call}$  the increased code size due to inserted operations to write LOG type 1. For inlining to be beneficial for the function under consideration, we must have

$$(S_{original} + S_{Instr\_func})n < S_{call} \quad (1)$$

## 5. Implementation and Experiments

### 5.1 Implementation

We have implemented a preliminary version of the proposal tool targeting WSN applications based on TinyOS 2x executed on TelosB motes. A TelosB has 48KB program memory and 1MB external flash memory. The program analyses and transformations proposed in this paper are incorporated in an Open64 C compiler [13] which is a widely used compiler infrastructure that supports a rich set of code analysis and transformation features.

Figure 3 shows a diagram for the framework of our dependence-based multi-level tracing and replaying tool described in Section 2.4. A TinyOS application written in the nesC language, with invariants specified for certain program scopes, is first preprocessed by a tool to automatically insert the invariant checking operations in the nesC program. The program is then compiled by a nesC [20] compiler (version 1.2.9) into a C program which is analyzed by a customized Open64 C compiler before translating into two copies of C programs, one for execution on the motes, and the other for replay.

Each invariant inserted in the WSN application specifies a certain correctness property based on local information only. If a property concerns a global behavior, it is first decomposed into a set of “local” invariants before they are inserted in the nesC program. In this paper, we consider only those global properties that can be decomposed into a set of local ones. The issue of decomposing global properties into logical expressions over local properties will not be addressed in this paper.

Currently, we use a trace buffer of the size of 2KB in the RAM for LOG recording which is transferred to the external flash memory when the buffer is full.

### 5.2 Experiment

For experiments, we have used the following three test cases.

- TC1 (BlinkC) -- This is a published TinyOS 2x application. We insert an invariant which requires that the frequency of three LED’s blinking must follow a user specified pattern. We then add a long running task which increases the latency of Timer.fire(), causing a violation of the invariant.

- TC2 (TestSerialCO2) -- This application monitors indoor CO2 data in multiple locations inside a building. We require that, from each mote, the base station must receive new CO2 reading with a period of two seconds or less. This property is specified by two invariants. The base station must make sure that it receives a new piece of CO2 reading from each mote every two seconds or less. Each mote must make sure that, within a period of two seconds it receives at least one piece of data from its own sensor and sends it to through the radio channel.
- TC3 (EasyCollectionC) -- This is a published code which collects data using implemented Collection Tree Protocol. We insert invariants require that the data must be sent in sequence.

Table 1 compares the number of the functions traced using the dependence information against those without such information. The data indicate that, with a single invariant consisting of fewer than 3 variables, the dependence information allows between 40% and 85% of the functions (not including interrupts handlers) to be skipped for tracing. However, the number of functions to be traced remains to be large for test cases TC2 and TC3.

Figure 4 shows the effect of inlining. Over 70% of the functions are called only once and, based on the simple cost model, can be inlined. Table 2 lists the code size under different instrumentation schemes in comparison with its original size  $S_{original}$ . For the baseline code size,  $S_{baseline}$ , we include the inserted operations to record all types of log information without taking advantage of dependence information. The data show that the baseline size is too large for the program memory on TelosB motes. The column  $S_{no-inlining}$  shows the remaining code size if we do not trace functions which have no effect on the invariants. It is much smaller than the baseline size, but still large. Take TC2 for example, the size of its  $S_{no-inlining}$  is 50534, which exceeds the TelosB memory boundary size 48K. The column  $S_{inline}$  shows the code size after selective inlining. After inlining, the code size is decreased further. Of course, if many invariants are checked in the same program or some invariants involve many variables, then the use-def chains may cover more functions and the instrumented program size may increase. In the worst case, the code size may be too large to fit in the program memory, in which case multi-level tracing will be needed.

**Table 1** Functions Instrumented Using Dependence Information as a Fraction of the Total Functions

Test case	# of traced functions	# of total functions	%
TC1	46	299	15.38
TC2	605	1499	40.36
TC3	604	1385	43.61

**Table 2** Code Size (bytes)

Test case	$S_{original}$	$S_{baseline}$	$S_{no-inlining}$	$S_{inline}$
TC1	2650	18760	13760	13296
TC2	24302	80058	50534	42878
TC3	18670	73214	45090	37778

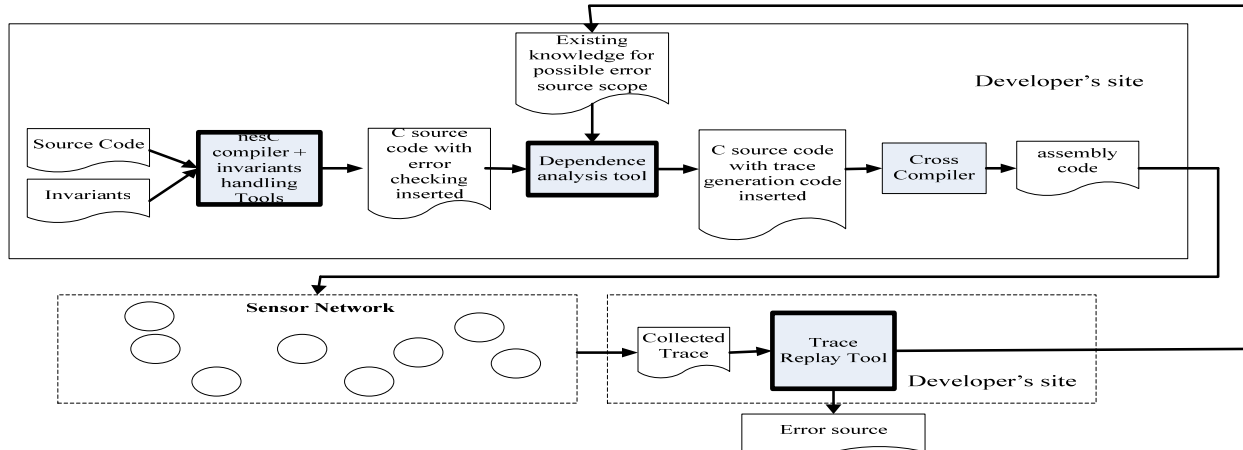


Figure 3. Framework of dependence-based multi-level tracing and replay for WSN debugging

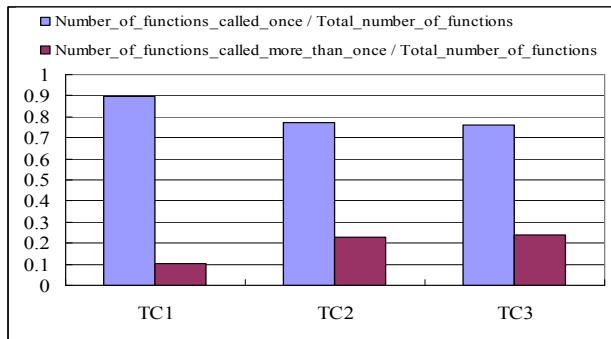


Figure 4. Inlined functions as a fraction of the total

Table3 shows the overhead due to instrumentation (with slicing and inlining optimization). For each call to a task function which does not contain an anchor point, the storage used for log trace is 4 bytes (2 bytes for function entry and 2 bytes for function return). At each anchor, each saved variable requires a record of 5 bytes, including 2 bytes for the variable name, 1 byte for the variable type, and 2 bytes for the variable value. To save a nondeterministic input or the current #gv\_reference value, each variable also takes 5 bytes. For TC1 overhead is measured from the beginning of the program to the first time when the error is caught. For TC2, we measured the overhead during each sampling period. For TC3, overhead is measured between the start to send a message till the message is sent, and we call the measured time interval “sending period” for short. For TC3, we compares the overhead with and without counting the cost to write the log to the external flash, listed in two rows respectively. Since the buffer size we set is 2KB, writing external flash is called about every 2.5 sending periods. Therefore, in the second row of TC3, the added overhead of writing external flash is the average overhead for each sending period. It is quite common that there is an idle period between two message sends long enough to be used for writing logs to the flash, as in TC2. Hence we marked the execution time overhead as negligible. When an error occurs, if the log buffer in RAM is large enough to store the entire log, the mote can directly send the log to the base station, rather than reading it from the external flash first.

Table 3 Instrumentation Overhead

Test case	Log Size (bytes)	Execution Time		Energy	
		Overhead (10 <sup>-6</sup> s)	Percentage (%)	Overhead (10 <sup>-3</sup> Joule)	Percentage (%)
TC1	56	70	1.01	0.039	2.21
TC2	1496	negnegible	negnegible	2.11	20.2
TC3	838	1970	13.32	0.129	15.5
		15050	101.76	0.304	36.7

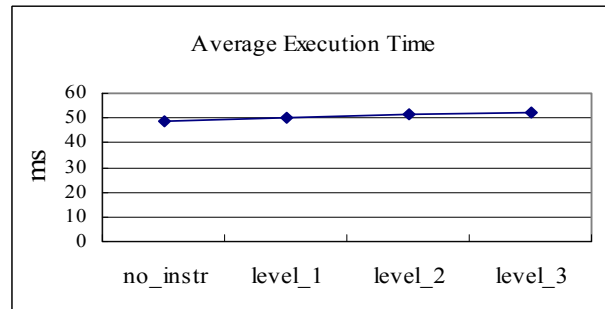


Figure 5. Comparing average execution time (TC3) between two message sends with and without Instrumentation

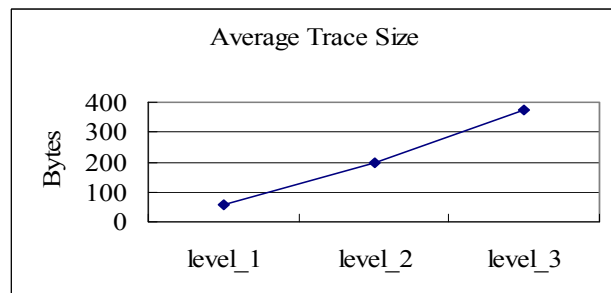


Figure 6. Comparing average trace size between two message send operations with different levels of instrumentation for TC3



We used TC3 for the multi-level tracing and replay experiments. In this program, we send a piece of data (called a message) from the mote every 50ms. When a TinyOS program sends a message, it first checks to see whether the send-busy flag is raised (which indicates that the send buffer being full). If not, it is unsafe for the program to start sending a message. If the frequency of messages is low, failure to check the send-busy flag may not cause lost messages because the buffer is more likely to be free anyway. However, at a higher frequency, e.g. when the motes communicate frequently to form a cluster or to execute a security protocol, the chance for the buffer to become full increases, so do lost messages. We injected a programming error which lets the sender send the message without checking the send-busy flag first. We then load various versions of the instrumented code on the motes to execute, as separate experiments.

The run-time overhead due to instrumentation increases with the number of instrumented functions. For TC3, we measure the time interval between two `Send.sendDone` events. At each event a message in the send queue is sent. Figure 5 compares the average time interval for no instrumentation (`No_Instr`), level-1 instrumentation (`level_1`), level-2 instrumentation (`level_2`), and level-3 instrumentation (`level_3`). Figure 6 shows the recorded trace size for each kind of instrumentation. From these figures, we observe that, until errors occur, the instrumented code does not incur much overhead in time and space.

## 6. Related Work

Methods for error diagnosis and debugging for wireless sensor networks can be loosely classified into three categories, namely simulation/emulation [4,6,9,24,37], interactive debugging [7,14], and run-time logging [1-3,8,11]. Simulation offers considerable flexibility but often takes significantly more time than direct execution. Another factor to consider is that the simulated cases may not be sufficient extensive to catch errors that may happen during the real operation. The simulated operation environment may also be quite different from the operational environment.

Interactive debugging allows programmers to interact with sensor nodes by sending commands. The set of commands usually include those which set break points, watch points, and initiate step-by-step tracing. This methodology works particularly well if the programmer already knows what kind of errors will happen and where are the places to look. Otherwise, the step-by-step execution can be quite slow and tedious, with no guarantee that the anticipated error will surface in the debugging mode. In other circumstances, especially when the number of motes to be debugged simultaneously is large, it seems much more convenient to have execution traces ready when an error is detected.

Run-time logging has gained increased importance recently. The critical questions encountered when adopting this approach include what kind of errors should be monitored, where and how to log information for later debugging, and how to analyze the logged information to find out the error cause. Among recent efforts, *Sympathy* [1] focuses on data-collection applications. The metrics generated by each node are sent to a data sink, and a decision tree is applied to the collected data to find the failures. *Dustminer* [2] is a tool for uncovering bugs in networked sensing applications due to nondeterministic and incorrect interactions between different nodes. This tool collects a sequence of events and uses data mining techniques to recognize abnormal behaviors. *PAD* [3] is a light-weight packet marking scheme for collecting necessary hints, and it uses a probabilistic inference model residing at the sink to capture unique features of the sensor networks. *Passive Distributed Assertions* [11] allows the programmer to define certain properties of a distributed system.

The state information of each affected node is collected and analyzed through a separately-deployed sniffer network. *PD2* [8] focuses on the data flows generated by an application. It relates poor application performance to significant data losses or latencies of certain data flows (called problematic data flows) as they go through the software modules on individual nodes and through the network.

Replay has long been widely used for bug reproduction. As mentioned in the introduction, this approach has mainly been used on resource-rich distributed and parallel systems. We briefly describe software-only deterministic replay techniques, given that our work is software-only. A typical and popular idea is to record all possible factors (referred to as non-determinism) that affect the program's execution before re-executing the program. The idea is straightforward, but potential overhead is large.

A significant number of prior efforts have focused on how to reduce the overhead in terms of space and execution time [32-35]. Several techniques are developed recently to capture sources of nondeterminism in multicore parallel programs and to perform replay under such nondeterminism [30,31,36]. The nature of nondeterminism on multicores is quite different from that arising from distributed systems. The latter are due to factors such as interrupts, network delays and unreliable communication, among other things. Moreover, the replay techniques mentioned above cannot be used practically on WSNs which generally have severe resource limitation.

## 7. Conclusion and Future Work

In this paper, we have presented a multi-level tracing method based on dependence information. Our experiments show that the approach has made it possible to instrument several test programs on WSN under the stringent program memory constraint and find injected errors.

Although our current experiments are performed on TinyOS-based applications, the proposed methodology and tool can be applied to all embedded systems which satisfy the assumptions made in the introduction. It can also be extended to a broader range of embedded systems.

Several improvements are considered for future work. Most importantly, additional experiments are needed to apply the tool to a broader range of WSN applications and other types of distributed embedded systems. We also plan to cover a larger set of realistic errors.

## Acknowledgment

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