# Power-Based Side-Channel Attack for AES Key Extraction on the ATMega328 Microcontroller

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Abstract—We demonstrate the extraction of a private-key from Flash program memory on the ATMega328 microcontroller (the microcontroller used on the popular Arduino Genuino/Uno board). We loaded a standard AVR-architecture AES-128 implementation onto the chip and ran this implementation to encrypt 500 randomly chosen plaintexts. By carefully measuring the chip's power consumption, we were able to correlate the consumed power with the input plaintexts and key values that might be used to encrypt each AES block, and extract the hard-coded key used for AES encryption. We describe here our test infrastructure for automated power trace collection, an overview of our correlation attack, sanitization of the traces and interesting stumbling blocks encountered during data collection and analysis, and the results of our attack.

Index Terms—AES, side-channel, power consumption, AT-Mega328, Correlation Power Analysis

# I. INTRODUCTION

Recent concerns about data privacy have brought attention to the necessity of encryption algorithms. One of the more popular symmetric-key algorithms, Advanced Encryption Standard (AES), has been the U.S. government standard since 2002 (ISO/IEC 18033-3), and is used in a multitude of applications: SSL/TLS protocols [1], Kerberos [2], and demonstrably secure embedded devices [3]. This last application in particular, embedded devices, has seen much growth in recent years, given the advantages of computation on smaller embedded devices: low power, lower system latency, and generally smaller device size.

Small hardware implementations, however, are notoriously vulnerable to a range of side-channel attacks [4]. Timing, electromagnetic radiation, and power consumption are just three commonly exploited vectors used to leak information about ongoing computations and data on the chip. Knowing that a device architecture is amiable to side-channel exploitation is useful in deciding whether to execute unprotected sensitive computations or store data on devices with similar memory and processor characteristics.

We aim to demonstrate a reasonably realistic power-based side-channel attack on AES-128-ECB software implementation on one such embedded device: the ATMega328 micro-

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controller produced by Atmel. The ATMega328 is the basis for the widely popular development board, Arduino Uno <sup>1</sup>.

In section two, we review for the reader, the theoretical ideas underpinning our attack. In section three, we describe our implementations - our hardware setup, power measurement infrastructure, correlation methodologies, instructive problems that we encountered, and overview the structure of our source code. In section four, we quantitatively describe the results of our attack.

### II. PRELIMINARIES

# A. Controller Specifications

The ATMega328 family of chips is an 8-bit microcontroller series with 32 KB of NAND-type flash and 2KB of SRAM. The controller runs off a 16 MHz external clock on the Arduino board. Typical power consumption of the chip is a 20mA current draw from 5V power supply, but it can vary depending upon the peripheral and I/O pin usage [7]. Out attack exploits the NAND-type flash memory architecture that consumes marginally more power when accessing addresses that store value-zero (discharge) bits <sup>2</sup> [8].

The encryption program running on our ATMega328, AESLib, uses an Arduino-specific port of the avr-crypto-lib by Davy Landman and Bochum Hackerspace [5] [6]. AESLib is one of the more widely-used AES implementations for Arduino, and includes support for ECB and CBC-modes of AES. Our team decided that ECB-mode would be more amiable to a power correlation attack, and correspondingly chose to exploit the library's AES-ECB implementation. We discuss ECB in further depth in section 3.D.

# B. Correlation Power Analysis

Correlation Power Analysis (CPA) is a type of side channel attack that relies on power consumption information. On a high level, CPA attempts to correlate observed power consumption with expected power consumption. To a greater extent than more basic forms of power analysis such as Simple Power Analysis, CPA attacks are able to extract secret keys from noisy data. This requires collecting the power consumption

<sup>1</sup>Other models of the Arduino, such as the Arduino Mega and Arduino Genuino Micro use ATMega chips as well, that have a similar architecture to the ATMega328. It is possible that this attack could be adapted to those chips as well.

<sup>2</sup>In a highly simplified power consumption model, NAND-flash charges a central bit line connected to a series of memory cells. Depending on the value stored in the accessed memory cell, the line is discharged or not. Thus, the line requires data-dependent recharging.

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of a device performing encryption over many different plaintexts with the same key. We can then build a power model that contains the expected power consumption of the device performing a particular operation during encryption over the given plaintexts with every possible key.

In our case, we used CPA against AES encryption. There are several operations during AES that can be good candidates to model power consumption for AES, depending on the software implementation. Attacks tend to model power from the first round of AES because it provides the best data regarding which bytes of plaintext and key are getting combined. Power analysis tends to target the XOR operation in the AddRoundKey or the SBOX substitution during the SubBytes operation, since these can consume predictable amounts of power. Different implementations use different estimates to correlate power consumption with, most commonly the Hamming Weight of the operation result or the Hamming Distance of the input and output of the operation. These may be correlated with the amount of power consumed because reading a "0" or a "1" from memory may require different amounts of power.

Using CPA against AES requires collecting the amount of power consumed over hundreds of plaintexts. We then calculate the expected power consumption for each of these plaintexts with every possible key. Trying every possible key with AES is possible because a different byte of the key is used for every byte of the plaintext. This reduces our search space to  $2^8$  possibilities for each key byte, which allows us to build a power model that takes every one of these  $2^8$  key byte possibilities into account for each byte.

After building a power hypothesis consisting of the amount of power consumed for each possible plaintext with every possible key byte, we can calculate the correlation coefficients between these expected amounts of power and the amount of power observed during encryption. One advantage of CPA is that we don't need to know exactly when our targeted operation occurs during encryption; we can calculate the correlation coefficient between the power hypothesis and the power trace (collected power consumption over time) at each point of the trace. We then take the key byte that gives us the maximum correlation coefficient as our best guess key byte. Repeating this process 16 times gives us best guesses for all 16 bytes of the key.

### III. PROTOCOLS AND PROCEDURE

# A. Data Collection Infrastructure

A central piece of our work was developing the serialconnection based data collection framework to feed plaintexts for encryption to the Arduino, and read the resulting power trace from the oscilloscope. An outline is given in Fig. 1.

We needed a subset of the power trace that correlated strongly with the input plaintext and key. Specifically, we were interested in finding the portion of the trace that corresponded to the xor(plaintext,key) operation, and the the SBOX permutation taken over the xor result. In order to automate slicing to this part of the trace, we modified the AESLib SBOX assembly code to insert a flag on a memory-mapped

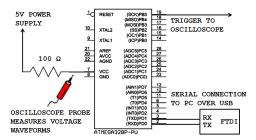


Fig. 1: The oscilloscope probes voltages on the chip's power line, starting automated power trace on a trigger that signals the start of AES

register that pulled up pin 13. Our oscilloscope triggered on this output, and automatically captured the part of the trace immediately after the rising edge on pin 13.

Central to our data collection was a Tektronix 5054B computing oscilloscope that collected samples at 4GHz with internal memory bank of at most 16 million points. The sampling rate limited the resolution of traces that we were able to capture; we originally thought this physical cap on data quality was causing correlation issues we ran into, until we discovered arbitrary DC shifts in the traces. We discuss this challenge in more detail in Section III.C. We used the oscilloscope's GPIB (IEEE-488 General Purpose Interface Bus) query interface to automate configuration and downloading of traces.

In the final iteration of our system, we have an orchestrating computer C send plaintexts to the Arduino for encryption every 2 seconds over the Arduino's serial port (Fig. 1). The pin 13 trigger resulted in an oscilloscope trace capture, which was subsequently sent back to C.

More recently, we have been attempting to use the Tektronix FastFrames feature to take capture batches of 2,500-point traces at once, and use one memory-read and GPIB-write operation to transfer these traces to the computer. This would allow us much faster trace measurement, which is currently bottlenecked by the GPIB-write operation. As we will discuss in Section 4, the number of key bytes we can recover is directly correlated with the number of plaintexts we can capture and average.

Photos of our collection framework can be found at https://www.dropbox.com/sh/usialgelvfqlsdr/AACvqOHKEWoumWNYi2WRIebCa?dl=0. Of perhaps small interest is the grounded aluminum box encapsulating the ATMega328 setup, which reduced the EM noise and interference which we noticed in our power traces.

# B. Implementation of CPA and Power Model

When we were first deciding what operation to model, we examined AESLib to try to determine which AES steps might be best to estimate the power consumption for. The XOR operation from the AddRoundKey step consisted of two operations, a load and an XOR: 1) ld r0, X+, and 2) eor param, r0, where param was a byte of the key and X+ was a byte of the plaintext. The SBOX operation from the

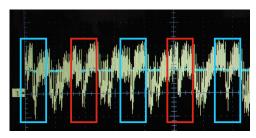


Fig. 2: XOR operations alternated between results of all "0"s and all "1"s. The power consumption was noticeably different depending on the Hamming Weight of the result.

SubBytes step consisted of a move and load program memory instruction: 1) mov r30, ST00, and 2) lpm ST00, Z. We hypothesized that reading from memory might require different amounts of power depending on whether we were reading a "0" or a "1". We first chose to try to model the power consumed during the SBOX operation, since its nonlinearity would make for clearer key results. However, when we built a power model based on the SBOX operation and then tried to correlate it to our first set of traces, we found no useful correlation. It later became clear that this was a problem with our data rather than our power model (as outlined in III.C). At the time, however, we were concerned that maybe the power consumed by the Arduino was for some reason not proportional to the SBOX output.

To verify that the results of the SBOX and XOR operations were actually correlated by the amount of power the Arduino consumed, we experimented with modelling the expected power consumption from both operations atomically. We examined the power consumption of just the AVR assembly operations corresponding to these steps on the Arduino. We were unable to easily make out any difference in power consumption between when the result of the SBOX operation was all "0"s or all "1"s, but we were able to easily see a diffference in power consumption between when the result of the XOR operation was all "0"s or all "1"s (Fig. 2).

Based on these results, we chose to move forward by correlating the power consumption with the Hamming Weight of the XOR result. After collecting more reliable traces (as explained in III.C), we re-ran CPA using this metric and were able to recover many of the key bytes. However, we ran into a symmetry issue. Each key byte had an equal correlation with the power consumption as its complement with respect to 255 (e.g. key byte candidates such as 1 and 255 or 3 and 252 showed the same correlation) when we used the result of the XOR. When the plaintext byte was x and 255-x, we got XOR outputs y and y, respectively. These opposites were equally correlated (or anti-correlated) with our power model. Taking this into account, we were able to correctly guess  $\frac{11}{15}$  key bytes down to the correct key byte k or 255-k.

This symmetry from the XOR output meant we wouldn't be able to recover the correct key without applying brute force guessing after running CPA. Using the output of the SBOX for the power model would have the advantage of avoiding this symmetry, giving us one correct key. After getting more reliable traces, we retried CPA with a power model employing

the Hamming Weight of the SBOX output and found that this was actually a reliable power model to use. Using Hamming Weight of SBOX output while increasing the number and reliability of traces we used, we were able to recover all key bytes.

In later iterations of our code, we aimed to speed up analysis of waveforms, and obtain results like those in Fig. 3 more quickly; so we replaced our correlation function with a faster iterative correlation function that calculates the correlations given  $1, 2, 3, \ldots, i, \ldots, num\_plaintexts$  traces, without recalculating correlations for the previous i-1 traces.

# C. CPA Challenges and Solutions

During the course of the experiment, we faced several challenges in data collection and interpretation. They are listed below, along with our solutions:

- Our initial idea was to measure the voltages at the two ends of a  $1\Omega$  resistor connected between the VCC pin of the microcontroller and the power supply, and measure their difference using a Tektronix ADA400A Differential Pre-amplifier. However, as with any practical amplifier, the ADA400A has a gain-bandwidth product limitation, and we could achieve a gain of 10 at our required bandwidth. Also, the amplifier introduced its own noise into the measured power traces, which reduced our chances of a successful CPA attack. To resolve this issue, we finally decided to get rid of the differential measurement setup, and measure only the voltage at the VCC pin. We also replaced the  $1\Omega$  resistor with a  $100\Omega$  one, in order to get better gain.
- Another challenge in CPA data collection is dealing with DC shifts in the power waveform. Minor fluctuations in the power supply voltage are natural, but they can mask or scramble the power spikes due to the AES operations. Our solution was to measure power traces for 10 iterations of AES encryption on the same plaintext, and taking the average of these 10 waveforms for CPA. The averaging operation was done using the oscilloscope, and it indeed provided significant improvements in our attack mechanism.
- We noticed that some of our AES computations took different lengths of time than others, even though they were supposedly doing the same operations. We suspected that these differences in computation duration may have been due to interrupts. To test this hypothesis, we disabled interrupts during AES computation by clearing the Global Interrupt flag. This greatly reduced the timing differences from trace to trace, improving trace alignment during correlation.
- We also faced the issue of missing traces. When the Arduino encrypted some number of plaintexts, the oscilloscope would record the power consumption from most, but not all, computations. This made it difficult for us to match power traces with the correct plaintext. We realized that the oscilloscope was missing traces because it did not always have time to reset itself between different plaintexts. Adding a delay before sending the next plaintext to the Arduino gave the oscilloscope enough time to

- reset and correctly record power traces from all of our plaintexts.
- CPA essentialy relies on statistical algorithms. Therefore, it is extremely important to have large sets of data samples to analyse. We started our experiment with analysing only 100 power traces (100 random plaintexts), but we were able to reliably recover only 10-11 of the 16 key bytes. Soon, we realized that we needed more data, and repeating the experiment for 300-400 traces enabled us to recover all the key bytes. It has to be noted that some keys needed even more power traces, and we estimate that 1000 traces are enough to recover any key. Details of our experimental results can be found in the link mentioned in Section III.A.

# D. Drawbacks

Aspects of our attack implementation are unlikely to be possible in real-world attack scenarios; we address these concerns and suggest possible remedies:

- We chose to attack the Arduino library's implementation of the AES-ECB mode. Although ECB is not semantically secure (i.e. you can derive information about the plaintext from the ciphertext), ECB is still (unfortunately) used as the default option in a number of crypto-suites, avr-crypto-lib included. This is because of its relatively simple implementation, compared to other more sophisticated modes of AES. Furthermore, our attack does not exploit the plaintext-ciphertext correlations in ECB to derive the key; rather, it uses the power sidechannel. For our team's first power-trace based attack, we chose a mode that we were confident that might have some correlation with the plaintext-key-guess XOR (the first computation in the first step of ECB). It might be possible to adapt our attack to CBC-mode as well.
- We modified the AESLib assembly code to pull high one of Arduino's I/O to signal the oscilloscope when to begin collecting traces (the scope's trigger). In a real world attack, it is unlikely that we will be able to insert a convenient signal to aid our trace collection and analysis result. Nonetheless, careful manual analysis of one trace could yield a constant time frame of interest, which, barring waveform time shifts, we could use to automate trace collection and trace slicing. We have demonstrated ways to reduce time-shift errors in our work.

# E. Overview of Source Code

All our source code can be found at https://github.com/skoppula/aes-sidechannel. Files in the source that might be of interest:

- cpa/cpa.py contains the source that reads in the waveform binary data (with helper wfm2read\_fast.py) and subsequently runs CPA. It outputs the top ten key byte guesses per byte of key, and a correlation visualizations like Fig. 3.
- data-capture/arduino-aes-2 runs AES encryption on a new plaintext 10 times, everytime

- a 'run' command is received on the terminal. The ten traces are later averaged on the oscilloscope. data-capture/arduino-aes-1 runs AES encryption on a plaintext sent over the serial port.
- data-capture/scope-interface-2 runs a Python script that interfaces with the Arduino to run AES at regular intervals, and interfaces with the oscilloscope to collect the corresponding traces. data-capture/scope-interface-1 is a Matlab implementation of similar functionality that we originally used to interface with the oscilloscope over GPIB; interfacing with the Arduino was done seperately in this version of the code (in data-capture/send-plaintexts-processing)
- data-capture/process-wfms contains the scripts we put together initially to parse and plot the first \*.wfm waveform binaries that we received from the oscilloscope. This was later integrated into cpa/cpa.py

# IV. RESULTS

We found more robust results by triggering our traces to start from the beginning of the AES EBC-mode  $\mathtt{xor}(\mathtt{plaintext}, \mathtt{key})$  and continue until SBOX substitutions are complete. These computations empirically correlated well with our key guesses. Furthermore, we found much higher rates of correct key guesses by disabling the chip's serial output and disabling interrupts. This seemed to eliminate inter-trace time-shifts that messed with our correlation analysis. In addition, averaging ten traces at a time seemed to eliminate DC power bias that shifted the power magnitude up and down between traces run on the same plaintext. Only after these corrections were we able to find any meaningful correlations and extract our first correct key guess.

We conducted the experiment three times, with three different private-keys - two randomly generated keys and one non-random key <sup>3</sup>. In all three, we were able to discover the correct key.

However, interestingly, the number of traces required to get complete accuracy differed between the keys. Specifically, it took 600 trace averages (each corresponding to a plaintext) to get complete accuracy on the non-random key, 300 trace averages to completely uncover the first random key, and 400 trace averages to uncover the second random. We were interested in understanding the performance of each key guess as the number of input plaintext traces increased, so for each run, we created a plot that tracked each key guess's correlation with the trace data as the amount of trace data increased (Fig. 3)

It takes roughly 30 minutes for our infrastructure to collect the traces for the encryption of 100 plaintexts. Data collection time seems to scale linearly with the number of plaintexts we process: encrypting and collecting the traces for 500 traces, takes on average two and half hours. Processing these 500

 $^3By$  non-random, we mean the key <code>[0x0 0x1 0x2 0x3 0x4 0x5 0x6 0x7 0x8 0x9 0xA 0xB 0xC 0xD 0xE 0xF]</code>. This was the test key chosen during the development stage of our project, as we were building the trace-collection infrastructure and writing the CPA code.

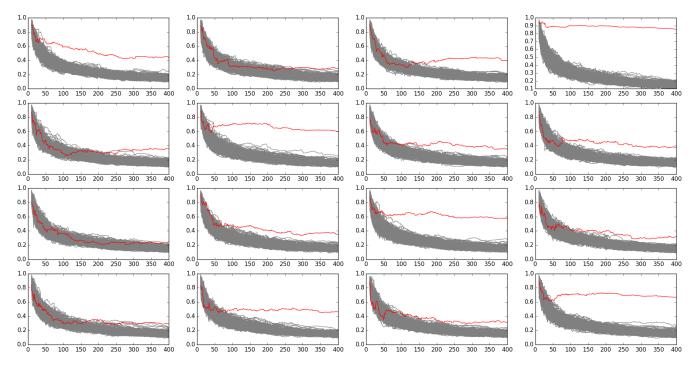


Fig. 3: Each graph corresponds to one of the 16 blocks/16 plaintext bytes/16 key bytes in our AES implementation. A single graph plots the correlation of all 256 key guesses (y-axis) with the power trace data, as more data is fed into the correlation (x-axis). The red line represents the correct key guess. Notice that by the time we feed the 400th trace into our CPA implementation, the correct key byte is the key guess with the highest correlation with all the traces (visible in the height of each red line at x = 400). Results for the other two CPA runs can be found in the Dropbox link.

traces, and extracting the correlation values and key estimates over i plaintexts for all i (Fig. 3) takes roughly five to ten minutes.

Our data and results can be found at https://www.dropbox.com/sh/07xni6s4tu4klme/AABnrBK-QZCVO1tMK4GFeQ5ta?dl=0.

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