Physical-Layer Discrimination of Power Line Communications

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Abstract—Power Line Communication (PLC) is consistently looked at as a cost effective and elegant solution for many large scale control and automation communication problems. This includes many critical infrastructure Supervisory Control and Data Acquisition (SCADA) systems. Because of this, PLC is investigated for the purposes of Wired Signal Distinct Native Attribute (WS-DNA) Physical-Layer (PHY) classification and validation as an effective intrusion detection method for PLC networks. This investigation captured intentional PLC messages, extracted WS-DNA fingerprints, and utilized Multiple Discriminant Analysis, Maximum Likelihood (MDA/ML) to perform device discrimination. The modulated communication signals of six Insteon Hub devices were investigated to assess the ability to perform device discrimination and validation. For all six devices, an average correct classification of $\%C = 90\%$ is achieved at Signal to Noise Ratio (SNR) ≥ 40 dB and $\%C = 99\%$ at SNR ≥ 46 dB. Receiver Operating Characteristic (ROC) curves are used to illustrate rogue detection results with Equal Error Rate (EER) of 10% achieved at SNR = 40 dB.

Index Terms—Communications Security, Power Line Communication, Physical-Layer Discrimination, RF-DNA, WS-DNA, Wired Signal.

I. INTRODUCTION

In the last several years the number of network devices have increased significantly with the advent of the Internet of Things (IOT). This has placed an increased demand on network security as many of these devices have intermittent connectivity. Media Access Control (MAC) addresses offers a single layer of authentication with it's own strengths and weaknesses. One key weakness is the threat of an attacker spoofing an authentic device in order to steal credentials or other information [1]. A unique solution in the ever growing problem of cyber security and bit level spoofing is to augment bit level credentials with an additional layer of security via Physical-Layer (PHY) discrimination. [2]–[6].

The goal of various PHY fingerprinting investigations in the past has been to improve the verification of devices through the unique physical attributes of their modulated signal [1] [7]. These attempts have focused on the identification of devices based on their radio frequency communication's "unique analog circuitry" [7]. Signal features, or fingerprints, are calculated for regions of interest selected based on signal content within the region [7]. PHY fingerprinting has also been implemented on wired devices in which wired Ethernet is passively tapped [8] and actively tapped [2] for the purpose of creating fingerprints to perform an added layer of network security.

Power Line Communication (PLC) has attracted the attention of industry as an elegant and cost effective solution for large scale control and automation communication networks [9], [10]. This includes Supervisory Control and Data Acquisition (SCADA) networks for smart grids, energy management systems, and other critical infrastructure communications. The appeal of PLC networks is that new infrastructure is usually not required for implementation as the communication lines are already present in the physical powerlines that make up a power grid. PLC networks are yet another example of a technology growing faster than the security designed to protect said technology. Many current PLC networks lack robust intrusion detection and the very nature of the power grid presents PLC as an unmonitored, possibly covert, communications network. Because power supplied by the power grid is required most everywhere, this grants PLC the ability to bypass most current network security measures to extract data from or inject data onto secure systems. To address this problem, the Wired Signal Distinct Native Attribute (WS-DNA) fingerprinting approach along with Multiple Discriminant Analysis, Maximum Likelihood (MDA/ML) are used in an attempt to demonstrate successful PLC device discrimination based on physical signal attributes.

This work is organized as follows. Section II discusses background information and related papers on recent works in device fingerprinting. Section III discusses the methodology and experimental setup, followed by device discrimination results in Section IV and summary and conclusions in Section V.

II. BACKGROUND

It is the very entropic nature of the manufacturing processes that introduce distinct variations in electronic components which makes hardware fingerprinting possible. These distinct hardware variations introduce PHY differences in Radio Frequency (RF) emissions that are unique to individual devices and can be used to discriminate devices [11]. These differences can be seen in many hardware components to include capacitors, amplifiers, oscillators, inductors, and other electronic components that effect the fingerprints of each device [11], [12]. The variations in these components in-turn create slight variations in the modulated communication signal which can cause Amplitude Modulation (AM) - Phase Modulation (PM) conversions, alter symbol rates, or alter the observed center frequency [11]. These variations in signals and components also apply to PLC devices. Because of

MATLAB[®] is used to post process the PLC modulated signals and to generate the WS-DNA fingerprints. During

TABLE I
DEVICES UNDER TEST

Transmit Devices		
Device	Address	Collected SNR
Hub 1	39:30:05	45.2 dB
Hub 2	39:32:86	45.1 dB
Hub 3	39:21:82	44.8 dB
Hub 4	39:20:DC	44.7 dB
Hub 5	39:29:7F	44.9 dB
Hub 6	39:17:E3	45.3 dB
Receiver Device		
On/Off Outlet	39:A0:02

 Fig. 3. Typical Time Domain Response of a Modulated PLC *On* Message Sent From an Insteon Hub Illustrating Bursts, Messages, and Repeated Messages.

this process a 16th order butter-worth software filter centered at 131.65 KHz with a 30 KHz bandwidth is used to process the PLC signals prior to fingerprint generation.

To reduce the potential for outside noise and interference all nearby hardware devices are powered down. However, it is important to determine the effectiveness of WS-DNA and device discrimination in conditions that are less than optimal. Therefore, like-filtered Additive White Gaussian Noise (AWGN) is added to the filtered collected signal to obtain a lower Signal to Noise Ratio (SNR) of $[-10 : 50]$ dB in 2 dB steps.

The DUT chosen for this analysis is the Insteon Hub that transmits on/off commands to the Insteon On/Off Outlet (receiving device). Multiple PLC *On* messages sent to the same On/Off Outlet will be collected from six different Insteon Hubs and later used to generate WS-DNA fingerprints. The Hubs and the On/Off Outlet are initially linked according to manufactures direction, however during collection the On/Off Outlet is off network to force the Hub to retransmit messages. This increases the number of messages sent thereby decreasing the time needed to collect a sufficient number for fingerprint generation. Table I summarizes the transmit and receive devices along with estimated collected SNR. To ensure configuration control and integrity of the collection process a test fixture was devised as shown in Figure 2. Each Hub from Table I is individually connected at D1 and the EMI filter at D5 as seen in Figure 2. *On* messages are then transmitted via the *Insteon for HUB* application until 400 messages are collected. A single message consists of 5 packets, or bursts, therefore 2000 bursts/packets are collected for each hub device. Figure 3 displays typical *On* messages from an Insteon Hub and the repeated messages due to the On/Off Outlet being off network.

 Fig. 4. Typical Time Domain Response of Single Burst From a PLC Modulated *On* Message Sent From an Insteon Hub. ROI illustrated.

 Fig. 5. Representative 353 μ s ROI Corresponding to the First 303 μ s of a Burst From a PLC Modulated Insteon Hub *On* Message, Including 50 μ s Transient Ramp Up Region, Divided into $N_{reg} = 30$ Subregions.

B. WS-DNA Fingerprinting

The approaches and processes used in WS-DNA Fingerprinting are adapted from RF-DNA literature [4]–[6], [17], [18]. As presented in Section II-B each of the 5 bursts/packets in a message contain symbols that correspond to start/sync bits. These start/sync bits within messages are a steady state response and do not change from one device to another. Referring to Figure 1, the first 4 symbols of any burst/package will always be the same no matter what message is sent, or what the sender/receiver is. Figure 4 displays an illustration of this region including what appears to be a transient ramp up period that occurs approximately 50 μ s before the first symbol is transmitted. The region that contains these start/sync symbols along with the transient ramp up period is the Region Of Interest (ROI) and corresponds to first 353 μ s of each burst. The ROI is separated into $N_{reg} = 30$ equally spaced, adjoining sub-regions. Each sub-region is comprised of n discrete time samples and can be seen in Figure 5. A total of, $N_{Resp} = 3$ Instantaneous responses to include 1) amplitude $\{a(n)\}$, 2) phase $\{\phi(n)\}$, and 3) frequency $\{f(n)\}$ are calculated for each of the $N_{Reg} = 30$ subregions of the ROI. For each of these instantaneous responses, $N_{Stat} = 4$, statistical features are created including: 1) standard deviation (σ), 2) variance (σ^2), 3) skewness (γ), and 4) kurtosis (κ). Together with the entire ROI, there are $N_{Ireg} = N_{reg} + 1 = 31$ total sub-regions that are used to form the regional fingerprint vectors:

$$F_{R_i} = [\sigma_{R_i} \quad \sigma_{R_i}^2 \quad \gamma_{R_i} \quad \kappa_{R_i}]_{1 \times 4}, \quad (1)$$

where $i = 1, 2, \dots, N_{treg}$ [4]. Each vector from (1), are concatenated to form each of the instantaneous response vectors:

$$\mathbf{F}_{I_{a,\phi,f}} = \begin{bmatrix} \mathbf{F}_{R_1} & \mathbf{F}_{R_2} & \mathbf{F}_{R_3} & \dots & \mathbf{F}_{R_{N_{treg}}} \end{bmatrix}_{1 \times 4(N_{treg})}, \quad (2)$$

where the I denotes each instantaneous response $\{a(n)\}$, $\{\phi(n)\}$, and $\{f(n)\}$ [4]. For each instantaneous response vector, the final composite WS-DNA fingerprint vector is created as:

$$\mathbf{F}_C = \begin{bmatrix} \mathbf{F}_a & \mathbf{F}_\phi & \mathbf{F}_f \end{bmatrix}_{1 \times 4(N_{treg}) \times 3}, \quad (3)$$

resulting in fingerprints with at total of $N_{feats} = 3 \times 4 \times 31 = 372$ features [4].

C. Device Discrimination

Five different Monte Carlo noise realizations are added to each of the experimentally collected realizations of each SNR step prior to fingerprint generation. As mentioned in Section III-A, SNR is varied from -10 dB to 50 dB in 2 dB steps to simulate different channel noise conditions and to evaluate the process using degraded signals. Note, the way the SNR is varied does not suggest we improved SNR levels above the estimated collected SNR of the signal shown in Table I. The SNR_{Sim} is calculated by considering all collected signal and noise as contributing to signal power with the only noise contribution comprised of the AWGN component. This is a conservative estimate of SNR as the actual SNR is likely lower than SNR_{Sim} as the collected signal does include some noise.

MDA/ML classification was conducted for 6 classes/devices with the number of *Training* fingerprints equal to the number of *Testing* fingerprints per each class [3], [4]. A total of 2000 fingerprints were collected per class with five different noise realizations at each SNR level for a total of $F = 10000$ fingerprints in the WS-DNA process mentioned previously. Thus, $F_{trn} = 5000$ fingerprints were used for *Training* and $F_{tst} = 5000$ fingerprints used for *Testing*. K-fold cross validation is used during *Training* to increase reliability. An appropriate value of $K = 5$ is chosen consistent with common statistical practice [23]. Device discrimination will be assessed with an average percent correct curve, a confusion matrix, and Receiver Operating Characteristic (ROC) curves presented in section IV.

IV. RESULTS

Discrimination results for 6 devices shown in Table I are presented. These discrimination results are consistent with the RF-DNA fingerprint and MDA/ML processes discussed in section III [4]–[6], [17], [18]. A total of 1000 fingerprints were used for *Testing* with five different noise realizations equating to 5000 fingerprints per device. Figure 6 displays WS-DNA fingerprinting results for the 6 devices in average percent correct (%C) vs SNR. For all devices, %C = 90% is achieved at $SNR \geq 40$ dB and %C = 99% at $SNR \geq 46$ dB. Table II gives a confusion matrix displaying %C for $SNR = 40$ dB and 30 dB. This shows that Hubs 1, 5, 6 are more often misclassified with one another than the other Hubs. This could be due to

Fig. 6. Device Classification Results for 6 Different Insteon Hubs with Average Percent Correct (%C) with Varying Simulated SNR levels.

TABLE II
CONFUSION MATRIX FOR WS-DNA FINGERPRINTING AT $SNR = 40$ dB AND $SNR = 30$ dB WITH 5000 TRIALS PER DEVICE. RESULTS ARE PRESENTED AS %C AT 40 dB/30 dB.

	Hub 1	Hub 2	Hub 3	Hub 4	Hub 5	Hub 6
Hub 1	94.19/66.31	0/0	0/20	0/16	3.47/17.19	2.34/16.14
Hub 2	0/0	100.00/99.24	0/40	0/36	0/0	0/0
Hub 3	0/02	0/2/90	99.98/96.78	0/85	0/87	0/58
Hub 4	0/32	0/98	0/95	97.93/80.52	2.07/17.01	0/22
Hub 5	3.34/11.14	0/0	0/86	2.25/15.48	93.04/62.33	1.37/10.19
Hub 6	1.85/14.95	0/0	0/56	0/14	1.12/15.60	97.03/68.75

higher similarities in subcomponents of the devices when compared with the others.

To assess rogue detection, ROC curves are used to display how often rogue devices are rejected and authentic devices are accepted at specific SNRs. A benchmark of Equal Error Rate (EER) = 10% is established, i.e., 90% of unauthorized rogue devices are successfully rejected and 90% of authorized devices are accepted. To simulate a rogue device attempting access, fingerprints already created for Hub 4 are used for simulated intrusion detection. Figure 7 displays the rogue detection ROC curve with $SNR = 30$ dB. An EER = 10% is achieved for all devices except Hub 5 at 30 dB. The ROC curves in Figure 8 show rogue detection results of EER = 10% for all devices with $SNR = 40$ dB.

Fig. 7. ROC Curve for Rogue Detection with Hub 4 Representing Rogue Device at $SNR = 30$ dB, with EER = 10% illustrated by dashed box.

Fig. 8. ROC Curve for Rouge Detection with Hub 4 Representing Rouge Device at SNR = 40 dB, with EER = 10% illustrated by dashed box.

V. CONCLUSIONS

Performance for PHY device discrimination of PLC modulated signals based on WS-DNA fingerprints is presented in this paper. The WS-DNA fingerprinting process was applied to 6 different Insteon Hub devices with MDA/ML generated discrimination results.

Average correct classification performance was acceptable with $\%C = 90\%$ at $\text{SNR} \geq 40$ dB. This is well below the collected SNR of approximately 45 dB. The benchmark 10% EER for rogue intrusion detection was achieved at SNR = 40 dB, again below the collected SNR. These results show that an additional layer of security for PLC modulated signals based on WS-DNA fingerprinting is possible. The results of this research provide evidence that a 2-factor security authentication (WS-DNA and bit-level credentials) will vastly improve the systems intrusion detection/prevention.

There remains significant research on the topic of WS-DNA as applied to PLC devices. As MDA/ML was the process used for discrimination of the generated fingerprints, alternative discriminators can be investigated. Using Generalized Relevance Learning Vector Quantized-Improved (GRLVQI) as a discriminator would be an obvious next step. GRLVQI provides a better illustration of feature relevance ranking on decisions made by the classifiers [17]. An increase in feature relevance can improve performance and the possibility of real world application raises greatly [8]. Future work can also include specifically targeting the symbol boundaries. These transition areas could be rich with device specific features that can improve performance.

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