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Dimensional Reduction Analysis for Physical Layer Device Fingerprints with Application to ZigBee and Z-Wave Devices



**U.S. AIR FO**RCE

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  - Develop Additional DRA Methods for RF Fingerprinting



## **Problem Statement**



The AFIT of Today is the Air Force of Tomorrow.

**Investigate Suitability of p-**Values and Test Statistic Based **Dimensional Reduction Analysis** (DRA) Methods for Device **Fingerprinting Using Radio Frequency Distinct Native Attribute (RF-DNA) Features.** 



### Background

### **ZigBee & Z-Wave Devices**



	ZigBee <sup>®</sup> Alliance	<b>WAVE 11</b> Alliance <sup>m</sup>
	ZigBee	<b>Z-Wave</b>
Standard	IEEE	Proprietary
Frequency	2.4 GHz	906 MHz
Bit Rate	250 Kbits/s	40 Kbits/s
Saaurity	IEEE 902 15 1 Stondard	None: 200 and 300 Series
Security	IEEE 002.13.4 Stanuard	AES 128: 400 Series
Latency	50 to 100 mSec	~1000 mSec
Range	10 to 100 m	30 to 100 m
Message Size (Bytes)	127 (max)	64 (max)











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- Experimentally Collected ZigBee Emissions
  - 10 Like-Model Devices
- Collection Environments
  - CAGE Anechoic Chamber
  - LOS Hallway Line-of-Sight (LOS)
  - WALL Through Wall Propagation
- Authorized Devices
  - Emissions Collected in CAGE, LOS, & WALL for 4 of 10 Devs (Dev 1 – Dev 4)
  - N<sub>c</sub> = 4 Like-Model Auth Devs, Different Ser #s
- Rogue Devices
  - N<sub>Rog</sub> = 9 Like-Model Rogue Devs, Different Ser #s (Dev 5 – Dev 10)
  - Emissions Collected in Selected Environments (See Table)



ZigBee Experimental Collection Setup for LOS (A) & WALL (B) Environment Emissions [19,54]

	ZieDee ID	CACE	1.05	WATT
	ZigBee ID	CAGE	LOS	WALL
	Dev5		Х	Х
ĥ	Dev6		Х	Х
	Dev7		Х	Х
	Dev8	X		
	Dev9	X		
	Dev10	X		

ZigBee Rogue Device ID and Collection Environments [19,54]





### ZigBee Emission Processing [2, 13, 14]



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### **Time Domain (TD) RF-DNA Fingerprint Generation**





### **Device Classification: GRLVQI**



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- LVQ-Based Classifiers
  - Gradient Descent & Prototype Vector (PV) Approach for Classification
  - Gradient = 1<sup>st</sup> Derivative of Cost Function
  - Iteratively Examines PV-to-Data Distances
    - Correctly Classified PVs ... Move Toward data
    - Incorrectly Classified PVs ... Move Away From Data
- GRLVQI ... LVQ Extension [2, 9, 14]
  - G = Generalized ... Sigmoidal Cost Function
  - R = *Relevance* ... Gradient Descent Feature Relevance Ranking
  - I = *Improved* ... Improved Logic, PV Freq, Add'I Learn Rate, Etc.
- No Explicit Assumption / Knowledge Required for Data Distribution (PDF)
  - Appropriate PV Initialization Required
  - Normal PVs ⇒ Standardized Data



Artificial Neural Net (ANN)

Learning Vector Quant. (LVQ)

K-th PV



### Methodology Dimensional Reduction Analysis (DRA)



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Method #1: (Distribution Based): Two
 Sample Kolmogorov–Smirnov (KS) [13,14, 17]

$$KS = max(|F_1(x) - F_2(x)|)$$

Method #2: (Distribution Based): ANOVA
 F-Statistics [18]

$$F_{0(i)} = \frac{MS_{Feature(i)}}{MSE_{Model(i)}}$$

- Method #3: (Classifier Based) GRLVQI Relevance [9]
- Method #4: Dimensionality Assessment [18, 21]



**Amplitude (a)** : ZigBee Feats #1 - #243 Phase (φ) : ZigBee Feats #244 - #486 **Frequency (f)** : ZigBee Feats #487 - #729



### **DRA: Dimensionality Assessment**



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#### ZigBee Dimensionality Assessment by Significance Level

- Selecting quantity of features in subsets non-trivial
- Qualitative DRA
  - Previously Considered [13,14]
  - *N*<sub>DRA, ZigBee</sub> = [25, 50, 243]
- Quantitative DRA
  - Introduced Here
  - Removes Subjectively
  - Intrinsic Data Dimensionality
- P-value and Data Eigenvalue methods considered
  - P-values Overestimate Required N<sub>DRA</sub>
  - Data Eigenvalue Methods Yield
    N<sub>DRA</sub> Consistent with Prior Work
  - *N*<sub>DRA, ZigBee</sub> = [17, 123]
  - N<sub>DRA, Z-wave</sub> = [7, 34]

SNR (DB)	Method	SIGNIFICANCE LEVEL				
	MILINOD	0.1%	1%	5%	10%	
0	F-TEST	196	264	350	402	
0	KS-TEST ( $\Sigma$ P-VALUES)	37	74	130	160	
10	<b>F-TEST</b>	589	639	674	688	
	KS-TEST ( $\Sigma$ P-VALUES)	337	414	512	557	
19	<b>F-TEST</b>	706	713	720	722	
18	KS-TEST ( $\Sigma$ P-VALUES)	666	692	711	716	
20	<b>F-TEST</b>	718	725	727	728	
30	KS-TEST ( $\Sigma$ P-VALUES)	727	729	729	729	

#### ZigBee Dimensionality Assessment by COV Eigenvalues







### **DRA: Test Statistics vs p-Values**

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- Recent RF-DNA DRA Research Focused on p-values for feature relevance ranking [1, 2, 13-14, 28-29]
  - Test Statistic to p-Value Conversion Req'd
- Computing Test Statistic Values
  - Ratio between quantities or a simple relationship
- Test Statistics vs. P-Values
  - p-Values Represent Area Under a Probability Curve
- Computing p-Values Requires [26]
  - 1. Stated Hypothesis Test
  - 2. Test Statistic Value
  - 3. Degrees of Freedom
  - 4. Distributional Assumption
  - 5. Reference Distribution
  - (Not all are always considered / stated in DRA, e.g. [1, 2, 13, 14] )

- The mapping between test statistic and *p*-value is typically nonlinear
- Simple F-Test Stat. [18]

$$F_{0(i)} = \frac{MS_{Feature(i)}}{MSE_{Model(i)}}$$

• Complicated F-Test p-value [18]



 The KS-test involves a similar nonlinear mapping [17]









**Device Classification: ZigBee & Z-Wave** 

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 Test statistic methods offer comparable or better performance to p-value based methods





## Results



## **Device ID Verification: ZigBee** The AFIT of Today is the Air Force of Tomorrow.

- Based on "one vs one" claimed identity scenarios
- Presented as:
  - %TVR = True Verification Rate
  - % RRR = Rogue Rejection Rate
  - Bold Entry Best or Statistically Equivalent Performance •

DRA METHOD	KS TEST STATISTIC		KS	ΣP-VALU	JE	
$N_F$	17	50	123	17	50	123
TVR	0%	0%	0%	0%	0%	0%
RRR	8.33%	8.33%	0%	52.8%	2.78%	0%
DRA METHOD	F TEST STATISTIC			F TI	EST P-VAL	LUE
$N_F$	17	50	123	17	50	123
TVR	0%	0%	0%	25%	0%	0%
RRR	8.33%	5.56%	0%	38.9%	19.4%	0%
DRA METHOD		GRLVQI	[			
$N_F$	17	50	123			
TVR	25%	50%	50%			
RRR	52.8%	66.7%	72.2%			



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## Results



## **Device ID Verification: ZigBee** The AFIT of Today is the Air Force of Tomorrow.

- Based on "one vs one" claimed identity scenarios
- Presented as:
  - %TVR = True Verification Rate
  - % RRR = Rogue Rejection Rate
  - Bold Entry Best or Statistically Equivalent Performance •

DRA METHOD	KS TEST STATISTIC			KS	ΣP-VALU	JE	
$N_F$	17	50	123	17	50	123	
• Distribution-based DRA offers noor verification							
performance with non-linear GRI VQI classifier $\frac{100}{100}$							
	1 1	LIALG 167	5110	11 '1	EST P-VAL	LUE	
$N_F$	17	50	123	17	50	123	
TVR	0%	0%	0%	25%	0%	0%	
RRR	8.33%	5.56%	0%	38.9%	19.4%	0%	
DRA METHOD	GRLVQI						
$N_F$	17	50	123				
TVR	25%	50%	50%				
RRR	52.8%	66.7%	72.2%				



## **Conclusions & Future Work**



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## Conclusions

- Introduction of F-test for DRA in RF Fingerprinting
- Test Statistic Methods vs P-values
  - P-values Susceptible to Converge on 0 [26]
  - Test Statistic DRA Offers Robustness
- Introduction Quantitative Dimensionality Assessment
  - $N_{DRA} = 123$  (quantitative) better than  $N_{DRA} = 243$  (qualitative) of [14]
- Comparison of 5 DRA Methods for RF Fingerprinting
- First Look RF-DNA Fingerprinting Using Z-Wave Devices

## **Future Work**

- Expand Z-Wave Assessments to Include Rogue Devices
- Reevaluate with an MDA-based classifier



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