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Power Amplifier enabled RF Fingerprint Identification

Yuepei Li & Yuan Ding

The Institute of Sensors, Signals and systems (ISSS), Heriot-Watt University
yl12@hw.ac.uk

Outline

1.1 Wireless device authentication

- IoT devices will be three times higher than then global population by 2021 [1].

- Conventional device identification methods are modifiable via software [2].

- Radio frequency fingerprint (RFF) identification - identify wireless device through unique features existed in radio frequency stages.

- The hardware characteristics is one of the uncontrollable factors in manufacturing process, which is also called PHY layer RFF.

[1] Cybercrime magezone. [Online]. Available: https://cybersecurityventures.com/.
[2] J. Yang, Y. Chen, and W. Trappe, "Detecting sybil attacks in wireless and sensor networks using cluster analysis," in *Proc. 5th IEEE Int. Conf. Mobile Ad Hoc Sensor Syst.*, Atlanta, GA, USA, pp. 834–839, Sep. 2008.

1.2 PHY layer RFF related work [3]

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- The unique non-linear I/O characteristics of power amplifier (PA).
- Power amplifier behavior model Volterra series was used in [4].
- The I/O characteristics of the PA by using the behavioral model to compute the element of the vector.
- Generalized likelihood ratio test to classify the vector of the unknown device.

[3] A. Polak, S. Dolatshahi, and D. Goeckel, "Identifying wireless users via transmitter imperfections," *IEEE J. Sel. Areas Commun.*, vol. 29, no. 7, pp. 1469–1479, Aug. 2011.
[4] P. Wambacq and W. Sansen, *The Distortion Analysis of Analog Integrated Circuits*. Kluwer, 1998.

1.3 PHY layer RFF related work [5]

- The manufacture process variations of silicon physical unclonable function (PUF) was explored in this work.

- The bias voltage V_{BA} is generated by PUF and a digital to analogue converter (DAC) to randomize the PA spectral regrowth by varying the PA bias.

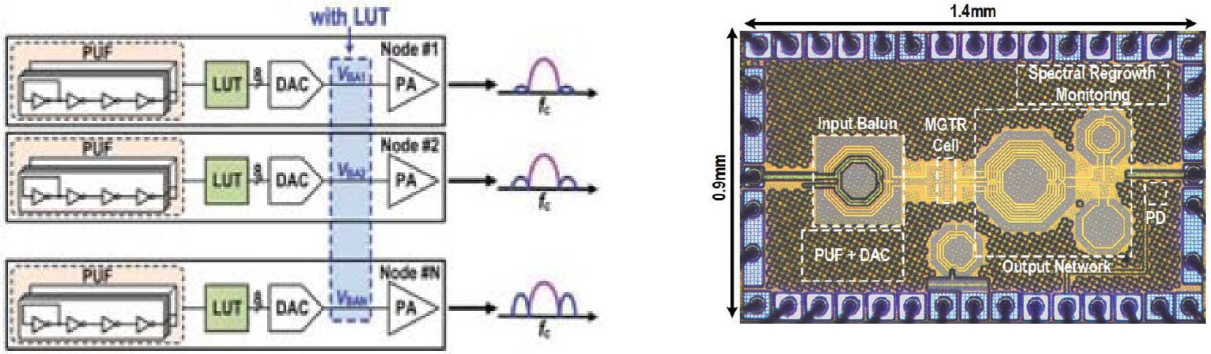

Fig.1 PUF- RFF reported in [5]

[5] Q. Zhou, Y. He, K. Yang and T. Chi, “Exploring PUF-controlled PA spectral regrowth for physical-layer identification of IoT nodes,” *2021 IEEE Int. Solid-State Circuit Conf.*, San Francisco, CA, USA, 2021, pp. 204-206

2.1 Proposed PHY layer RFF feature

- Bessel- Fourier behavioral model was used to describe PA characteristics.
- The non-linear memory effect generates by the cascade of matched RRC filters and a non-linear PA inserted in-between.

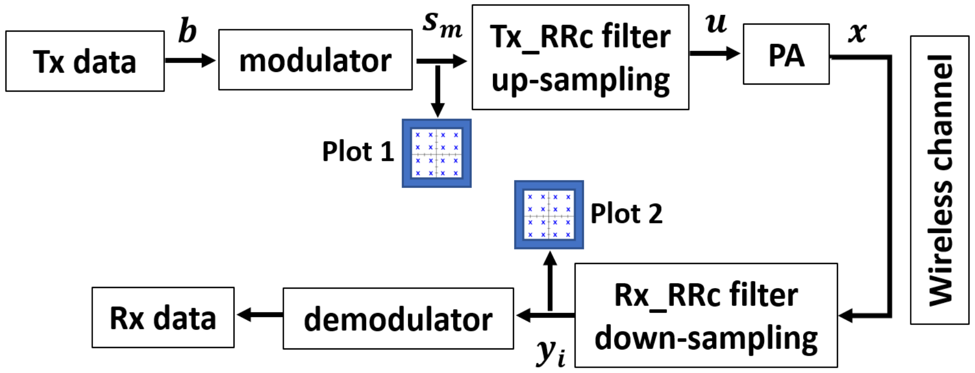

Fig.2. RF link model

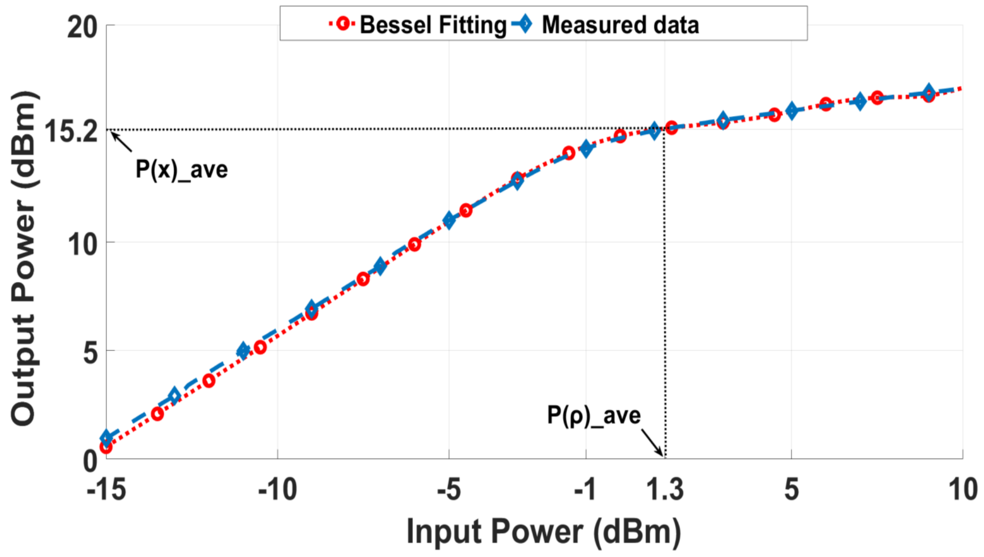

Fig.3. Measured and Bessel- Fourier fitted AM/AM curves of a PA (model: ZJL- 4HG+)

2.2 RFF feature extraction

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- The irregular shape of the constellation symbols is caused by the non-linear memory effect produced by RRC filters and PA.

- The received signal constellations are further converted to density trace figure (DTF).

- The DTF is used to illustrate the statistical density of each constellation symbol in the IQ space.

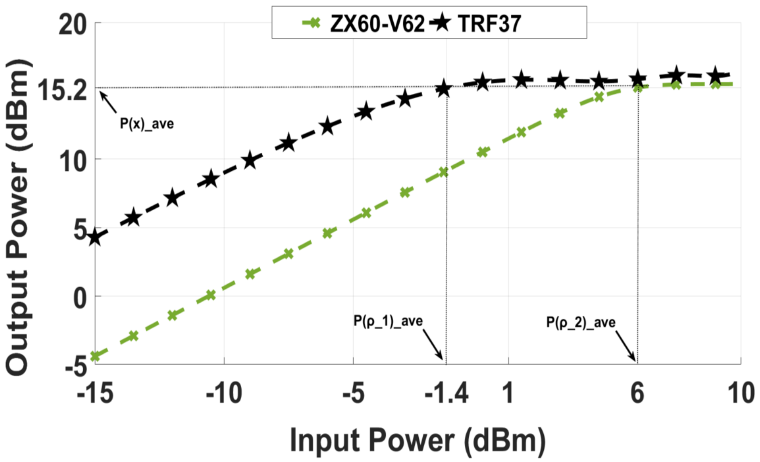


Fig. 6. (a) Bessel-Fourier fitted AM/AM curves of two different PAs (Model: ZX60-V62 and TRF37).

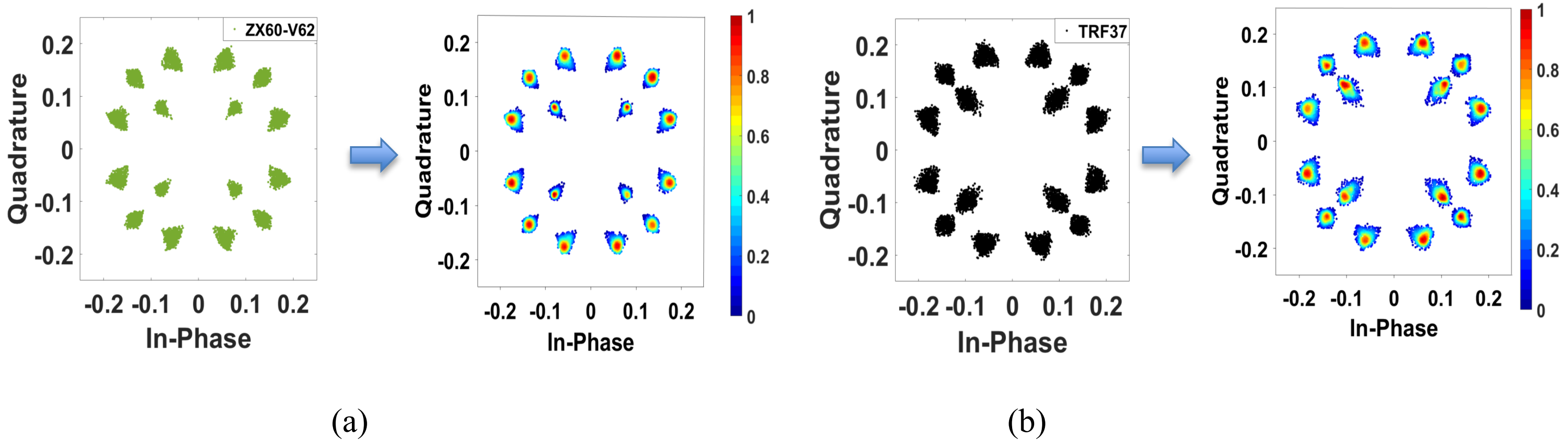


Fig.7. (a) Received constellation diagrams and DTF of the PA model ZX60-V62 (b) Received constellation diagrams and DTF of the PA model TRF37.

3.Convolutional neural network (CNN) classification

- CNN classification algorithm was employed to classify RFF features.
- Proposed CNN architecture consists of 3 convolutional layers, 2 max polling layers and 1 fully connected layer.
- In the training stage, the DTF in the dataset were randomly divided into 80% of the training dataset and 20% of the validation dataset.

TABLE I.
LAYERS OF THE CNN CLASSIFICATION

Layer	Matrix dimension	Trainable parameters
Input	Image size: [400×500×3]	-
Convolution 2- D + ReLU function	Filter size: [10 × 10], No. filter: 16	1616
Max pooling	[2×2]	-
Convolution 2- D + ReLU function	Filter size: [10×10], No. filter: 32	51232
Max pooling	[2×2]	-
Convolution 2- D + ReLU function	Filter size: [10×10], No. filter: 64	204864
Fully connected	Final image size: [100 × 125 × 3]	800000

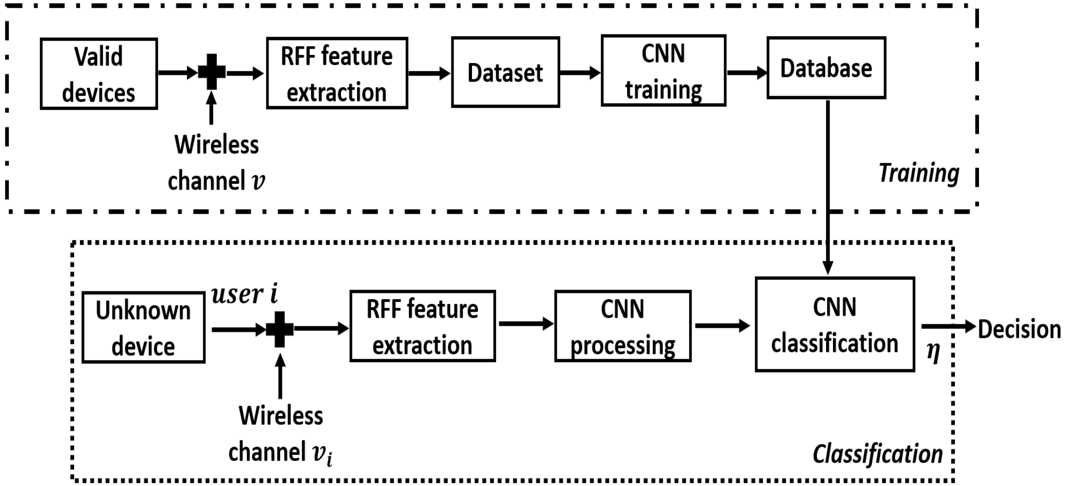


Fig. 8. CNN training and classification process.

4.1 Numerical results

- In the identification stage, we assume 5 individual transmitter systems with 5 different PAs with similar operation output power range.

- The training dataset includes 1520 units of DTF, and validation dataset includes 380 units of DTF. The SNR range of the DTF is from 1 dB to 25 dB.

- The DTFs of each PA with SNR range from 1 dB to 25 dB (2 dB per step) were used as the test dataset, 7500 units of DTF in total.

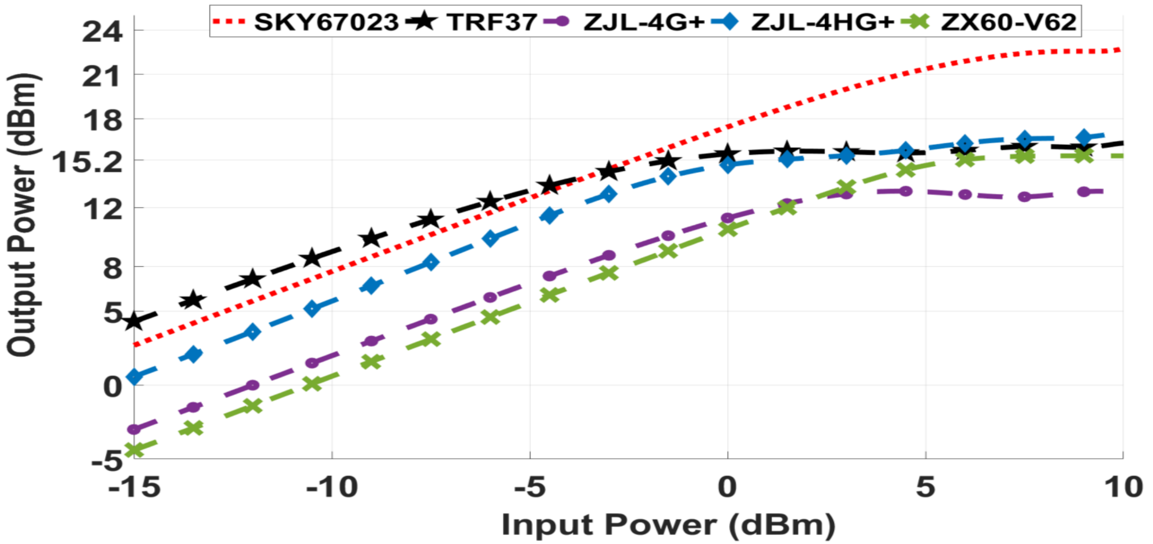


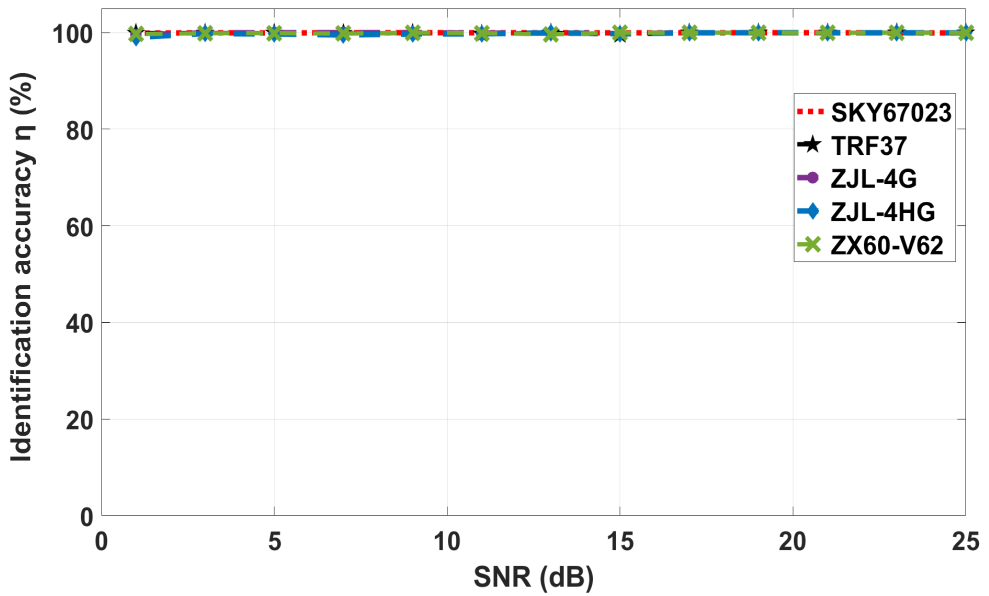
Fig. 9. PA AM/AM characteristics fitted using the Bessel-Fourier model. (Mini-Circuits: ZJL-4G+, ZX60-V62, ZJL-4HG+; SKYWORKS: SKY67023; Texas Instruments: TRF37).

4.2 Numerical results

➢The result of identification accuracy vs SNR averaged over 20 trials.

➢In the SNR range from 1 dB to 25 dB, the overall identification accuracy rate exceeds 99%.

➢Since the SNR of the test data is identical to the SNR of the trained dataset, high accuracy rate is achieved.



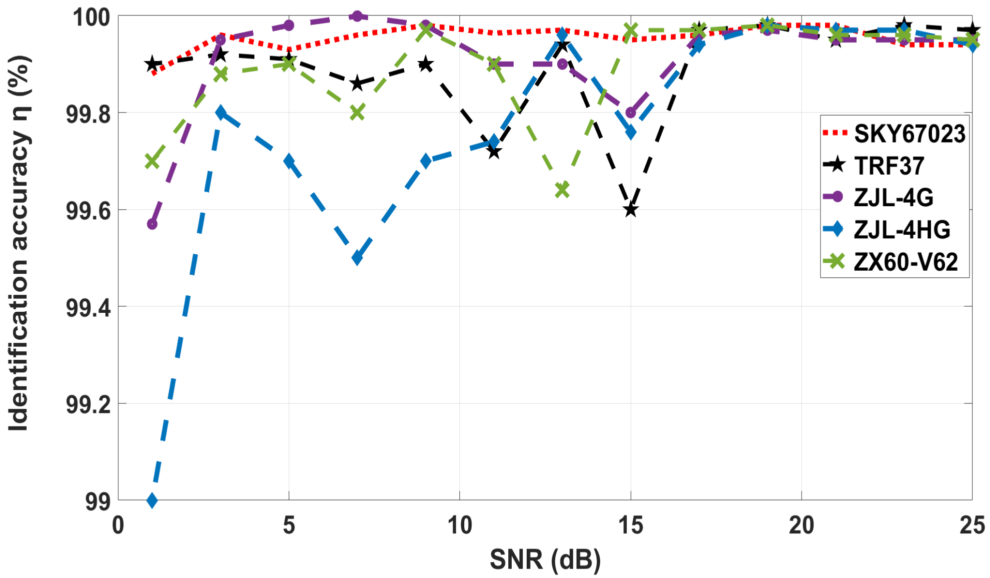


Fig. 10. CNN classification results vs. SNR in the range of 1 dB to 25 on 7500 units of test data, the overall identification accuracy rate is 99%. (a) plot zoom out. (b) plot zoom in.

5.Conclusion and future work

- We proposed a unique RFF feature of non-linear memory effect based on the power amplifier.
- The unique feature is presented in density trace figure, and we employ the CNN image recognition method to extract the feature in different brand of power amplifiers.
- Finally, the classification results validate the proposed RFF feature to identify different wireless systems/devices
- The proposed system will be experimentally demonstrated in the future.

Thank you for your attention!

6.Acknowledgment

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