Digital Walkie-Talkie Identification scheme based on Sparse Representation with Multiple features

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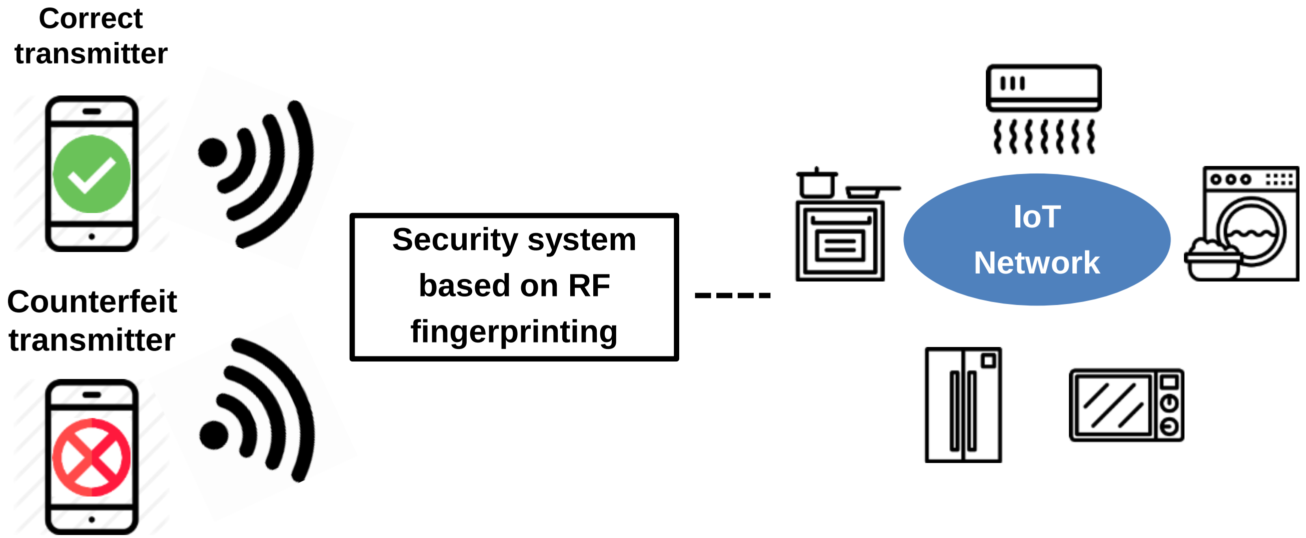
Contents

I. Introduction

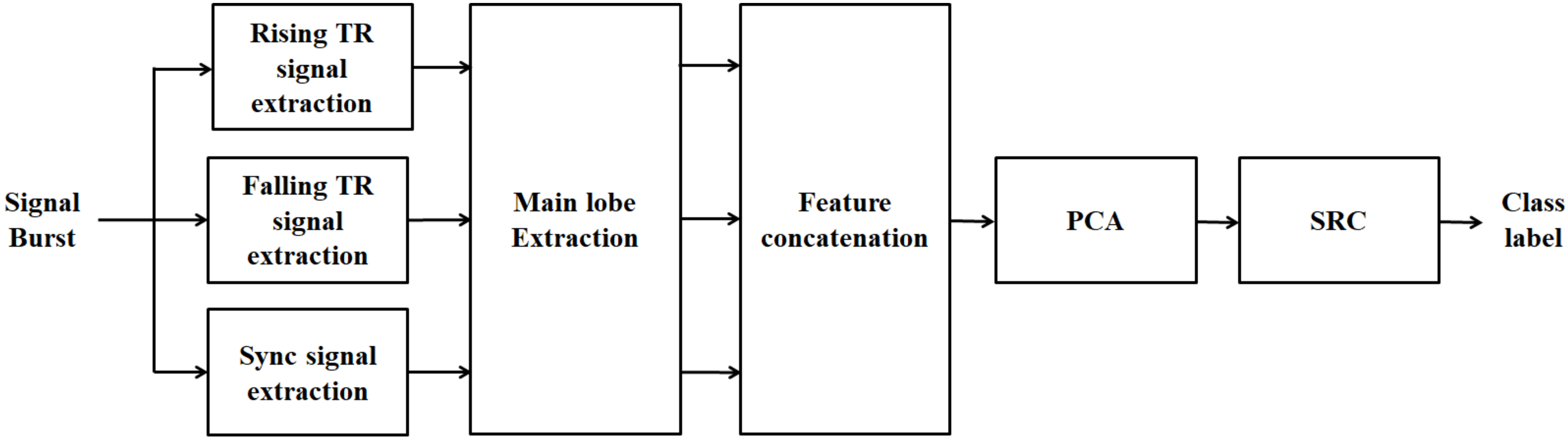
- Motivation
  - For the efficient support in the electronic warfare, the ability of exact detection and analysis on the enemy's transmitter is necessary.
  - In the Internet of Things (IoT) network, the technique for identifying the access of the counterfeit transmitter is needed.



- Identification of the radio transmitters using the transmitted signals is called ***<u>RF (Radio frequency) fingerprinting</u>***.

I. Introduction

- Proposed system

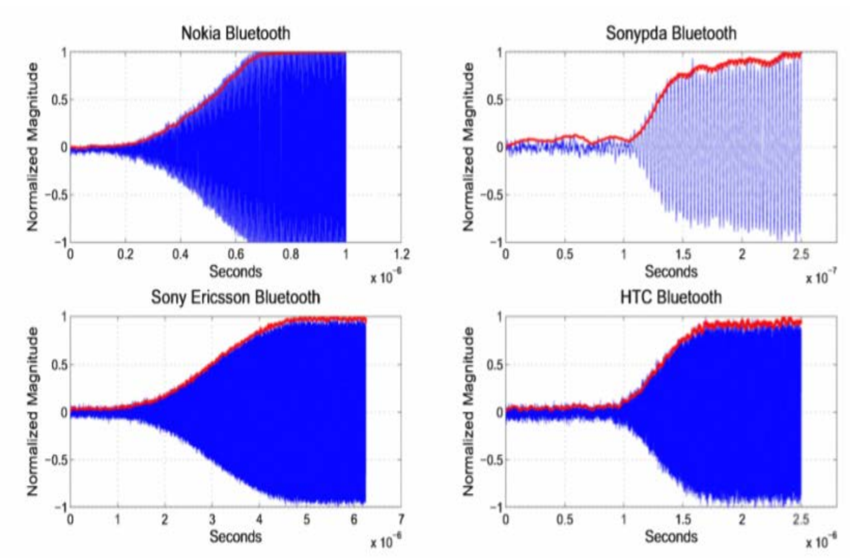


- A ***feature*** is a sample vector cultivated from the transmitted RF signals and bears unique information about the pertinent device.

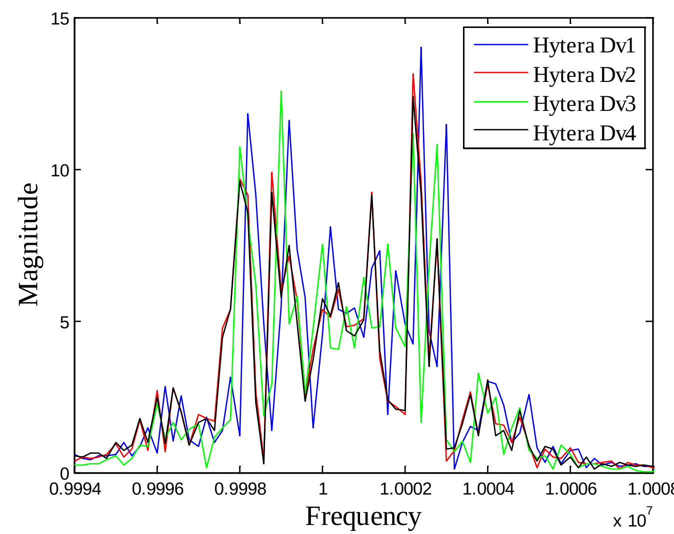
- **Goal**
  – We want to check if the performance will be increased or not once ***multiple features*** – rising transient feature, falling transient feature, and sync feature – are used ***simultaneously***.

I. Introduction

- The feature is occurred by
  - Element characteristic
  - A part design such as filter, amplifier etc.
  - PCB material, soldering etc.
- The feature types



Transient signals [1]

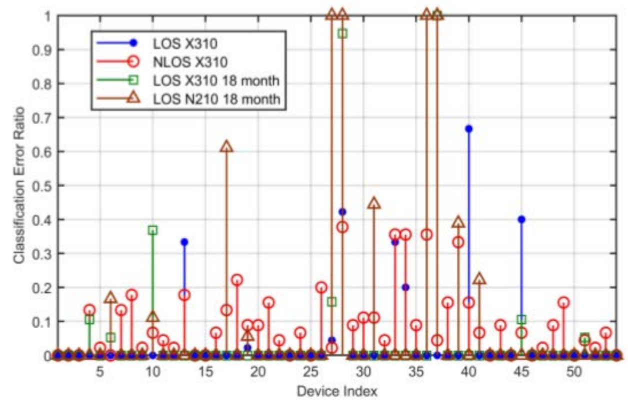


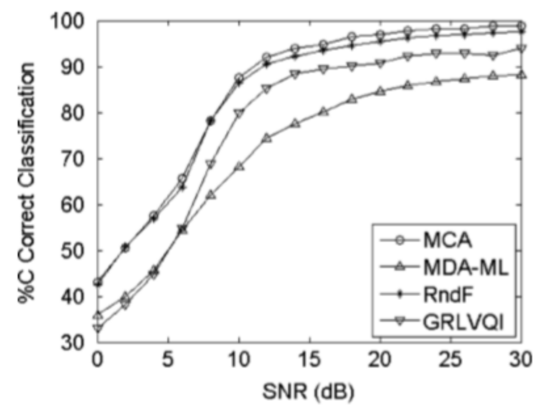
Steady-state signals [2]

I. Introduction

- Related works
  - Merchant *et al* [3]
    - Convolutional neural network
  - Peng *et al* [4]
    - Differential constellation trace, carrier frequency offset, and 2 features of the error on I/Q domain
  - Patel *et al* [5]
    - Random forest and AdaBoost

Actual Device \ Predicted Device	1	2	3	4	5	6	7
1	85	2	1	0	0	0	1
2	0	93	2	0	0	0	9
3	1	8	92	0	0	0	0
4	0	3	0	103	0	0	0
5	0	0	2	0	86	14	2
6	1	0	0	0	3	87	0
7	0	0	0	5	0	0	100





II. Contribution

- The ***combination*** of ***rising transient feature***, ***falling transient feature***, and ***sync feature*** has not been used in the previous studies.
  - Falling transient feature has not been used.
  - We show that the performance of the proposed scheme is improved when more feature is included.
  - There are no experiments on RF fingerprinting with multiple features based on sparse representation-based classification algorithm (SRC).

III. Research Process – Signal acquisition

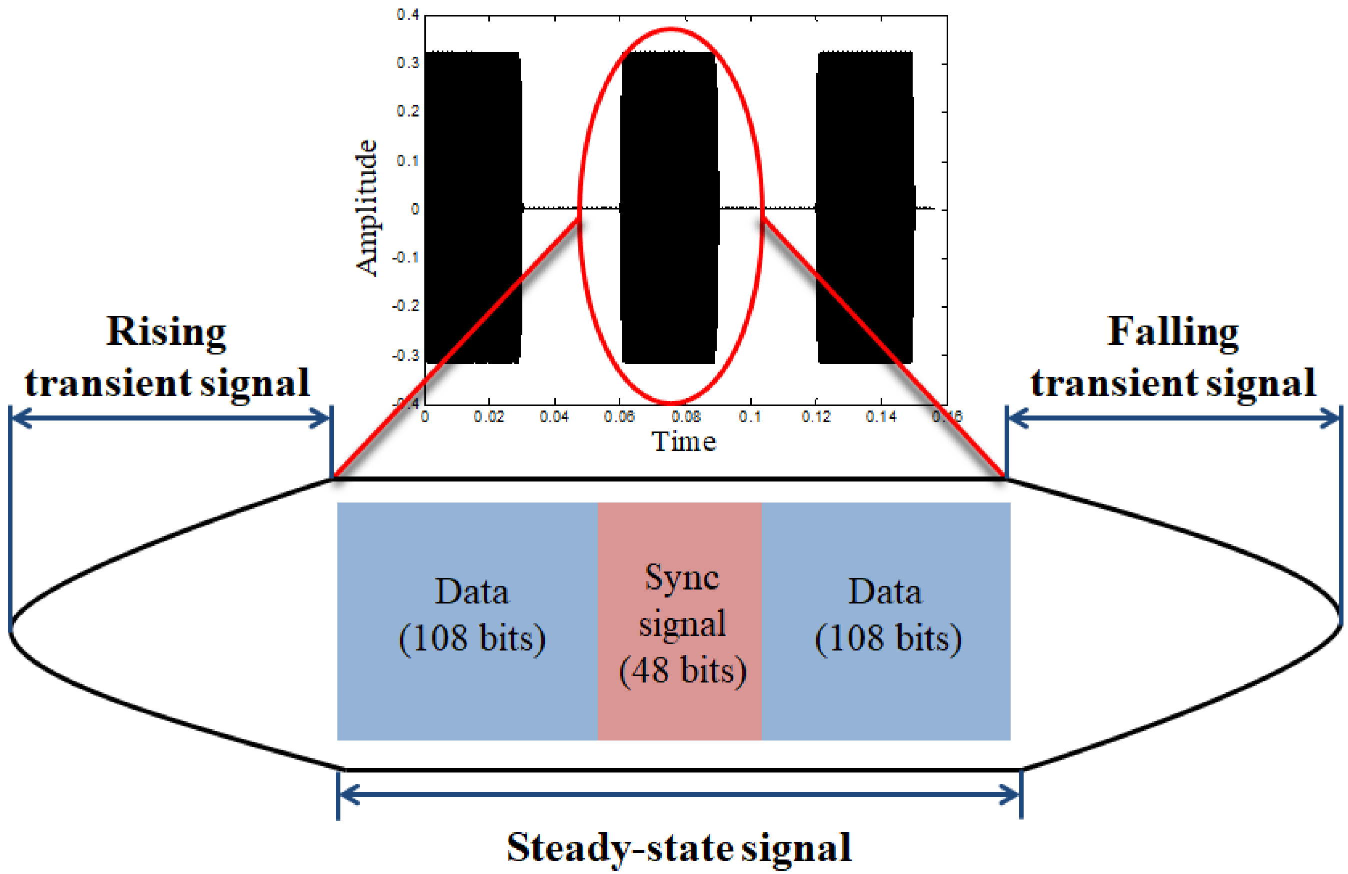
- The digital walkie-talkie models

Two models follow **DMR standard**

Model name	SL1M (2014)	BD-358 (2017)
Manufacturer	MOTOROLA	HYTERA
Frequency	UHF (CH1 : 423.1875MHz)	UHF (CH1 : 423.1875MHz)
# of devices	4	4

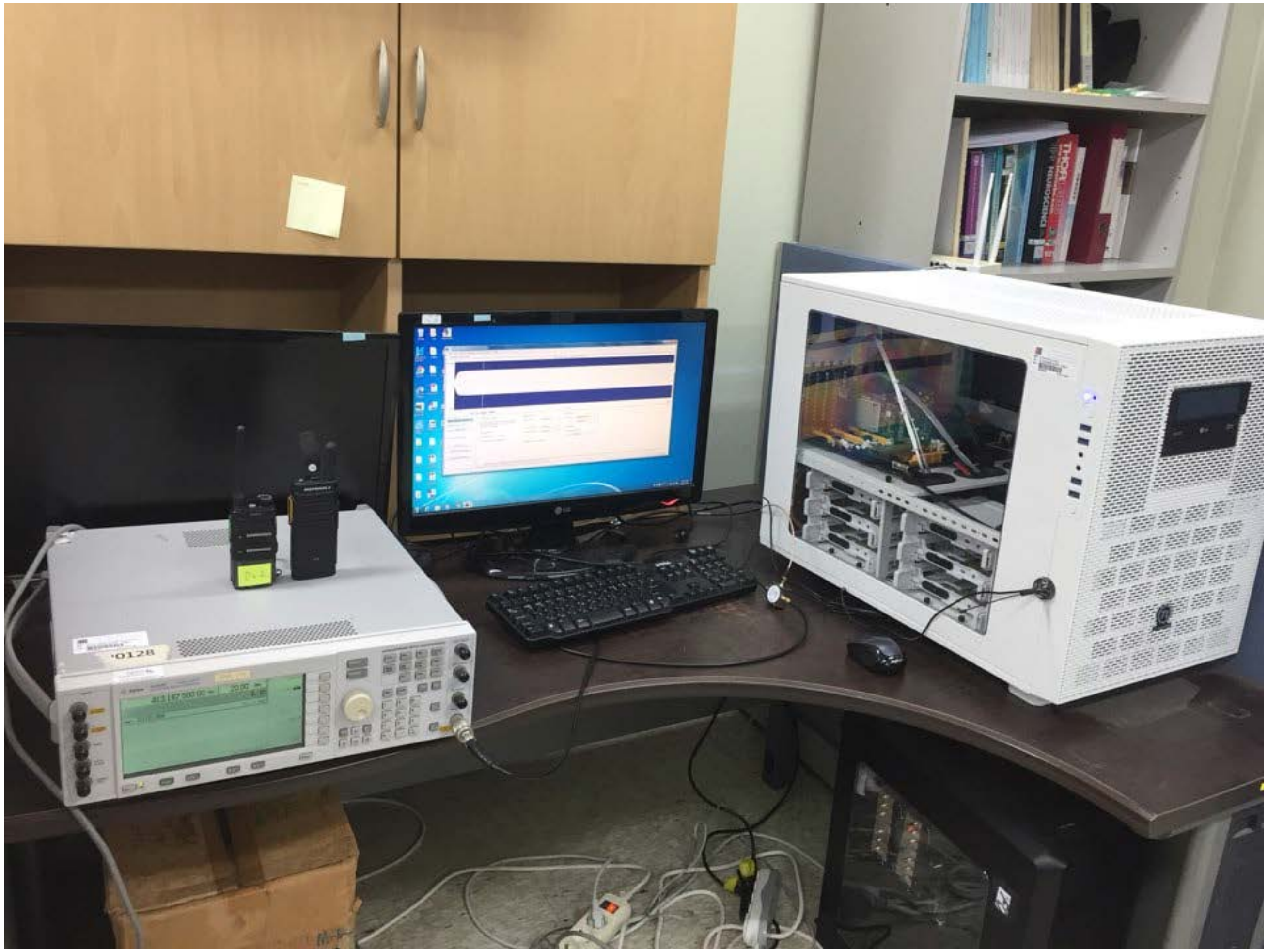
III. Research Process – Signal acquisition

- Digital Mobile Radio standard [6]
  - 2-slot Time-division multiple access (TDMA) method
  - 4 level frequency shift-keying modulation



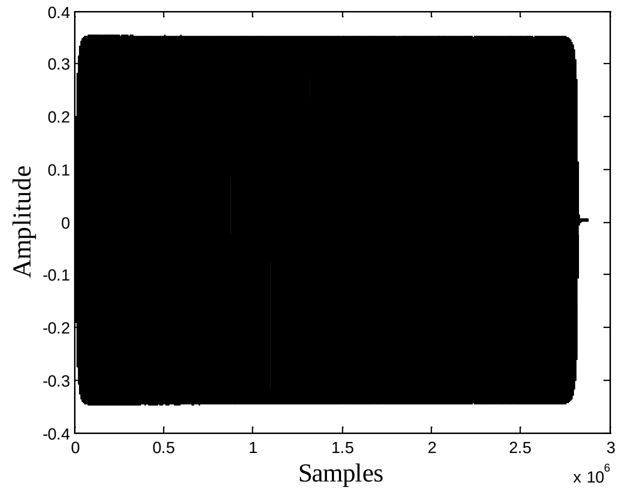
III. Research Process – Signal acquisition

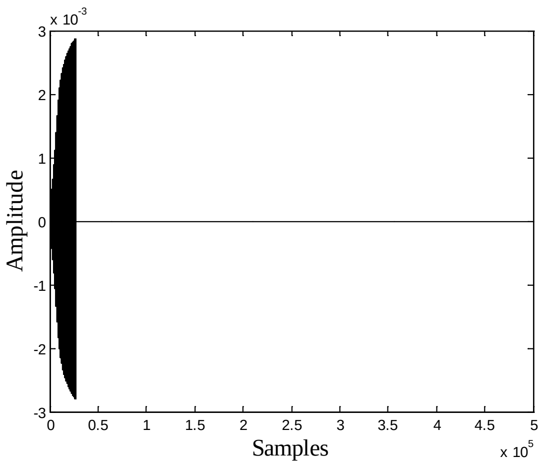
- Procedure for signal acquisition
  - In LOS environment, the receiver gets the transmitted signal.



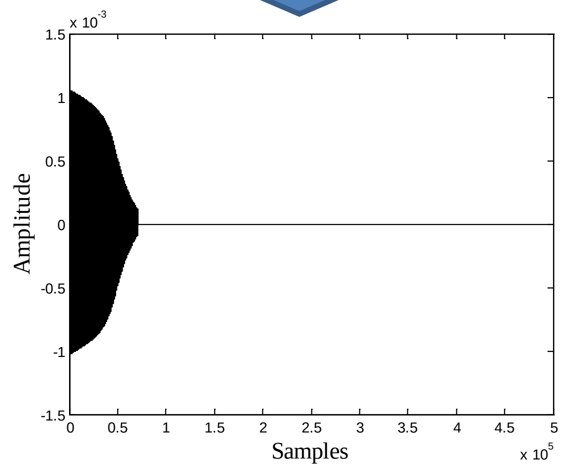
III. Research Process – Feature extraction

- Threshold method to extract interest signals

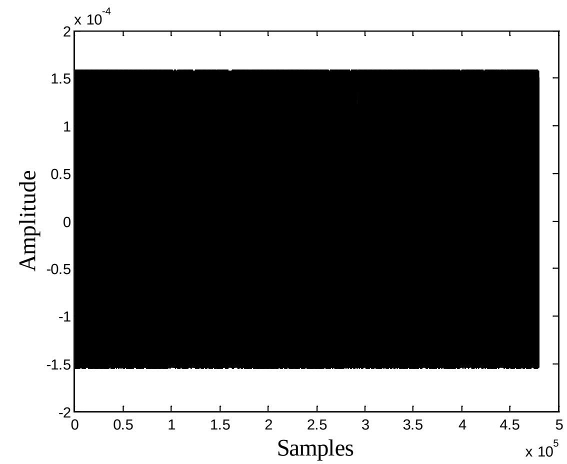




Rising transient signal



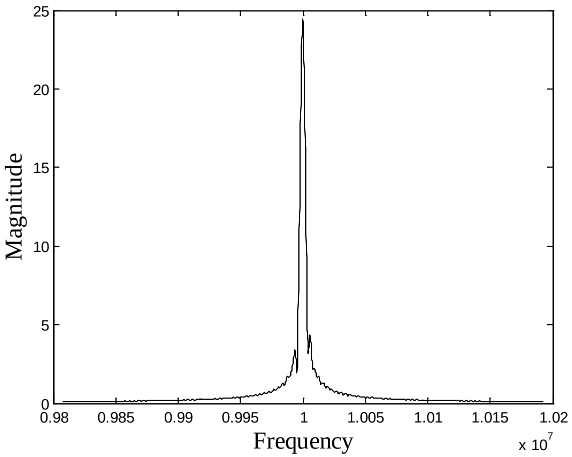
Falling transient signal



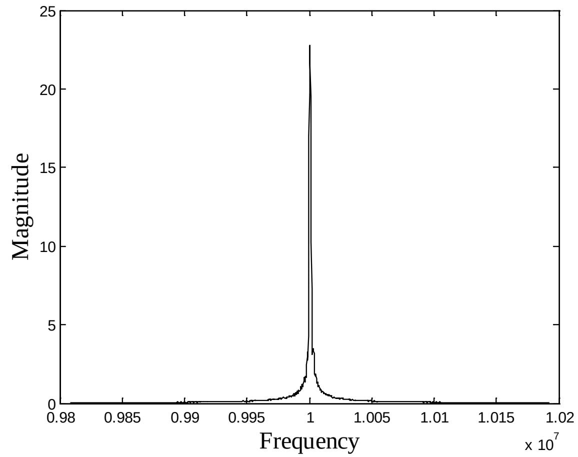
Sync signal

III. Research Process – Feature extraction

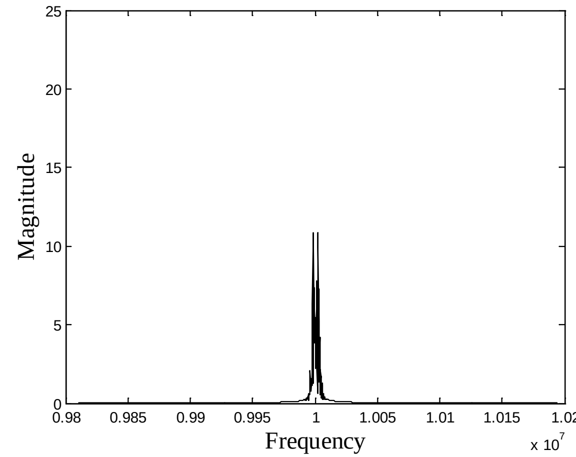
- Main lobe extraction
  - Since main lobe occupies most of the energy of each signal part, the main lobe is used as a feature.



Main lobe of
rising transient signal



Main lobe of
falling transient signal



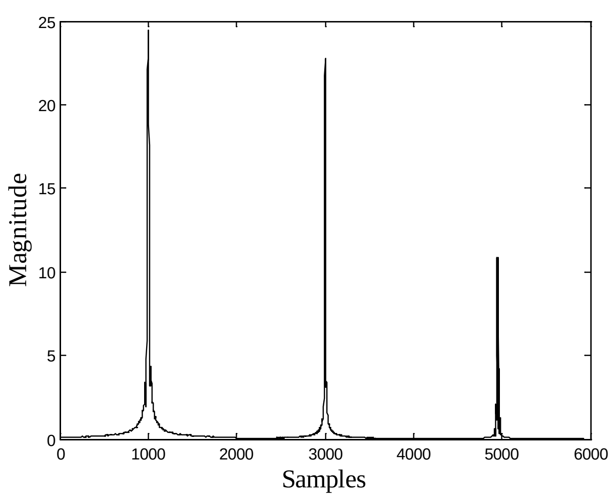
Main lobe of
sync signal

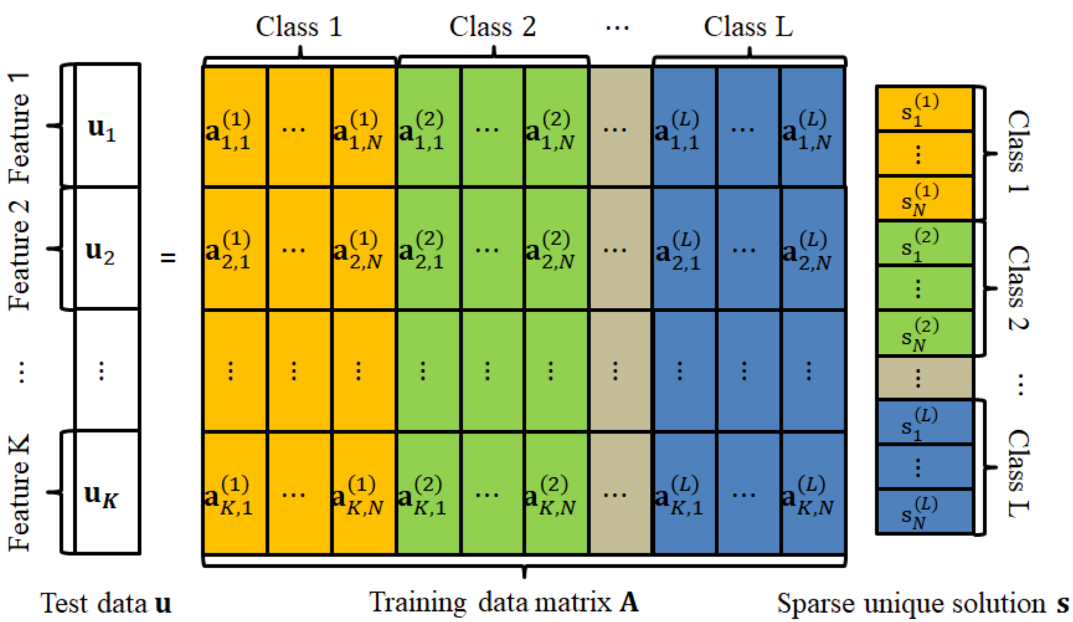
III. Research Process – Feature concatenation

- The extracted features – rising transient feature, falling transient feature, and sync feature – are ***concatenated***.
- In the system,

$$\mathbf{u} = \mathbf{A}\mathbf{s},$$

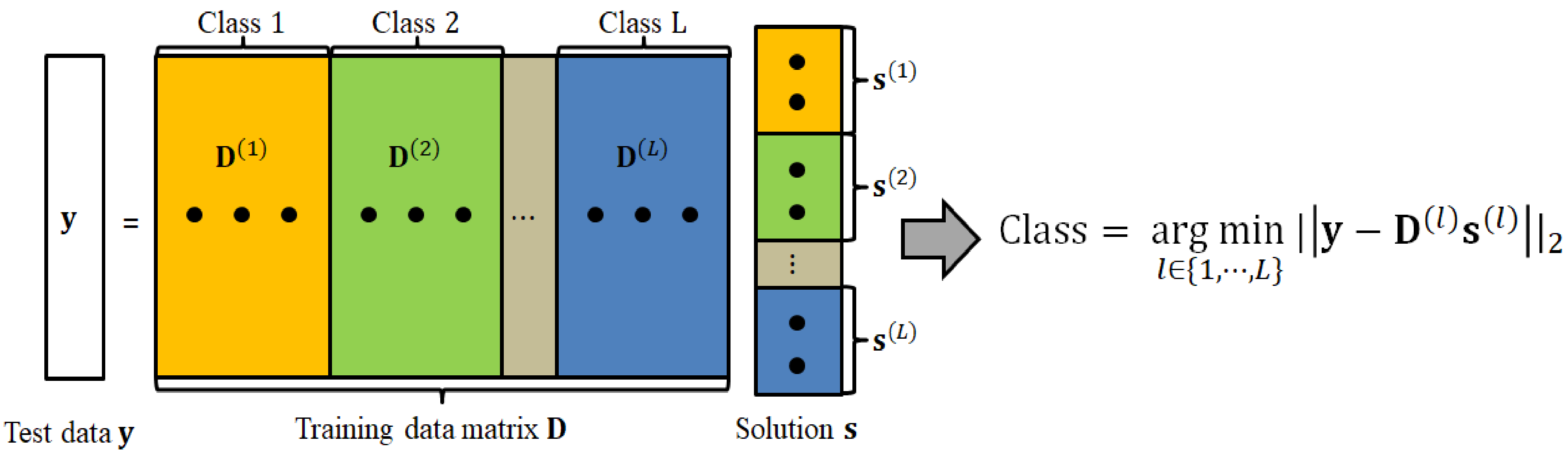
the concatenated features for training data are arranged to the columns of $\mathbf{A}$ and the feature for test data is put into $\mathbf{u}$.





III. Research Process – SRC

- Sparse representation-based classification scheme
  - In the underdetermined system $\mathbf{y} = \mathbf{D}\mathbf{s}$, $\mathbf{s}$ has infinite cases of solutions and SRC finds a sparse solution $\mathbf{s}$.
  - The condition to find the sparse solution $\mathbf{s}$ is sensitive to the mutual correlation between columns of $\mathbf{D}$.



III. Research Process – SRC & Test

- Sparse representation-based classification scheme
  - Principal component analysis (PCA) removes correlations among columns of $\mathbf{A}$.
  - $\mathbf{u} = \mathbf{A}\mathbf{s}$ is changed to $\mathbf{y} = \mathbf{D}\mathbf{s}$ by PCA.
  - The sparse solution $\mathbf{s}$ is obtained by basis pursuit algorithm

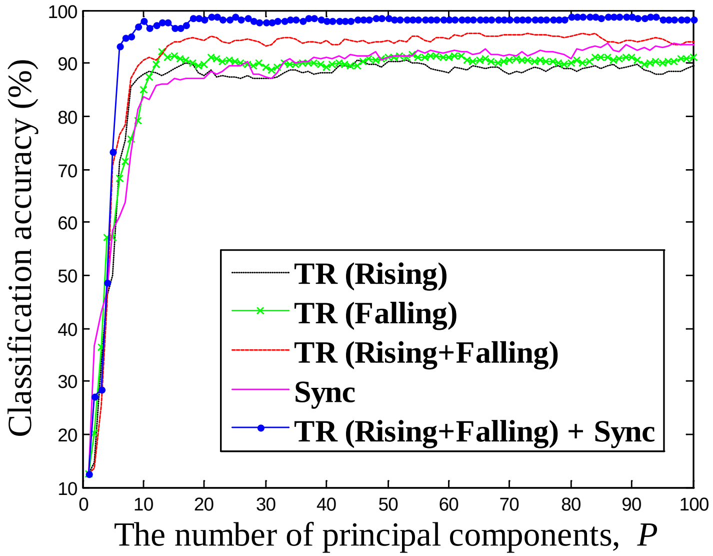
$$\min_{\mathbf{s}} ||\mathbf{s}||_1 \text{ subject to } \mathbf{y} = \mathbf{D}\mathbf{s}.$$

  - The class of test data is output from SRC

- Test
  - We used 5 cross validation technique.
  - Fifty data were captured per a digital walkie-talkie.

IV. Results

- When ***additional feature*** is included, ***the performance of SRC is improved***.
- The accuracy recorded ***98.75%***.
- Falling transient signal could have unique information for RF fingerprinting.



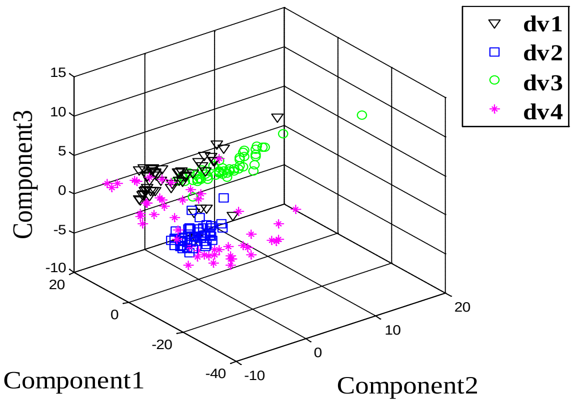
Accuracy rate of the proposed method

	4 BD-358	4 SL1M	4 BD-358 4 SL1M
	Accuracy rate (Minimum number of PC)		
TR(R)	88% (24)	82% (48)	90.5% (45)
TR(F)	87.5% (45)	90% (12)	92.25% (13)
TR(R + F)	**93% (49)**	**92% (20)**	**95.5% (63)**
Sync	99% (45)	83.5% (22)	93.75% (86)
TR(R + F) + Sync	***99% (44)***	***98.5% (22)***	***98.75% (21)***

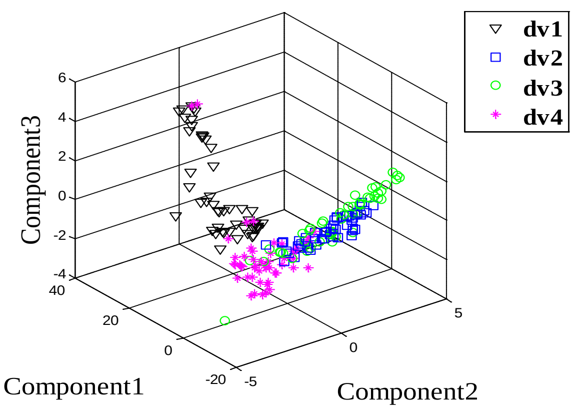
R: Rising, F: Falling, PC: Principal components

IV. Results

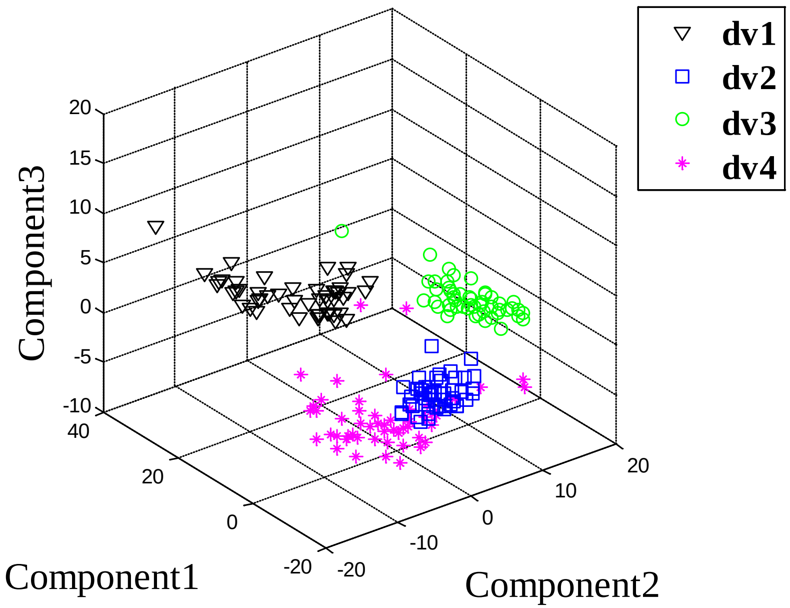
- ***The cluster on each class is distinctly formed*** when the concatenated feature is used.



SL1M transient (rising+falling) features



SL1M sync features



SL1M transient (rising+falling) + sync features

IV. Results

- It is noticeable that ***the highest accuracy rate*** is recorded even though ***the less number of training data*** is used relatively.
- The comparison experiment is necessary for more accurate comparison.

Method	Number of Devices	Experiment condition	Accuracy rate	Number of training data per a device
The proposed method	8 (Digital walkie-talkies)	1m LOS	98.75%	40
Patel et al. [3]	4 (Zigbee devices)	12 dB	Higher than 90%	1500
Peng et al. [4]	54 (Zigbee devices)	1-3m LOS	96%	1 (template feature)
Merchant et al. [5]	7 (Zigbee devices)	28 dB	92.29%	900

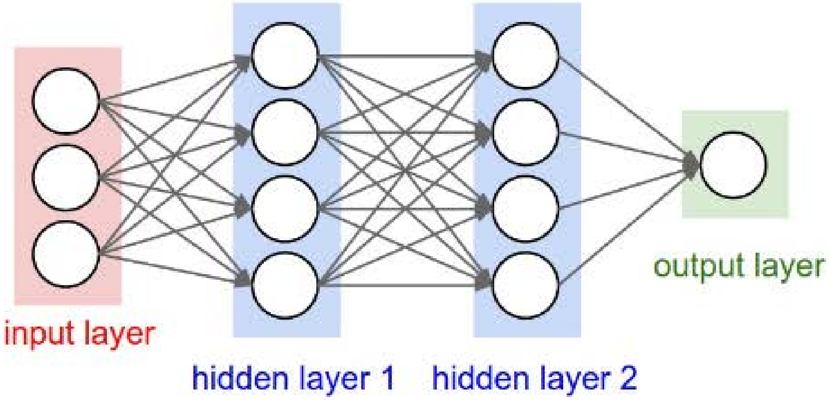
V. Conclusion

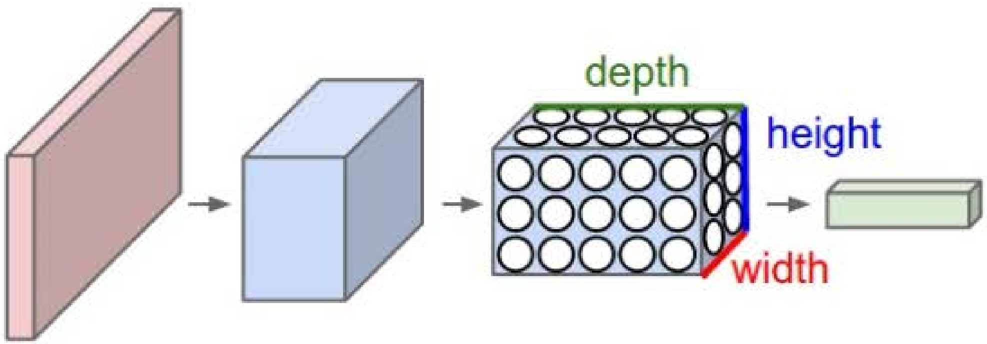
- We proposed the RF fingerprinting scheme based on SRC with multiple features.
- As a feature, the ***main lobes*** of rising transient signal, falling transient signal, and sync signal were used ***simultaneously***.
- When many features were used as concatenation, the accuracy rate was increased.
- The accuracy rate of the proposed method recorded ***98.75%***.
- As a future work, we need to study on RF fingerprinting scheme based on SRC with the various features besides the used features.
- The paper on this study is under revision.

Thank you

VI. Appendix

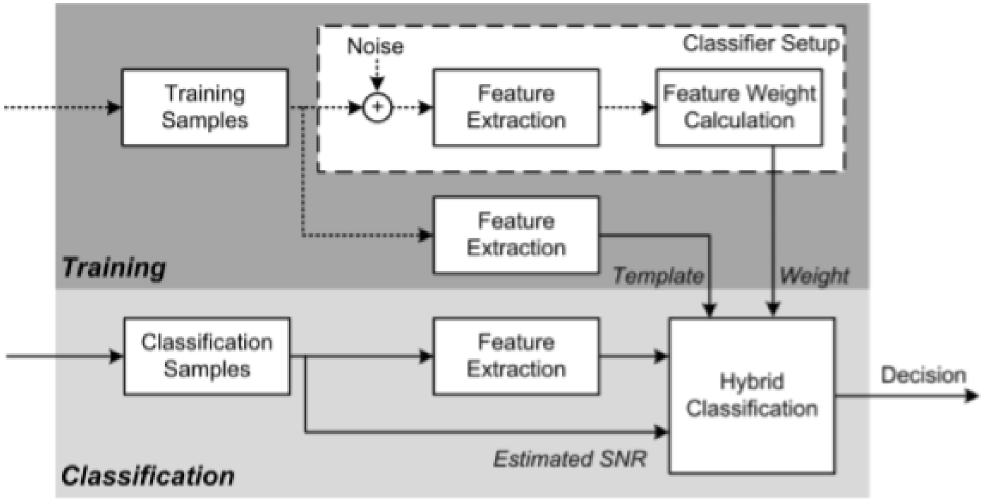
- Deep learning for RF device fingerprinting [3]
  - They used the convolutional neural network (CNN) for the RF fingerprinting.
  - They collected 7,000 data from 7 devices.
  - Each full dataset of 7,000 transmissions was randomly partitioned into 80% training data, 10% validation data, and 10% testing data.
  - The overall correct identification rate is 92.29%

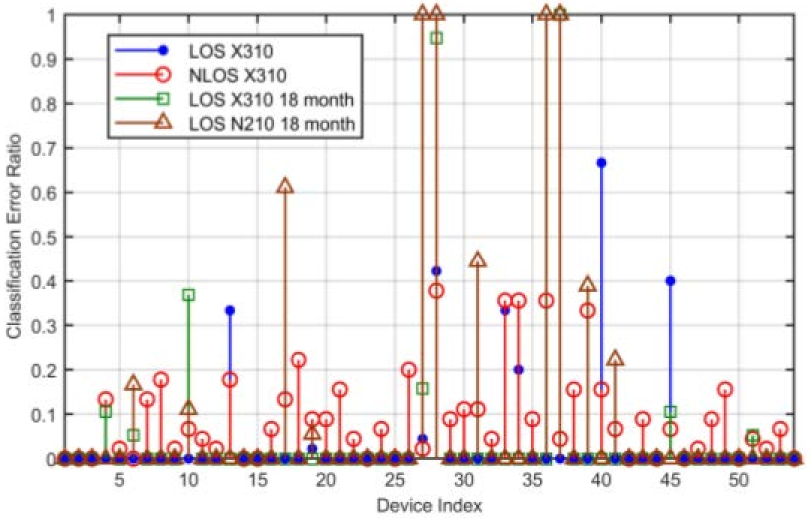




VI. Appendix

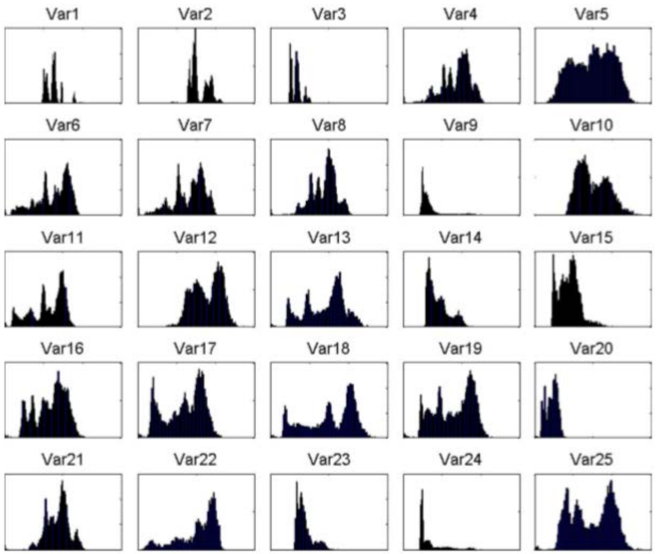
- Hybrid RF fingerprint extraction and device classification scheme [4]
  - They used 4 features simultaneously – differential constellation trace figure, carrier frequency offset, and 2 features of the error on I/Q domain.
  - The experiment is performed on the total 54 Zigbee devices.
  - They did the experiment on the 4 environment.
    - Line of sight / Non line of sight
    - Line of sight after 18 month with same receiver and different receivers

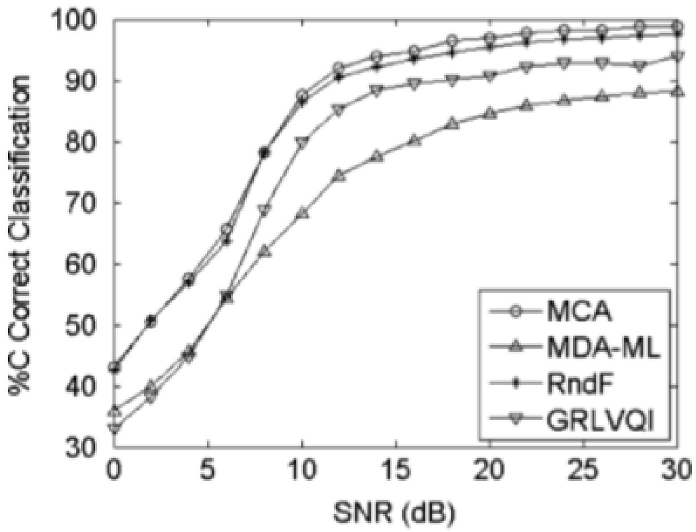




VI. Appendix

- Improving zigbee device network authentication using ensemble decision tree classifiers [5]
  - The used RF DNA features contain information on variance, skewness, and kurtosis, within a preamble response.
  - They showed the result of 'Random Forest' and 'Multi-class AdaBoost' for RF fingerprinting.
  - The top-ranked 25 variables selected by Variable Importance (VI) metric built in Random Forest classifier on 4 zigbee devices are used.





VI. Appendix

- Principal components analysis [7]
  - PCA is a method to project the original data onto the new space on the variance.
  - Let $\mathbf{u} = \mathbf{A}\mathbf{s}$, where $\mathbf{A}$ is the training data matrix and $\mathbf{u}$ is the test data.
  - A covariance matrix of $\mathbf{A}$ is eigen-decomposed as,

$$(\mathbf{A} - \mathbf{m}\mathbf{1})(\mathbf{A} - \mathbf{m}\mathbf{1})^T = \mathbf{W}\mathbf{\Lambda}\mathbf{W}^T$$

where $\mathbf{m} = \frac{\mathbf{1}}{N}\sum_{n=1}^{N} n \text{ th columns of } \mathbf{A}$, $\mathbf{1} := [1\ 1\ \cdots\ 1]$.

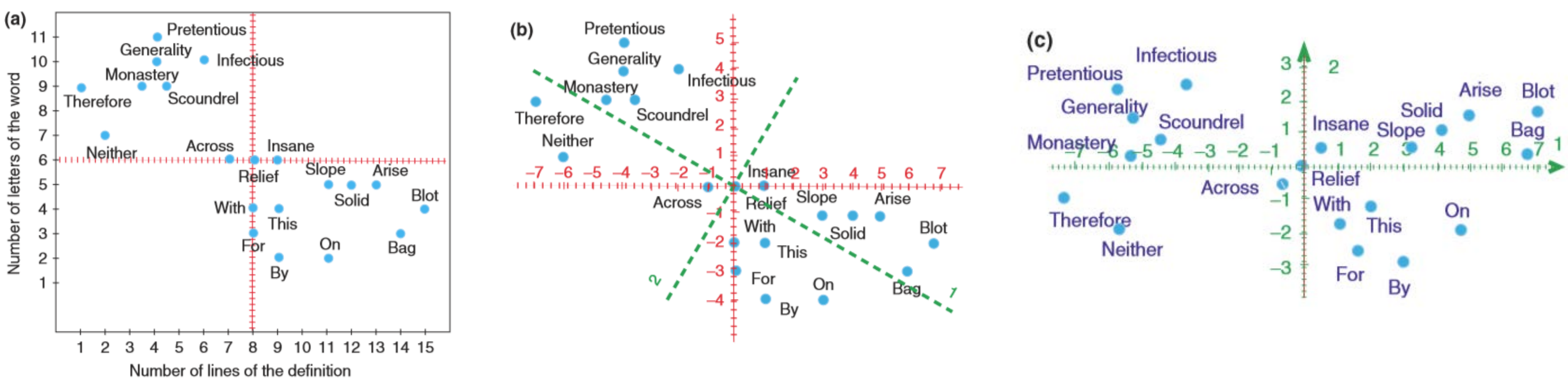
  - The eigen-vectors of the covariance matrix are orthonormal.
  - The eigen-value matrix $\mathbf{\Lambda}$ is proportional to the variance of $\mathbf{A}$,

$$\mathbf{W}^T(\mathbf{A} - \mathbf{m}\mathbf{1})(\mathbf{A} - \mathbf{m}\mathbf{1})^T\mathbf{W} = \mathbf{\Lambda}.$$

  - Let the eigen-values $\lambda_1, \lambda_2, \dots \lambda_n$ of the eigen-value matrix $\mathbf{\Lambda}$ be rearranged in order of the sizes.
  - Let the eigen-vectors $\mathbf{w}_1, \mathbf{w}_2, \dots \mathbf{w}_\mathrm{n}$ of the eigen-vector matrix $\mathbf{W}$ be also rearranged by the eigen-values.

VI. Appendix

- Principal components analysis [7]
  - Since the eigen-vectors of the covariance matrix are orthonormal and the eigen-value matrix $\boldsymbol{\Lambda}$ is proportional to the variance of $\mathbf{A}$, the eigen-vectors can be basis for the creating the new space on the variance of $\mathbf{A}$.
  - The training data matrix $\mathbf{A}$ and the test data $\mathbf{u}$ is transformed to the new space by $\mathbf{D} = \mathbf{W}^T(\mathbf{A} - \mathbf{m}\mathbf{1})$ and $\mathbf{y} = \mathbf{W}^\mathbf{T}(\mathbf{u} - \mathbf{m})$.
  - PCA removes correlations among columns of $\mathbf{A}$.
  - Also, PCA can remove the size of the columns of $\mathbf{A}$.



VI. Appendix

- L_p norms [8]

$$||\mathbf{x}||_p = \left(\sum_i |x_i|^p\right)^{\frac{1}{p}}$$

- Uniqueness of sparse solution (L_1) [8]
  - Suppose $\mathbf{y} = \mathbf{D}\mathbf{s}_0$ with

$$||\mathbf{s}_0||_0 < \frac{1}{2}\left(1 + \frac{1}{\mu(\mathbf{D})}\right),$$

where $\mu(\mathbf{D}) = \max_{1 \le k,j \le m, k \ne j} \frac{|a_k^T a_j|}{||a_k||_2 \cdot ||a_j||_2}$

Then $\mathbf{s}_0$ is the unique optimal solution to

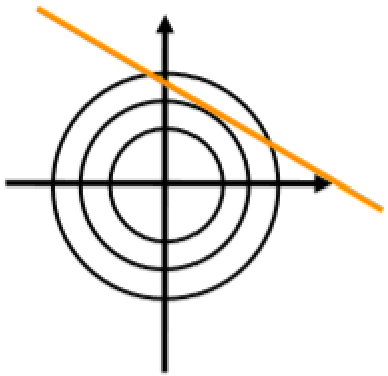
Minimize $||\mathbf{s}||_1$ subject to $\mathbf{y} = \mathbf{D}\mathbf{s}$.

- If the function f has a second derivative that is non-negative (positive) over an interval, the function is convex (strictly convex) over that interval. [9]

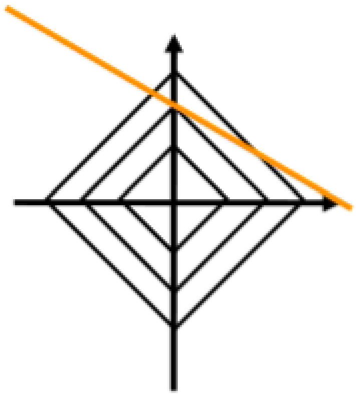
VI. Appendix

- L_p norms level sets

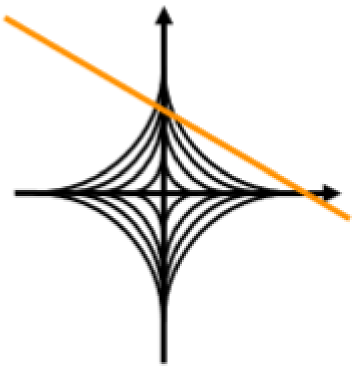
Strictly convex when p>1



Convex p>1



Nonconvex p<1



- Basis pursuit algorithm [10]
  - The mathematical optimization problem of the form

$$\min_{\mathbf{s}} ||\mathbf{s}||_1 \text{ subject to } \mathbf{y} = \mathbf{D}\mathbf{s}.$$

  - To solve the problem, ‘Primal-Dual Barrier method’ is used.

VI. Appendix

- Primal-Dual Barrier method [11]
  - A certain class of algorithms that solve linear and nonlinear convex optimization problems.
  - Consider the dual pair for Linear programming problem

$$\min c^T x \quad s.t. Ax = b, x \geq 0, \min b^T \lambda \quad s.t. A^T \lambda + s = c, s \geq 0$$

  - The Karush-Kuhn-Tucker conditions for both equation are

$$\begin{cases} A^T \lambda + s = c \\ Ax = b \\ x \geq 0 \\ s \geq 0 \\ x^{(i)} s^{(i)} = 0, \ 1 \leq i \leq n \end{cases}$$

  - Let $s = (s^{(1)}, s^{(2)}, \cdots, s^{(n)}), S = \mathrm{diag}(s)$, and $e = (1,1,\cdots,1)$. We can rewrite the constraints into

$$\tilde{F}(x, \lambda, s) = \begin{bmatrix} A^T \lambda + s - c \\ Ax - b \\ XSe \end{bmatrix} = 0$$

VI. Appendix

- Primal-Dual Barrier method [11]
  - We relax the last constraint $x^{(i)}s^{(i)} = 0$ to $x^{(i)}s^{(i)} = \mu$ and obtain

$$F(x, \lambda, s) = \begin{bmatrix} A^T\lambda + s - c \\ Ax - b \\ XSe - \mu e \end{bmatrix} = 0$$

  - The Jacobian will be

$$J = \begin{bmatrix} 0 & A^T & I \\ A & 0 & 0 \\ S & 0 & X \end{bmatrix}$$

and the Newton's method read

$$\begin{bmatrix} 0 & A^T & I \\ A & 0 & 0 \\ S & 0 & X \end{bmatrix} \begin{bmatrix} d_X \\ d_\lambda \\ d_s \end{bmatrix} = \begin{bmatrix} -A^T\lambda - s + c \\ b - Ax \\ -XSe + \mu e \end{bmatrix}$$

  - Solve

$$\min B(x_k, \mu_k) = c^T x - \mu \sum_{i=1}^{n} \log x_i \,, \mu > 0$$

VI. Appendix

- Primal-Dual Barrier method [11]

Algorithm 2 Primal-Dual Newton Barrier Method for LP

$\mu_0 \leftarrow 1, \rho \in (0,1)$
Generate (x_0, λ_0, s_0), s.t. $x_0 > 0, s_0 > 0$
for $k = 1, 2, 3, \ldots$ **do**
    $\mu_k \leftarrow \rho \mu_{k-1}$
    Solve

$$\begin{bmatrix} 0 & A^T & I \\ A & 0 & 0 \\ S_{k-1} & 0 & X_{k-1} \end{bmatrix} \begin{bmatrix} d_X \\ d_\lambda \\ d_s \end{bmatrix} = - \begin{bmatrix} A^T \lambda_{k-1} + s_{k-1} - c \\ A x_{k-1} - b \\ X_{k-1} S_{k-1} e - \mu_k e \end{bmatrix} \tag{21}$$

    Solve

$$\begin{aligned} &\min_{\alpha > 0} B(x_k, \mu_k) \\ &s.t. \ (x_k, \lambda_k, s_k) = (x_{k-1}, \lambda_{k-1}, s_{k-1}) + \alpha(d_X, d_\lambda, d_s) \end{aligned} \tag{22}$$

    $(x_k, \lambda_k, s_k) \leftarrow (x_{k-1}, \lambda_{k-1}, s_{k-1}) + \alpha(d_X, \lambda_k, s_k)$
    Check stop criterion.

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