A Practical Cross-Domain ECG Biometric Identification Method

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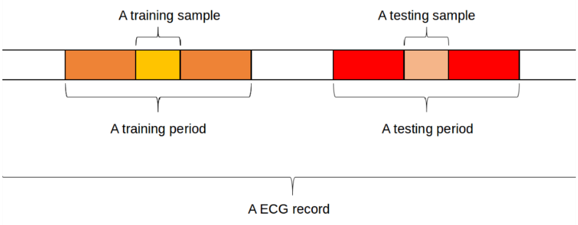
Why ECG is used for identification?

- Biometric methods, such as fingerprint identification and face identification, which are widely used, are vulnerable to **forgery attacks**.
- ECG identification is of **higher resistance** against such attacks and receives research attention.

Problems In Practical Application



- Samples are not enough(fiducial) and effective.
- There is no significant interval, the extracted features are temporal sensitive.
- The features highly relevant to the performance are not utilized sufficiently.

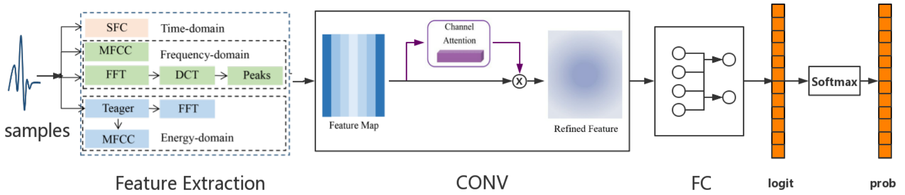
Our Contributions

- We **evaluate the parameter performance** of the non-fiducial random sampling method to obtain enough effective samples for each individual.

- We propose a method to extract **individual-distinguishable** feature insensitive to timespan between feature collection and recognition period via utilizing deep features across time, frequency and energy domain.

- We introduce a **channel attention module** into the CNN and **modify the activation function** to optimize the recognition performance.

Architecture Overview

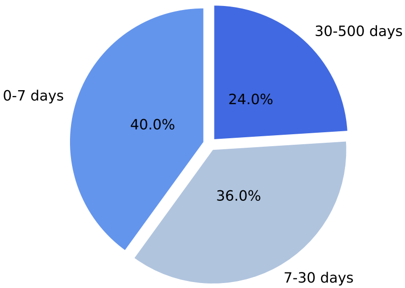


- The architecture of our proposed method contains three modules.
  - **Sample acquisition**: preprocessing, random start point;
  - **Feature extraction**: time, frequency and energy feature;
  - **Deep network**: convolutional layer, modified channel attention module.

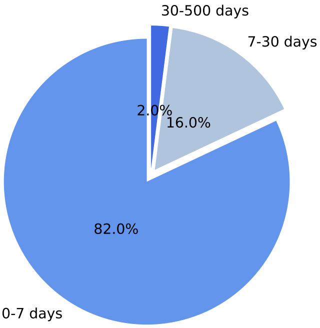
Dataset

PTB	ECG-ID
290 individuals (549 records)	90 people (310 records)
more than 50 individuals 2 or more records	default config at least 2 records (!33)
Each record contains Lead I (On the wrist)	Storing Lead I ECG signal (On the wrist)

Interval distribution



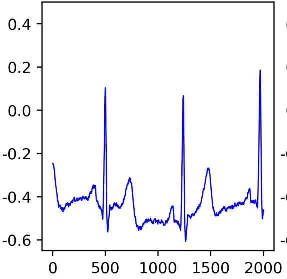
(a) PTBDB



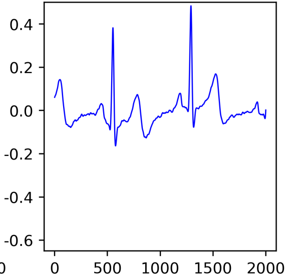
(b) ECG-ID

Preprocessing

- power frequency interference, random noise and baseline drift.
- filter bank: Butterworth filter and IIR filter.

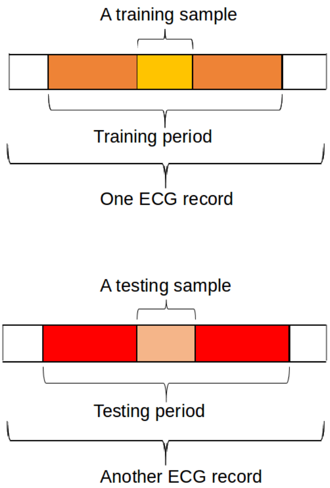


(a) Raw ECG signal.



(b) Filtered ECG signal.

Sample Acquisition



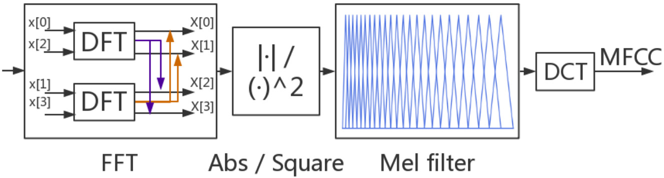
$$X_s^i = R_s^j[P_i : E_i] \tag{1}$$

$$j = \begin{cases} 0, & \text{record} = \text{visit0} \\ 1, & \text{record} = \text{visit1} \end{cases} \tag{2}$$

$$E_i = P_i + t * f \tag{3}$$

Feature Extraction

- **Time Domain**: mean, standard deviation, kurtosis, skewness.
- **Frequency Domain**: MFCC and DCT of FFT.
- **Energy Domain**: FFT of Teager and MFCC of Teager.



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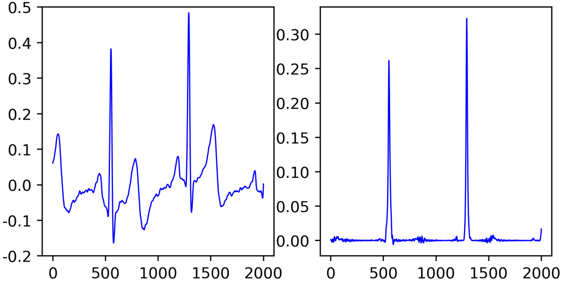
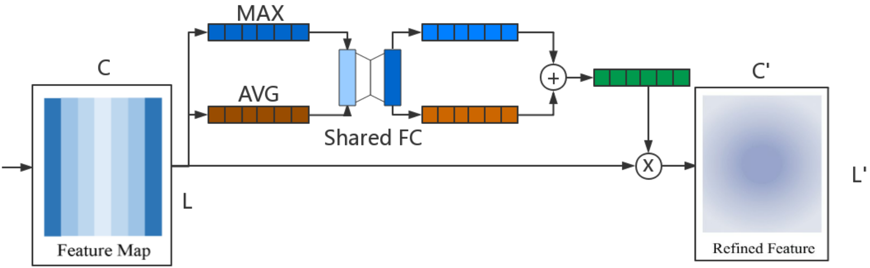


(a) Filtered ECG signal. (b) ECG signal after Teager.

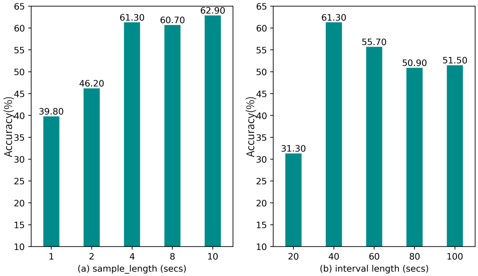
Channel attention module



- replace Relu with sigmoid.

Setup

length & Interval length



- Other Parameters
  - (Train Valid Test)samples: 300, 150 and 300.
  - Neuron numbers: 1024 and 256.
  - Activation function: ReLU –> Leaky ReLU.

Results with different intervals

Table: Continuous and discontinuous sampling

	PTBDB	ECG-ID
10-C-B	97%	–
10-C-O	99.2%	–
50-C-B	–	93%
50-C-O	96.6%	94.89%
50-N	40.24%	71.2%

Results of different methods

Table: Recognition results in different methods

	PTBDB	ECG-ID
DWT	40.24%	71.2%
MFCC+Peaks	50.62%	82.03%
MFCC+Peaks+SFC	53.04%	84.53%
MFCC+Peaks+SFC+FFT	**56.93%**	**85.94%**

Thanks!

- Questions?