GMM-UBM based Person Verification using footfall signatures for Smart Home Applications

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Introduction

- Proposed a *person verification system* based on the footfall signature using GMM-UBM.
- The footfall generated ground vibration is used a *biometric modality*.
- The proposed system is *evaluated* on an indigenous dataset containing **7750** *footfall events* of **20** subjects.
- Robustness of the system is evaluated by varying the number of *registered* and *non registered* users.
- Performance parameters: Half Total Error Rate (HTER)
- Compared with the existing state of the art techniques: SVM[1] and CNN[2].

[1] S. Pan, A. Bonde, J. Jing, L. Zhang, P. Zhang, and H. Y. Noh, "Boes: building occupancy estimation system using sparse ambient vibration monitoring," in SPIE Smart Structures and Materials+ Nondestructive Evaluation and Health Monitoring, vol. 9061, Apr. 2014

[2] O. C. Reyes, R. Vera-Rodriguez, P. Scully, and K. B. Ozanyan, "Analysis of spatio-temporal representations for robust footstep recognition with deep residual neural networks," IEEE Trans. Pattern Anal. Mach. Intell., vol. 41, no. 2, pp. 285–296, Feb. 2019.

Drawbacks with the existing biometric system

- Require active cooperation of an individual for verification.
  - Camera based system: An individual has to stand in front of a camera under proper lighting condition.
  - Fingerprint based system: Individuals need to place their finger on a scanner.
  - Speech based system: Individuals need to speak in a low noise environment.
- Vulnerable of privacy invasion and data leakage: A detailed database (facial image/fingerprints/voice) of the registered users are maintained.
- Leakage can lead to identity theft as these data are related to the users' individuality.
- Biometrics systems can also be subjected to spoofing or presentation attack.

Ground vibration generated by footfall

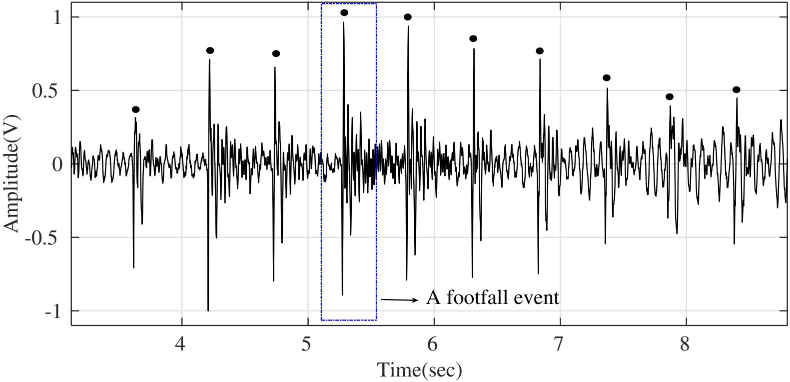

Figure 1: Signal generated from the footfalls

System Architecture

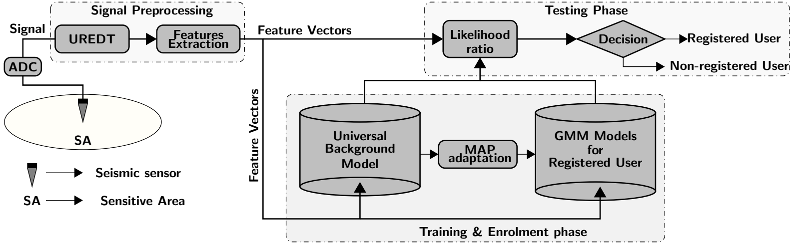

Figure 2: Footstep based person verification system using GMM-UBM[3].

[3] Reynolds, Douglas A., Thomas F. Quatieri, and Robert B. Dunn. "Speaker verification using adapted Gaussian mixture models." Digital signal processing 10.1-3 (2000): 19-41.

Signal Recording and Preprocessing

- UREDT [4]
- Windowing technique is used to prevent spectral leakage.
- Spectral leakages introduce high frequency harmonics in the frequency domain of the seismic signal and deteriorates the performance of the system .

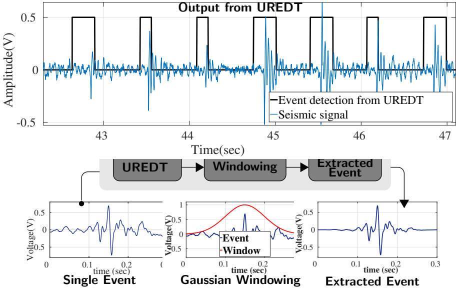

Figure 3: Illustration of the event extraction process.

[4] S. Anchal, B. Mukhopadhyay, and S. Kar, "UREDT: Unsupervised learning based real-time footfall event detection technique in seismic signal," IEEE Sensors Lett., vol. 2, no. 1, pp. 1-4, Mar. 2018

Features of the footfall event

<table>
<tr><td rowspan="4">Time Domain</td><td>std</td><td rowspan="4">Hilbert Transform</td><td>mean
std</td><td rowspan="4">Frequency Energy Bins (2Hz.)</td><td rowspan="4">0
to
250 Hz.</td></tr>
<tr><td>skewness</td><td>skewness</td></tr>
<tr><td>kurtosis</td><td rowspan="2">kurtosis</td></tr>
<tr><td>event length</td></tr>
</table>

Experimentation Methodology

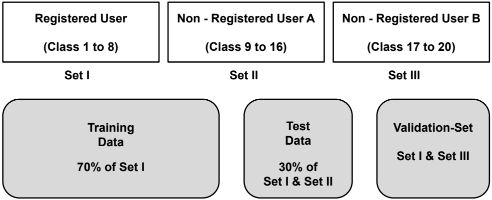

Figure 4: Partitioning of the dataset.

- Class specific threshold are utilized
- Validation set is used to determine the threshold using EER(Equal Error Rate) criteria
- Half Total Error Rate (HTER) is used as evaluation matrix

Evaluation Matrix: Half Total Error Rate (HTER)

- False Acceptance Rate (FAR): Imposters detected as Registered users
- False Rejection Rate (FRR): Registered users are detected as Imposters
- Half Total Error Rate (HTER):

$$\mathrm{HTER} = \frac{\mathrm{FAR} + \mathrm{FRR}}{2} \tag{1}$$

Optimal number of Gaussian mixtures

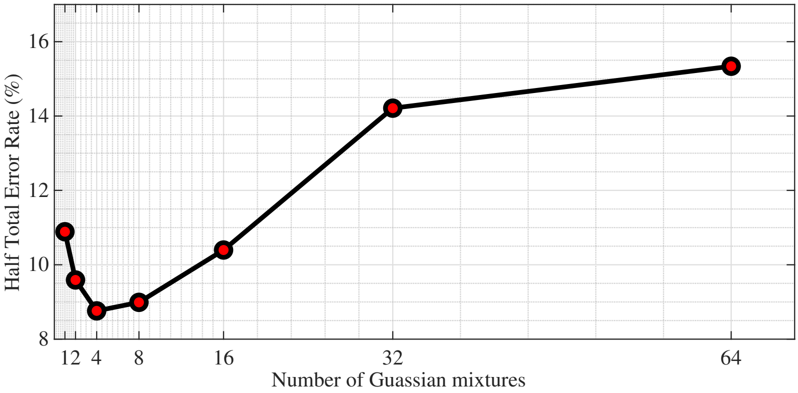

Figure 5: HTER of the test set corresponding to different numbers of Gaussian mixtures.

Tuning Parameters of the techniques used

- **GMM-UBM**: No. of Gaussian Mixtures = 4, Adaptation Coefficients = 5
- **SVM**: C = 100, $\gamma = 0.001$
- **CNN**: Input: 134x1. 4 CONV layers (64 filters, Kernel size 3, max-pooling), 1 FC layer (100), Softmax output layer. Optimizer: ADAM.

Experimentation Results

Table 1: Performance of GMM-UBM , SVM, and CNN in person verification.

(a) Performance of the techniques as r_{reg} is varied. ($r_{nreg} = 8$)

#Registered User	GMM-UBM			SVM-RBF			SVM-Lin			CNN		
	FAR	FRR	HTER	FAR	FRR	HTER	FAR	FRR	HTER	FAR	FRR	HTER
2	4.45	8.56	**6.51**	9.46	13.24	11.35	14.33	10.62	12.47	35.80	1.36	18.58
4	3.95	8.62	**6.29**	2.07	20.27	11.17	3.48	17.95	10.71	7.58	6.15	6.86
6	4.19	9.99	**7.09**	1.33	26.90	14.12	2.86	24.49	13.67	2.71	13.05	7.88
8	5.04	9.92	**7.48**	0.65	28.20	14.42	1.52	27.09	14.31	1.48	14.46	7.97

(b) Performance of the techniques as r_{nreg} is varied. ($r_{reg} = 5$)

#Non Registered User	GMM-UBM			SVM-RBF			SVM-Lin			CNN		
	FAR	FRR	HTER	FAR	FRR	HTER	FAR	FRR	HTER	FAR	FRR	HTER
2	4.19	10.00	**7.09**	0.24	28.31	14.28	0.48	26.60	13.540	1.62	12.60	7.11
8	4.50	9.93	**7.21**	0.66	28.68	14.67	1.56	26.88	14.220	4.20	12.60	8.40

Experimentation Results: HTER for individual classes

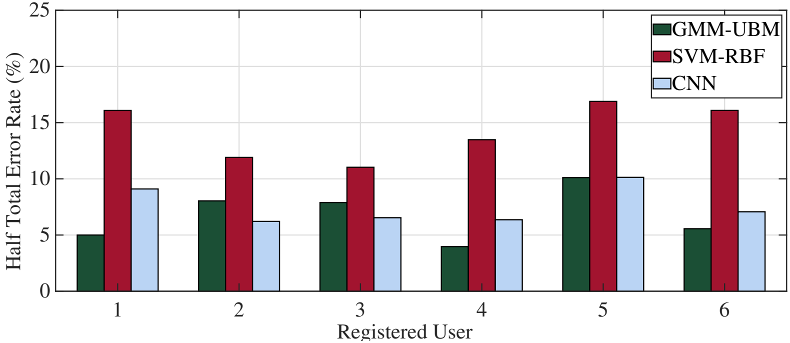

Figure 6: Performance of the GMM-UBM, CNN and SVM-RBF techniques when $r_{\text{reg}} = 6$ and $r_{\text{nreg}} = 5$.

Thank You!

Any Questions?

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