Weekly Report

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1 Progress

- Continue to work on the implementation of DDLM
  - It may take some more time to implement. Therefore, it may be better to give a priority to look for other open sources and compare them with the datasets that were used for DDLM.
- Read a paper titled "Identity Authentication in Two-Subject Environments Using Microwave Doppler Radar and Machine Learning Classifiers"[1]

2 Details of the paper[1]

The main challenge, and thus the focus of this research, is the recognition of closely spaced subjects within the beamwidth of the radar transceiver(=30 °). Two subjects with a similar physique were (otherwise) randomly paired and arranged in a seated position in front of the radar system as shown in Fig.1.

Figure 1: Human experiment setup in an anechoic chamber

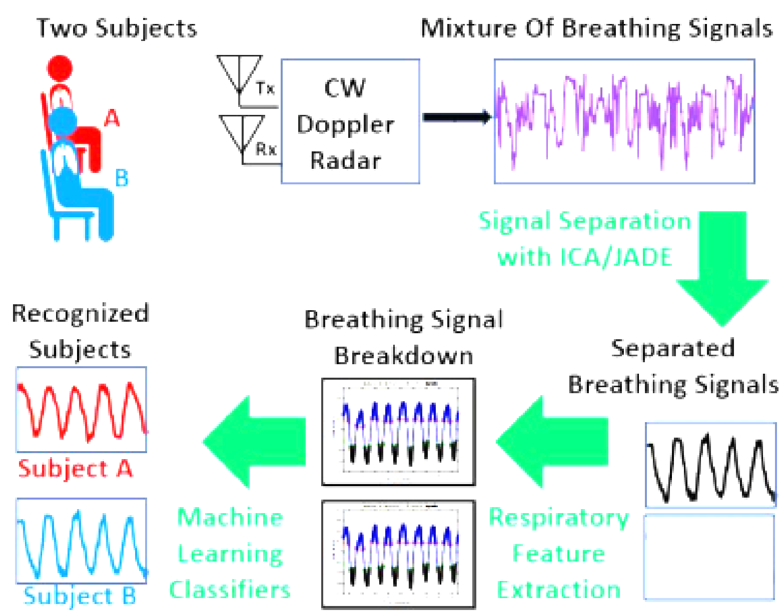

Figure 2: Proposed noncontact identity authentication system for two-subject environments

In this paper, accuracies of 97.5% for two-subject experiments and 98.33%

for single-subject experiments were achieved, which supersedes the performance of prior reported methods.

The investigated features have been classified into two different spaces shown in Table1. One of them is typical features and another one is hyperfeatures. The typical respiratory feature extraction process is described in prior work[2][3].

The extracted hyperfeature sets were then evaluated by integrating two different popular ML classifiers, k-nearest neighbor (KNN) and support vector machine (SVM), for subject authentication.

Table1: Extracted breathing dynamic-related features

Feature Space	Features
Typical features	• Breathing rate/heart rate • Average exhale cycle period • Standard deviation of exhale cycle period • Average inhale cycle period • Standard deviation of inhale/exhale cycle period • Dynamic segmentation
Hyper-features	• Exhale area • Inhale area • Inhale/exhale speed • Breathing depth

Proposed algorithm to determine the inhale and exhale areas, and speed (called hyperfeatures)

1. Preprocessing and separation of respiratory signal using ICA-JADE(: Independent component analysis with the joint approximation of diagonalization of eigenmatrices)

2. Segmentation of the signal for 12.8 second window

3. Create an array of local maxima and minima

4. Grouping of two consecutive maxima and in between one minima for triangulation (as shown in Fig.3)

5. Calculation of the area of the triangles (inhale and exhale episodes)

6. Average out the areas (inhale and exhale episodes)

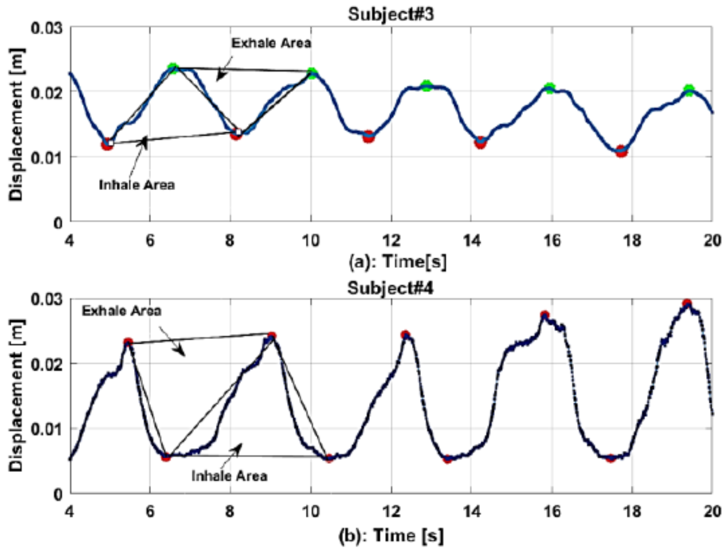

Figure 3: Illustration of inhale and exhale areas of two subjects

Table2: Accuracy of the different ML classifiers

CLASSIFIER	ACCURACY
KNN (CUBIC)	84.4%
KNN (COSINE)	86.4%
KNN (MEDIUM)	86.9%
SVM (LINEAR)	95%
SVM (QUADRATIC)	97.5%
SVM (FINE GAUSSIAN)	93.5%
SVM (MEDIUM GAUSSIAN)	96.5%

Among all classifiers, SVM with a quadratic function outperformed the others with an accuracy of 97.5%.

Table3: Comparison of this article with other recent relevant works

Reference & Year	Radar Type & Freq (GHz)	Subject in radar view	Number of Subject	Feature Extraction Algorithm	Accuracy (%)
[1] 2017	CW 2.4 GHz	1	78	Heart-based dynamics (fiducial based descriptor five points)	98.61%
[24] 2018	CW 24 GHz	1	4	Hear tbeat signal complexity	94.6%
[25] 2018	CW 2.4 GHz	1	6	dynamic segmentation (Area ratio)	93.33%
[27] 2020	CW 24 GHz	1	10	Short-time Fourier transform (heartbeat, energy and bandwidth)	98. 5%
this work For single subject	CW 24 GHz (Dataset of reference [25])	1	6	improved version of dynamic segmentation (inhale area, exhale area, breathing depth)	98.33%
[29] 2020	FMCW 77 GHz	2	3	Micro-doppler spectrogram with deep neural network	95.40%
this work for multi-subject	CW 24 GHz	2	20	improved version of dynamic segmentation (inhale area, exhale area, breathing depth)	97.5%

The proposed improved dynamics segmentation algorithm with an ML-based approach shows reasonable accuracy compared to the deep learning-based approach.

3 Next Plan

- Implement DDLM or search open sources to compare accuracy
- Consider other approaches

References

[1] slam, Shekh MM, Olga Borić-Lubecke, and Victor M. Lubecke. "Identity Authentication in Two-Subject Environments Using Microwave Doppler Radar and Machine Learning Classifiers." IEEE Transactions on Microwave Theory and Techniques (2022).

[2] . Ragman, V. M. Lubecke, O. Boric-Lubecke, J. H. Prins, and T. Sakamoto, " Doppler radar techniques for accurate respiration characterization and

subject identification," IEEE J. Emerg. Sel. Topics Circuits Syst., vol. 8, no. 2, pp. 350–359, Jun. 2018, doi: 10.1109/ JETCAS.2018.2818181.

[3] . M. M. Islam, A. Sylvester, G. Orpilla, and V. M. Lubecke, "Respiratory feature extraction for radar-based continuous identity authentication," in Proc. IEEE Radio Wireless Symp. (RWS), San Antonio, TX, USA, Jan. 2020, pp. 119–122.