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Machine learning of Multi-site Photoplethysmography (MPPG) pulse waveform in patients with Systemic Sclerosis

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Introduction (1)

- Systemic Sclerosis (SSc) aka “scleroderma” is a complex autoimmune disease

- Significant morbidity and mortality

- Difficult to diagnose

- Symptoms can resemble diseases: rheumatoid arthritis and systemic lupus erythematosus

Introduction (2)

- One early symptom of SSc manifests as Raynaud's phenomenon (RP)

- Useful clinically to differentiate between Primary Raynaud's phenomenon (PRP) (is idiopathic) and Secondary Raynaud's phenomenon (due to SSc)

Example episodic skin colour changes in Raynaud's phenomenon

Source: www.sruk.co.uk

Problem Statement

- Current methods of detecting SSc

- Expensive
- Requires skilled staff
- Extensive imaging techniques (capillaroscopy)

Source: google.com

Aims of my research

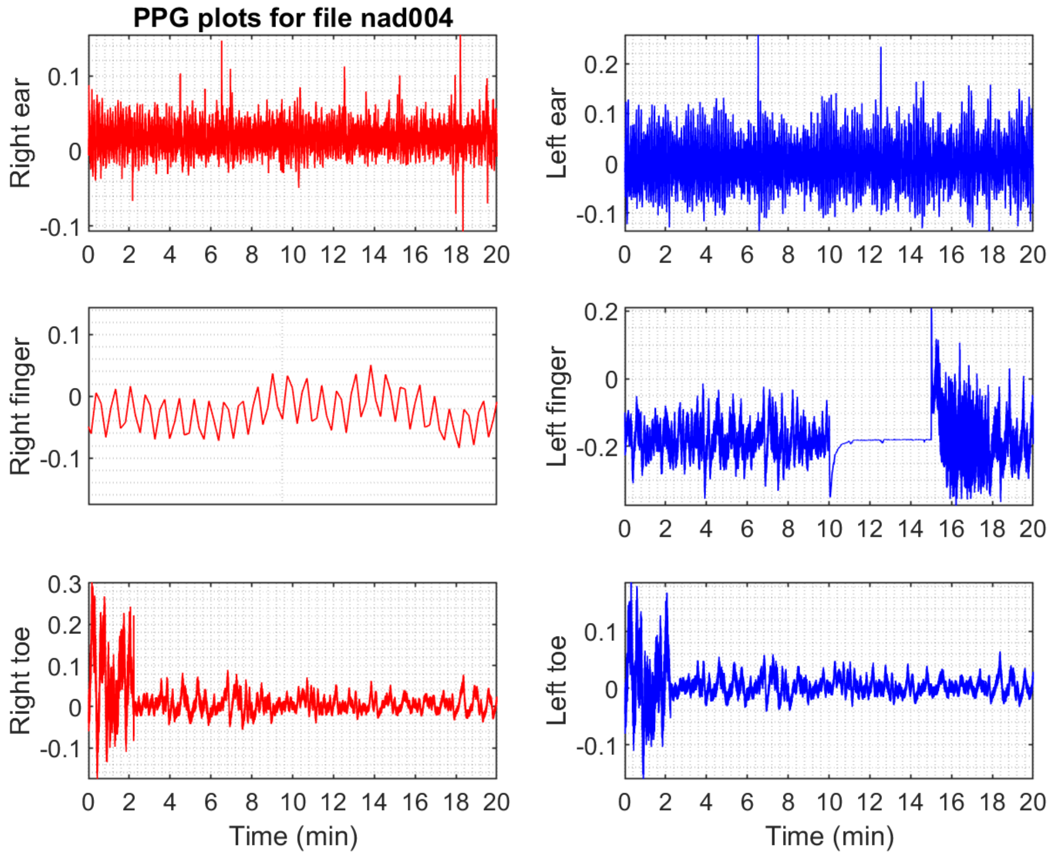
- Investigate a novel method of detecting SSc
- Explore and understand better Multi-site Photoplethysmography (PPG) waveforms.

Methods: Subjects

- 20 SSc and 49 non-SSc controls (30 Healthy controls + 19 PRP)
- Mean± SD age = 53.3 ± 17.5 years
- SSc diagnosed by an expert clinician

Methods - PPG

- PPG is a low cost, non-invasive, and simple to acquire optical pulse technique.
- Our PPG used NIR light (950 nm)
- Pulses easily obtained at ear lobes, index fingers and toes.
- Hold a wealth of potentially useful information e.g. endothelial function, arterial disease and autonomic function.



Multi-site PPG pulses over 20 min. Special protocol.
(Right finger shows a zoomed in view of PPG pulses.)

Methods: Data

- Unique multi-site PPG (MPPG) data set, collected by Dr. John Allen and his team in Northern Medical Physics and Clinical Engineering (NMPCE), Freeman Hospital [standard initial analysis by McKay, (1)].

- MPPG data for each subject: 20 minutes in length, subject comfortably supine. In temperature controlled room.
- Right and left ear lobes, index fingers and great toes. ECG also measured.

- 3 phases: Baseline (0-10 min), Cuff occlusion at left arm (10-15 min), then Reactive Hyperaemia phase (15-20 min).

Methods: Pulse characterization

Features:

“AMP” : Foot to peak amplitude of each PPG pulse, normalized to gain.

“pttf” : this is the time at which foot of PPG appears after the respective heartbeat (ECG R wave).

“pttp “ : this is the time at which peak of PPG appears after the respective heartbeat

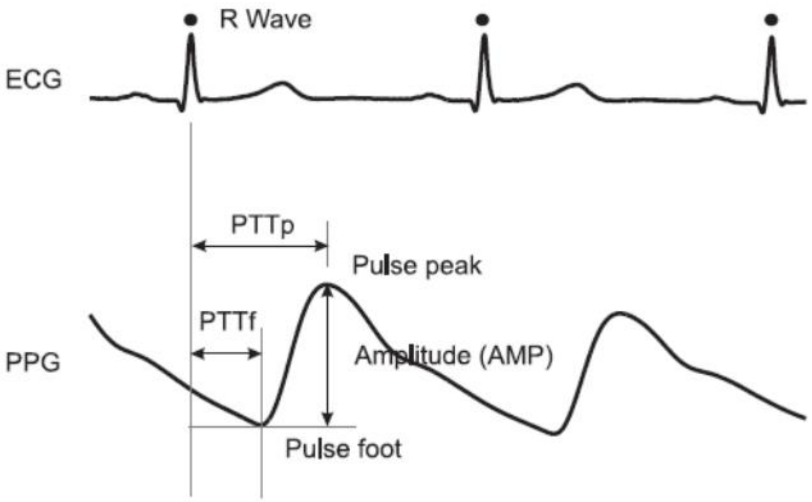


Figure shows PPG pulses appearing after each heartbeat & the 3 features per pulse at one body site.

Methods: AI

- Machine learning: Branch of artificial intelligence (AI) that deals with learning from data, identifying patterns and making decisions with minimal human intervention.

Methods: Machine Learning (ML) approaches explored …

- To explore if the ML techniques can distinguish between SSc and non-SSc controls using 6 MPPG body waveforms.

- 2 standard ML classifiers explored:

Linear Discriminant analysis (LDA)

K Nearest Neighbour (KNN, K=10)

Results

- Diagnostic test accuracy & performance (95% Confidence Interval ranges)

Flush Phase data	**LDA**	**KNN**
Accuracy	0.6772_CI(0.6711-0.6832)	0.6276_CI(0.6213-0.6338)
Sensitivity	0.5561_CI(0.5439-0.5683)	0.2844_CI(0.2733-0.2956)
Specificity	0.7239_CI(0.7170-0.7307)	0.7601_CI(0.7536-0.7666)

Results

- Diagnostic test accuracy & performance (95% Confidence Interval ranges)

Baseline Phase data	LDA	KNN
Accuracy	0.6974_CI(0.6914-0.7033)	0.6038_CI(0.5975-0.6101)
Sensitivity	0.5059_CI(0.4936-0.5182)	0.2671_CI(0.2563-0.2781)
Specificity	0.7707_CI(0.7642-0.7770)	0.7328_CI(0.7260-0.7395)

Discussion

- A, Se and Sp between Baseline and Flush phases nearly same

- Specificity higher than sensitivity (SSc class is positive)

- The 3 features in SSc subject can sometimes resemble controls. It may be the use of MPPG data from across 6 body sites and over 5 or 10 minute periods is actually blurring the detail that flush gradient alone for which significant differences have been shown [1].
- I would explore key patient data variables in the ML analysis such as disease subset, and severity of SSc.

Overcoming the limitations

- Deep Learning (DL): which can learn the patterns inherent in data.
- Should not need hand engineered features.
- Sensitive to noise however. Resilient pre-processing needed.

References

- McKay, N., Griffiths, B., Di Maria, C., Hedley, S., Murray, A., & Allen, J. (2014). Novel photoplethysmography cardiovascular assessments in patients with Raynaud's phenomenon and systemic sclerosis: A pilot study. Rheumatology, 53(10), 1855-1863.
- Urwin, S. G., Griffiths, B., & Allen, J. (2016). Quantification of differences between nailfold capillaroscopy images with a scleroderma pattern and normal pattern using measures of geometric and algorithmic complexity. Physiological measurement, 38(2), N32.
- Allen, John. "Photoplethysmography and its application in clinical physiological measurement." Physiological measurement 28.3 (2007): R1.
- Calamanti, C., Moccia, S., Migliorelli, L., Paolanti, M., & Frontoni, E. (2019). Learning-Based Screening of Endothelial Dysfunction From Photoplethysmographic Signals. Electronics, 8(3), 271.
- Z. Kun, J. Teng, D. Xiuzhen, Z. Wen, Extracting motional information from the photoplethysmography using reconstruction of the wavelet transforms modulus maxima, Conf. Proc. Int. Conf. Bioinform. Biomed. Eng. (2008) 1395–1398
- Sun, B., Wang, C., Chen, X., Zhang, Y., & Shao, H. (2019). PPG signal motion artifacts correction algorithm based on feature estimation. Optik, 176, 337-349.
- Yousefi R, Nourani M, Ostadabbas S, Panahi I: A motion-tolerant adaptive algorithm for wearable photoplethysmographic biosensors. IEEE J Biomed Health Inform 2013, PP(99):1.
- Craik A, He Y, Contreras-Vidal JL. Deep learning for electroencephalogram (EEG) classification tasks: a review. Journal of neural engineering. 2019 Apr 9;16(3):031001.

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Thank you !