Bioelectronic devices

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Sensing haemodynamics via wearables in sync

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Metrics of cardiovascular health, such as vascular resistance and cardiac output, can be monitored via synchronized sensors for electrocardiography and multispectral photoplethysmography that are placed on the chest and peripherally.

How haemodynamics are sensed non-invasively has not changed substantially since the first practical pulse oximeter was publicly introduced in 1974 (ref. 1). Yet, there remains a great deal of information to be learned about cardiopulmonary physiological states by combining pulse oximetry with multispectral sources of data and with other sensing modalities such as electrocardiography. As in so many other areas of data science, an integrative and multifaceted approach to cardiopulmonary monitoring may yield unique insights into health, wellness and fitness performance that are otherwise difficult or impossible to obtain. Such an approach requires the development of sensors and of tools for data analytics that make the acquired multimodal data intelligible and interpretable. Now reporting in *Nature Biomedical Engineering*, Daniel Franklin, John Rogers and colleagues[2] describe a multispectral and multimodal strategy for sensing haemodynamics that leverages synchronized, wearable sensors placed on the chest and peripherally to discriminate between sources of cardiovascular stressors (such as exposure to heat or cold, physical exercise and breath holding) and hence allows for actionable insights that are not otherwise available.

Franklin and colleagues used two types of synchronized on-skin sensors (Fig. 1a): a sensor for electrocardiography, placed on the chest, for capturing cardiac signals (to estimate the arterial pulse-wave velocity, a measure of arterial stiffness) and a set of nine optical sensors for

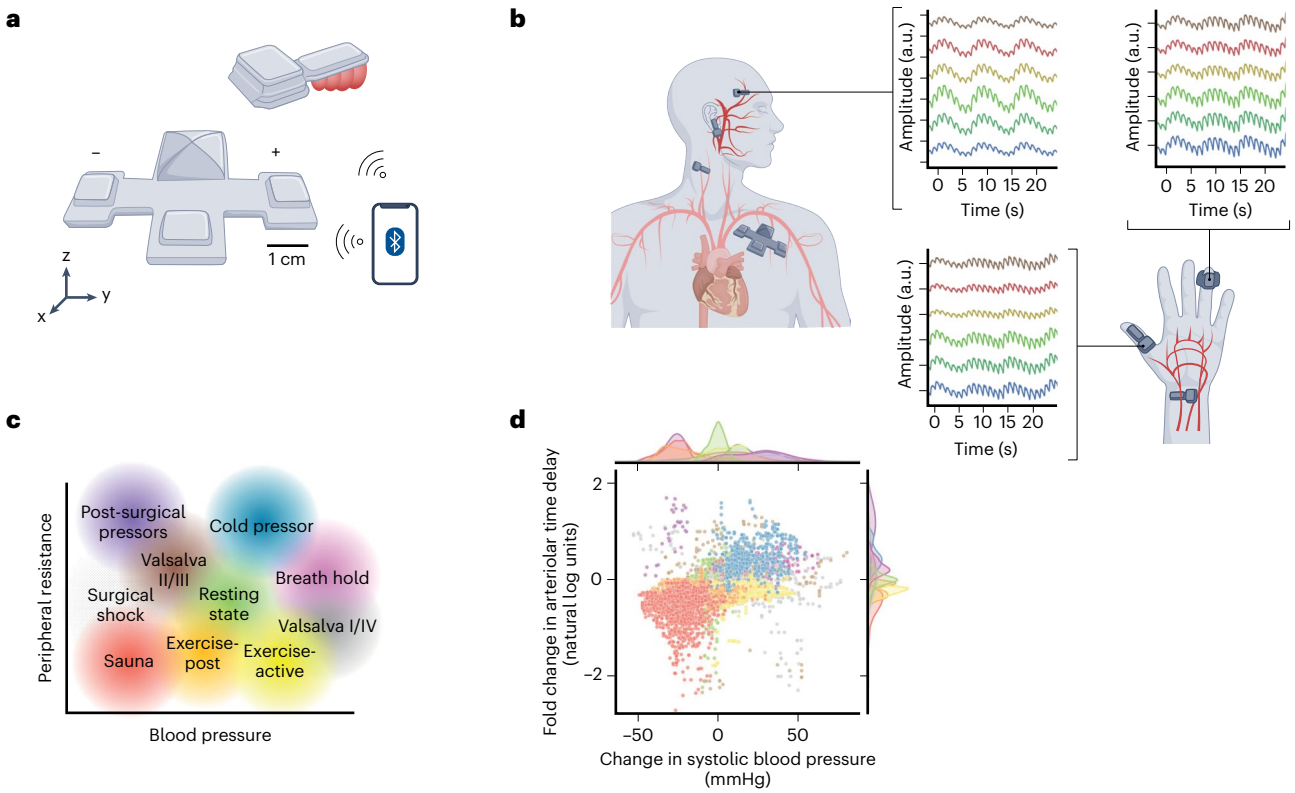

Fig. 1 | Synchronized wearable sensors for the monitoring of haemodynamics. a, Chest and peripheral wearable devices measure synchronized electrocardiography and multispectral photoplethysmography data, respectively, in addition to triaxial accelerometery and skin temperature (not shown). The data are streamed over Bluetooth Low Energy. **b**, The peripheral sensor can be placed at several locations to acquire data from local haemodynamics. a.u., arbitrary units. **c**, Sources of haemodynamic stress are assumed to be resolvable along the peripheral-resistance–blood-pressure axes (peripheral resistance is determined via a wavelength depth-dependent mixture model applied to multispectral photoplethysmography data, via arteriolar time delay in peripheral tissue beds). **d**, Sensor data collected from participants who underwent a series of haemodynamic stressors can be visually separated along the peripheral-resistance–blood-pressure axes. Figure adapted with permission from ref. 2, Springer Nature Ltd.

multispectral photoplethysmography, placed peripherally (on a finger, for example; Fig. 1b), for measuring arteriolar pulse-wave velocity and variations in the volume of circulating blood (the sensors capture light within the visible-to-near-infrared spectral range, thus allowing for measurements of light absorption by tissue at various depths). Both wearables sense skin temperature as well as forces via triaxial accelerometery, use Bluetooth Low Energy for data transmission, store data locally and are powered by batteries that are rechargeable wirelessly. They can be unobtrusively body worn at multiple physical locations and thus can take advantage of regional morphological differences in the vasculature.

Wearable devices for cardiopulmonary monitoring developed over the past decade[3] typically incorporate a single sensor selected on the basis of the device's form factor and intended use. In addition, single-modality wearables often trade diagnosticity[4] and specificity[5] for usability, which hinders the prospects for clinical use[6]. Remote cameras and other non-contact sensor technologies for cardiopulmonary monitoring have also yet to be adopted for clinical use[7]. The minimal intrusiveness of the multimodal devices[8,9] employed by Franklin and colleagues makes practical multiday use possible and may thus open up new opportunities and applications in cardiopulmonary monitoring.

Because the multispectral photoplethysmography sensor in Franklin and co-authors' wearable system can measure light absorption by tissue at varying depths (owing to the wavelength dependence of light penetration), the absorption waveform data can be separated such that arterial and capillary morphologies can be discriminated and used to estimate arteriolar time delay (the time for a pulse wave to propagate through arterioles, from the subdermal plexus to near-surface capillaries), which is specifically related to local vascular resistance. The authors leveraged arteriolar time delay, heart rate and pulse arrival time (the time needed for the pulse wave to arrive at the peripheral sensor) to discriminate, with high accuracies (0.93–1.0 for the receiver operator characteristic area under the curve), cardiovascular stressors that affect the blood-pressure–vascular-resistance–cardiac-output axis (Fig. 1c). Indeed, the authors show that the synchronized sensors placed in healthy people and in participants with hypertension could be used to distinguish the haemodynamic effects of a set of cardiovascular stressors that are assumed to elicit predictable changes in blood pressure and in arteriolar time delay (Fig. 1d). This was possible in part owing to the precise synchronization of the chest and peripherally measured cardiopulmonary time-series data. Synchronized chest and peripheral sensors, alongside electrocardiographic, heart rate, temperature and arteriolar time-delay data sources, may also lead to improvements in the accuracy of blood-pressure measurements from wearables, as each of these variables contributes to their variance.

Continuous monitoring has historically been restricted mostly to inpatient settings. For wearables to become pervasive in clinical diagnostics, the trade-off between diagnosticity and specificity will need to be lessened or eliminated. Although sensitivity and specificity are primarily influenced by the quality of the data[10], for wearable devices, data quality is not the only path towards improved diagnosticity; new techniques and algorithms for data analysis may be needed[11]. Inherent to algorithm performance is the information inherent in the data, and the combination of the data sources used by Franklin and co-authors was critical to their ability to discriminate between cardiovascular stressors. Their work therefore has implications for clinical practitioners, manufacturers of wearable medical devices and researchers working in cardiopulmonary sensing. First, the design, capabilities and unobtrusive form factor of the wearables makes them easy to use. Second, the estimates of vascular resistance via arteriolar time delay derived from the multispectral sensing data provide diagnostic information that is otherwise difficult to obtain and that can lead to clinically actionable insights. Third, such derivation of diagnostically relevant metrics via data analytics may be useful in other scenarios beyond the discrimination of haemodynamic states for clinical diagnosticity. Indeed, beyond clinical uses, the authors' devices and methods could have applications in affective computing (that is, emotion-aware computational systems) and mixed reality[12], safety monitoring[13], cognitive state assessment[14] and fatigue monitoring[15].

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References

1. Aoyagi, T., Kishi, M., Yamaguchi, K. & Watanabe, S. Improvement of an earpiece oximeter. In *Abstracts of the 13th Annual Meeting of the Japanese Society of Medical Electronics and Biological Engineering (Osaka)* **12** (Suppl.), 90–91 (1974).
2. Franklin, D. et al. *Nat. Biomed. Eng.* https://doi.org/10.1038/s41551-023-01098-y (2023).
3. Prieto-Avalos, G. et al. *Biosensors* **12**, 292 (2022).
4. Bayoumy, K. et al. *Nat. Rev. Cardiol.* **18**, 581–599 (2021).
5. Abu-Alrub, S. et al. *Front. Cardiovasc. Med.* **9**, 836375 (2022).
6. Haverkamp, W., Butler, J. & Anker, S. D. *Eur. J. Heart Fail.* **23**, 850–853 (2021).
7. McDuff, D. *ACM Comput. Surv.* **55**, 176 (2023).
8. Chung, H. U. et al. *Nat. Med.* **26**, 418–429 (2020).
9. Lee, K. et al. *Nat. Biomed. Eng.* **4**, 148–158 (2020).
10. Seshadri, D. R. et al. *Circulation* **141**, 702–703 (2020).
11. Sabor, N. et al. *IEEE J. Biomed. Health Inform.* **26**, 5918–5929 (2022).
12. McDuff, D. J. *Contact. Vital Signs Monitor.* https://doi.org/10.1016/b978-0-12-822281-2.00016-0 (2022).
13. Kiehl, Z. A. et al. *Struct. Health Monit.* **19**, 186–201 (2019).
14. Lohani, M., Payne, B. R. & Strayer, D. L. *Front. Hum. Neurosci.* **13**, 57 (2019).
15. Kayser, K. C., Puig, V. A. & Estepp, J. R. *Front. Neurosci.* **16**, 930280 (2022).

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Competing interests
The author declares no competing interests.