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EDITORIAL

Editorial on Remote Health Monitoring: from chronic diseases to pandemics

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1. Remote health monitoring

With billions of mobile devices worldwide and the relatively low cost of connected medical sensors, recording and transmitting medical data has become easier and faster than ever, and we can now easily obtain continuous and long-term dynamic physiological data. However, this 'wealth' of physiological data has seen very limited successes in being harnessed to provide actionable clinical information. Part of the challenge is due to the high variability in data quality, the lack of standards for data representation (e.g. amplitude resolution, sampling frequency, and metadata) and the development, in many studies, of relatively small datasets which fail to capture the vast range of variability across patients and time. Another part of the challenge is the lack of smart and robust algorithms that can decrypt the information contained in physiological time series.

The development of machine learning algorithms combined with existing and novel wearable biosensors offers an unprecedented opportunity to improve the screening and tracking of an individual's health, and support the management of patients' conditions, particularly through remote health monitoring (Malasinghe *et al* 2019). Remote health monitoring relates to the monitoring of individuals outside the classical hospital environment, typically in their home. This enables family, healthcare givers or even the patient to monitor an individual's well-being and to track changes in conditions or health status that may require interventions; this may include sleep quality (Dafna *et al* 2018), stress and other mental states (Behar *et al* 2019). Outpatient monitoring might be necessary following hospital discharge (e.g. after surgery to track infections or adverse events), for patients with chronic conditions (e.g. heart failure, chronic obstructive pulmonary disease (Taylor *et al* 2018), diabetes or chronic kidney disease). It can also be used to predict or identify exacerbations, to monitor individuals for improving their diagnosis or for the purpose of monitoring emergency patients before they arrive at the clinic. Finally, it can be used to monitor healthy people during their daily life activities such as sport or sleep.

Remote monitoring increases the spatial and temporal sampling of health variables. It provides more timely support and deeper insights into transient conditions such as silent atrial fibrillation. It can reduce costs and provide information that more closely reflects the 'natural' environment of an individual. This can also lead to delivery of care in a home-like setting, reducing stress, exposure to infections and the cost (in terms of time, money and pollution) of travelling to a centralized healthcare delivery center. In a time of increased awareness of pandemics, remote health monitoring is particularly in the spotlight.

2. This focus issue

This focus issue in *Physiological Measurement* offers an overview of leading research conducted in the field of remote health monitoring and a perspective on its role in the future of our healthcare systems. The scope of the focus issue includes novel algorithms, biosensors, and processes for intelligent remote health monitoring and for the purpose of designing individualized therapy, tools for supporting the management of outpatients' condition, wearable sensors for the purpose of remotely tracking vital signs, platforms and infrastructure for large-scale data acquisition, collection, storage and access. We accepted a total of nine original papers and one review paper.

3. Papers in this focus issue

Within the context of the novel coronavirus (COVID-19) remote health monitoring systems have been used more than ever, and novel technology and initiatives in that space have been born. The review from Behar *et al* (2020a) takes the narrative of the 'COVID-19 era' within the context of remote health monitoring to review the main initiatives taken in 20 states. With people stuck at home, the fear of contamination in clinical environments leading to a dramatic reduction to on-site referrals for regular care and the need to continuously monitor non-severe COVID-19 patients whether from their quarantine site at home or in specific government locations such as hotels. This has created a dramatic need for finding innovative ways to remote monitor individuals in an effective manner. In many ways the pandemic has stressed further the importance of remote health monitoring in our modern, connected and digital societies. This unique review also highlights the differences across states regarding the relative usage of remote health monitoring pre- and during the pandemic and important considerations on data protection.

Obstructive sleep apnea (OSA) is the most prevalent sleep disorder of breathing. It has been associated with the development of many cardiovascular conditions. The paper from Behar *et al* (2020b) evaluated the hypothesis that the predictive power of oximetry for OSA screening is not impaired when reference sleep stages are not available. Non-inferiority was demonstrated on a large general population sample ($n = 887$). This finding motivates further the usage of portable oximetry for OSA diagnosis. Given the high prevalence of OSA, with over 425 million individuals that would require treatment (Benjafield *et al* 2019), remote diagnosis and monitoring of OSA is one of the most critical challenges in the field of sleep medicine. The paper of Behar *et al* provides supportive evidence on a large dataset that oximetry may be used remotely for OSA diagnosis.

Premature beats (PB), typically presenting as premature atrial contractions and premature ventricular contractions, may foreshadow stroke or sudden cardiac death. In their paper, Cai *et al* (2020) developed a rule-based, real-time PB detection system for timely diagnosis of common PB in an ambulatory setting. The algorithm included features extraction from both electrocardiogram (ECG) morphology and beat-to-beat interval variability. It was evaluated on an independent test set ($n = 20$) of ECGs recorded using a wearable ECG device. The performance statistics on the test set were $F1 = 85.21\%$ and 94.52% for detecting premature atrial contractions and premature ventricular contractions, respectively. This research opens to the perspective of robust automated detection of PB through the usage of wearables.

Multiple sclerosis is a chronic inflammatory disease of the central nervous system which affects over 2 million people worldwide. The impairment of upper extremity function is widely reported across all subtypes of multiple sclerosis. Creagh *et al* (2020) offers a proof-of-concept study assessing the feasibility of using smartphone- and smartwatch-based tests to remotely monitor upper extremity function in people with multiple sclerosis. For that purpose, features motivated by disease pathology and upper extremity function were extracted from various shapes (e.g. a circle) traced on a smartphone touchscreen. These were used to predict the 'Nine Hole Peg' test which is a frequently used measure of manual dexterity. The feasibility of the approach is demonstrated on a total of 93 subjects recruited for the study. This research opens a perspective into remote, smartphone-based assessment of upper extremity function in a multiple sclerosis population sample.

Simple observation of breathing rate remains the first, and often the most sensitive, marker of acute respiratory dysfunction. Iozza *et al* (2019) present a camera-based ubiquitous technology providing continuous breathing rate estimation based on video-photoplethysmography (vPPG). The method derives respiration from beat-to-beat PPG rate and morphology changes in amplitude and width driven by the physiological relationships between vPPG and respiration. The results from 20 healthy subjects showed that respiratory frequencies in the regular range (0.2–0.4 Hz) may be estimated with a low relative error <2%, and interquartile range <5%. Periodic sampling with this non-invasive contact-less camera system opens new horizons for remote monitoring of respiratory dysfunction.

Emotion recognition is useful for diagnosing psycho-neural illnesses. Emotions modify the cardio-respiratory coupling between heart rate variability (HRV) and respiratory signals which can thus be used for non-invasive emotion recognition. Valderas *et al* (2019) present a method to quantify the inherent complexity of short-term HRV signals based on an auto-mutual information function, and the complex coupling between HRV and respiratory signals based on a cross-mutual information function. A test on a database of video-induced emotion ($n = 25$) verified that the method can detect five elicited emotions, i.e. relaxation (neutral), joy (positive valence), fear, sadness and anger (negative valences), with sensitivity, specificity and accuracy higher than 70%. These non-invasive tools measuring from smart-phones can continuously monitor emotional reaction variations as surrogates for stress status and other emotion dysfunctions.

Robust R-peak detection is particularly important for ambulatory monitoring because the detected R-peaks are often used as the main fiducial for further ECG processing. A single-lead QRS detector is the preferred strategy in most research but with a shortcoming of the detection relying on a single lead versus having some possibly valuable information redundancy across multiple leads. This may be beneficial, as an example, when some lead's quality is impaired but not others. Llamedo and Martínez (2019) present an R-peak detection quality metric used to rank R-peak detection performed on each individual ECG lead. This is used to create a lead selection strategy. The performance of the resulting algorithm was evaluated on a dataset of 1754 ECG recordings from 14 different ECG databases and led to an average sensitivity of 99.2%, positive predictive value of 98.3%, and F1 score of 98.7%. The results suggest that the lead selection strategy obtained better results than any of the single lead algorithms individually. Ambulatory monitoring is usually campaigned with signal quality reduction, or even signal loss, where these robust multi-lead strategies will be important to create more robust remote monitoring systems.

Automated electroencephalogram (EEG)-based sleep staging is a known research topic with many algorithms having been developed over the past two decades. Recent advances in deep learning have enabled further improvements in their performance but the algorithms still have shortcomings. One such limitation is the variability across individuals and the need for more a 'personalized' algorithm. Phan *et al* (2020) suggest one way to personalize an existing algorithm, SeqSleepNet (Phan *et al* 2019), by fine-tuning this model to each individual. This is achieved by using a Kullback–Leibler (KL) divergence regularized transfer learning approach. Practically, the KL divergence between the output of the subject-independent model and the output of the personalized model is added to the loss function during fine-tuning. The personalized model was 4.5% better than the general model on a test database with 75 subjects.

Loss of gravity affects ventricular repolarization (VR) which increases the risk of cardiac arrhythmias. Martín-Yebra *et al* (2019) present an estimate for T-wave alternans (TWA) to test whether an increase in VR heterogeneity could be detected after landing with restored normal gravity. A total of 63 healthy volunteers were recruited and recorded in several head-down bed-rest (HDBR) experiments and TWA was evaluated during the night period before, during and after long- (60 d), mid- (21 d) and short- (5 d) duration HDBR. TWA increased after long-term HDBR exposure, once normal gravity was re-established, underlining the importance of focusing future research on immediate effects after long-term microgravity exposure from space missions once gravity conditions are re-established, opening for efficient follow-up by monitoring for the risk evolution over time during recovery.

Finally, Chou *et al* (2020) investigate the potential of arterial blood pressure signals for the detection of subjects with life-threatening extreme bradycardia. For that purpose, they perform pulse decomposition analysis to quantitatively describe changes in blood pressure waves. This is then fed to a classifier to discriminate extreme bradycardia from non-extreme bradycardia subjects. They obtained a specificity of 99.74% $\pm$ 0.07% and sensitivity of 93.12% $\pm$ 1.24%. Using remote non-invasive continuous blood pressure monitoring may open a path to identifying life-threatening extreme bradycardia that would be missed otherwise.

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