

Editorial

Special Issue on “Human Health Engineering”

Jean-Marie Aerts 

KU Leuven, Department of Biosystems, Division Animal and Human Health Engineering, Measure, Model & Manage Bioresponses Group, Kasteelpark Arenberg 30, 3000 Leuven, Belgium; jean-marie.aerts@kuleuven.be

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1. Referees for the Special Issue

A total of 52 manuscripts were received for our Special Issue (SI), of which eight manuscripts were directly rejected without peer review. The remaining 44 articles were all strictly reviewed by no less than two reviewers in related fields. Finally, 25 of the manuscripts were recommended for acceptance and published in Applied Sciences-Basel. Referees from 10 different countries provided valuable suggestions for the manuscripts in our SI, the top five being the USA, Italy, Japan, Australia, and Spain. The names of these distinguished reviewers are listed in Table A1. We would like to thank all of these reviewers for their time and effort in reviewing the papers in our SI.

2. Main Content of the Special Issue

In the 1930s Walter Cannon introduced the term ‘homeostasis’, reflecting the idea that complex organisms, such as humans, are able to maintain their internal environment quasi-constantly in the face of (external) perturbations [1]. Although homeostasis was originally not discussed in terms of regulatory mechanisms, this changed in the 1950s and 1960s with the work of pioneers such as Norbert Wiener and Ludwig von Bertalanffy who envisioned complex organisms as complex systems that can be studied from an engineering system and/or control perspective [2–4]. This has been the start of the fast growing field of health engineering that uses concepts from control theory and fault-detection and diagnosis to study, monitor, and/or control health processes [2,5,6].

According to modern model-based monitoring and control theory there at least two conditions necessary to study and develop monitoring and control systems, namely continuous information of the relevant process variables (inputs and outputs) and a (mathematical) model describing the relationships between the process inputs and outputs [6,7]. The first condition stresses the need for sensors and sensing systems that allow capturing the necessary information on the considered biosystem, and the latter assumes access to advanced mathematical modelling approaches.

The field of sensor development and sensing systems for biological signals has evolved tremendously the last couple of decades and has resulted in advanced sensing elements that can, among others, harvest their own energy from the human body [8], measure real-time physiological information in biofluids, such as sweat, tears, saliva, and interstitial fluid [9,10], or continuously measure physiological variables (e.g., activity, heart rate, respiratory rate, and body temperature) using wearable technology [11]. In addition to this, the Internet of Things has also made it possible to interconnect many of these sensing systems with the internet, allowing the capture and exchange of information between connected devices, data storage systems, and relevant stakeholders [12].

The field of signal analysis and modelling has also evolved during recent decades. Although the more classic approaches of mechanistic modelling and data-based (or empirical) modelling are still very relevant and offer yet unexploited added value for health engineering (e.g., [13–15]), it can be expected that recent trends in artificial intelligence (e.g., big data approaches and deep learning algorithms [16,17]) will change the health engineering landscape (and life in general) in a radical way.

The fusion of sensing systems with powerful (real-time) modelling algorithms creates opportunities to, among others, monitor chronic patients at home [18], connect patients within a smart city environment with relevant caregivers [19], or even actively control physiological variables using smart actuators, such as wheelchairs [20] or electric bikes [21], to enhance physical condition of thermal comfort [22]. Last, but not least, also human-robot, interactions can be considered as means for actively controlling human health conditions, e.g., by supporting human gait using exoskeletons or exosuits [23].

In this special issue on “Human Health Engineering”, we invited submissions exploring recent contributions to the field of human health engineering, i.e., technology for monitoring the physical or mental health status of individuals in a variety of applications. Contributions can focus on sensors, wearable hardware, algorithms, or integrated monitoring systems. We organized the different papers according to their contributions to the main parts of the monitoring and control engineering scheme applied to human health applications, namely papers focusing on measuring/sensing of physiological variables [24–31], contributions describing research on the modelling of biological signals [32–38], papers highlighting health monitoring applications [39–42], and finally examples of control applications for human health [43–48]. In comparison to biomedical engineering, we envision that the field of human health engineering also covers applications on healthy humans (e.g., sports, sleep, and stress) and thus not only contributes to develop technology for curing patients or supporting chronically ill people, but also for disease prevention and optimizing human well-being more generally.

The first series of articles in this SI describes methods for (improved) measuring, sensing, or communication of physiological signals. The work of Chowdhury et al. [24] contributes to solving the problem of gradient artefacts (GA) in electroencephalography (EEG) signals when measured in combination with functional magnetic resonance imaging (fMRI) in MR scanners. They demonstrated that the use of realistically human head-shaped phantoms outperformed the standard used spherical phantoms for the characterization of GA in EEG data and thus improves the GA removal in the signal post-processing step. Fang et al. [25] investigated the usability of four different types of interfaces (text, diagram, image, and animation) for wearable devices with health management applications (app) for elderly people. Their research demonstrated that most (older as well as younger) users preferred animation interfaces for communicating health information, but that older adults, in contrast to younger users, were also open to text interfaces. Such research can contribute significantly to the development of useful health management apps for the growing elderly population.

Gircys et al. [26] developed a method for continuously measuring systolic blood pressure (SBP) using photoplethysmography (PPG) sensing elements. Since their method is based on cheap PPG sensing elements that can be integrated in wearables, this approach can significantly contribute to (preventive) health monitoring as, compared to classical (expensive) cuff-based methods, as it allows 24/7 measurements. The work of Mukunthan et al. [27] describes the use of a nine-zone thermal manikin head for measuring convective and evaporative heat losses from a human head wearing a bicycle helmet. They demonstrated that the design of the helmet, mainly characterized by the number and position of vent openings and the presence of internal air channels, has a significant effect on the heat losses of a human head when covered by a bicycle helmet. The results of this work demonstrate the use of thermal manikins for improving comfort and safety of cycling activities.

In their work, van der Have et al. [28] studied the effect of squat lifting versus stoop lifting in terms of joint and muscle loading when handling heavy materials. Their study demonstrates that squat lifting imposes higher peak full body musculoskeletal loading compared to stoop lifting, but similar lower back loading, which is an important factor in work-related musculoskeletal disorders (WMSDs). These results show the usefulness of 3D movement trajectory and force analysis in combination with electromyography for optimizing ergonomic guidelines. Wibowo et al. [29] studied the effects of in-shoe foot orthosis contours on heel pain due to calcaneal spurs. The applied method made use of force sensors for measuring 2D pressure information on the foot in combination with an algometer

for quantifying pain. By combining these measurements the authors were able to optimize insole geometry resulting in improved comfort by significantly reducing pain.

In their work, Bekteshi et al. [30] developed a dyskinesia impairment mobility scale (DIMS) for measuring the presence and severity of dystonia and choreoathetosis during powered mobility (electric wheelchair) in dyskinetic cerebral palsy. Such a scale could be a promising tool in clinical practice for assisting in accelerating the learning process of using a powered mobility wheelchair and for tailoring individualized mobility training programs. Rosales-Huamani et al. [31] studied the possible adverse effects of indiscriminate mobile phone use in Peruvian students, more specifically focusing on mental complaints when having no access to a mobile phone, also known as ‘nomophobia’ (no mobile phone phobia). Using a self-designed questionnaire, they identified three symptomatic factors of nomophobia. Their work was additionally relevant for this SI in demonstrating also the possible adverse health effects of wearable technology on users in daily life.

The second series of articles focuses on research related to modelling of biological signals in the framework of human health. Das et al. [32] used a mechanistic model to describe forced expiration in patients suffering from chronic obstructive pulmonary disease (COPD). In their work, they demonstrated that data of forced expiration maneuvers in combination with a physical knowledge-based model allowed to estimate airway resistance in the lungs. Such a model-based approach has especially clinical relevance for screening patients for COPD using classical spirometry in primary care. In their work, Fu et al. [33] developed a mechanistic finite element model to simulate forces and stresses inside knee joints during the landing phase in freestyle skiing aerial. These simulations helped quantifying which types of landings are most challenging in terms of ligament damage. Such results have high relevance for training design and nicely demonstrate how models can help preventing injuries in sports.

In their study, Cardarilli et al. [34] improved an existing mechanistic cardiac model based on four modified Van der Pol oscillators, each representing one of the main natural pacemakers. Their model allowed to reproduce healthy dynamic heart dynamics, as well as pathological rhythms in case of right bundle branch block (RBBB) and left bundle branch block (LBBB). The clinical relevance of such a model is that it allows simulation and evaluation of heart activity and dynamics under different types of pacemaker couplings. The study of Mwamba et al. [35] contributed to the diagnosis and management of attention-deficit/hyperactivity disorder (ADHD) by developing a tablet-based application (app) software using support vector machine (SVM) approaches from machine learning. Their approach demonstrated that (serious) games in combination with modelling approaches from the field of artificial intelligence can offer a useful tool for first line screening of children for ADHD by their parents and/or teachers.

Buekers et al. [36] applied a dynamic Box-Jenkins transfer function modelling approach for quantifying the VO_2 kinetics in patients with COPD performing a constant working rate test (CWRT). The added value of this work is that it contributes in optimizing clinical tests for objectively quantifying the physical capacity of patients. As such, measuring and modelling the kinetics of metabolic variables in COPD patients can contribute in managing their disease and in preventing hospital admissions due to exacerbations. Youssef et al. [37] applied a combination of a data-based transfer function modelling approach with a mechanistic model to develop a so called data-based mechanistic (or grey box) model to describe the thermoregulatory mechanisms of vasoconstriction and vasodilation to control body temperature during localized cooling. In their research, they demonstrated that dynamic data-based models are not only useful for monitoring or controlling complex biological systems, but can also be used to generate new insights (i.e., reverse engineering) in the working of biological control systems.

In their review article, Rajula et al. [38] describe methodological aspects related to the construction of a federated facility to optimize the analyses of multiple datasets, the impact of missing data and methods for handling missing data in cohort studies. The described database management systems permits the increase of the statistical power of medical multi-center studies, allowing for more advanced statistical analyses and answering research questions that might not be addressed by a single study.

The third series of articles describes applications of human health monitoring. Youssef et al. [39] showed in their work the possibilities and added value of integrating wearable sensors (heart rate, air temperature, and air humidity) in bicyclists' helmets. They developed a prototype of a smart helmet for monitoring thermal comfort based on adaptive personalized models. Such technology could be used in a next step to actively control thermal comfort of cyclists' head. Another thermal comfort application was studied in the work of Youssef et al. [40]. Here, the authors focused on developing a system for online personalized monitoring of thermal sensation. They used measurements of heart rate, metabolic rate, skin temperature, heat flux between skin and ambient air, and aural temperature in combination with least-squares support vector machine algorithms to estimate an individual's thermal sensation. The combination of these algorithms with wearable sensors allow, in a next step, to develop personalized indoor climate control systems by integrating online information from the occupants.

Gielen and Aerts [41] used physiological variables linked to thermoregulation to develop a drowsiness monitor for drivers. Since the process of falling asleep is accompanied by a shift/decrease in body temperature, online estimations of heat loss and heat production of drivers' can be used to monitor drowsiness. In their work, they measured heart rate, as indirect estimate of heat production, and nose tip and wrist temperature, as an indirect estimate of heat loss, to monitor changes in driver's thermoregulation. This proof-of-principle shows that wearable technology in combination with algorithms from machine learning can contribute to traffic safety.

In a another health monitoring study, Youssef et al. [42] demonstrated that a set of five vital signs (heart rate, respiration rate, oxygen saturation, arterial blood pressure, and body temperature) measured bi-hourly on patients in an intensive care unit (ICU) could be used to predict mortality. They combined a linear hard margin support vector machine (SVM) with a feature engineering approach to classify survivors and non-survivors during their stay at the ICU, demonstrating the added value of combining vital signs monitoring with machine learning for monitoring critically ill patients.

Finally, the fourth series of articles in this SI discusses examples of control applications for human health management. The study of Peña Fernández et al. [43] describes a model predictive controller (MPC) approach for managing human bodyweight using energy intake as the control input. Based on the data of the Minnesota starvation experiment, they show that the combination of weekly bodyweight and energy intake measurements with model predictive control theory allows to calculate future energy intake for following a predefined bodyweight trajectory. This nicely demonstrates how control theory could have a significant contribution in solving one of the major health challenges of today, namely obesity. However, the same technology could also be used to help elderly people suffering from underweight conditions.

Another application of MPC is described by Zhang et al. [44]. In their work, they demonstrate that MPC can also be successfully used to design smart four-wheeled rollators for elderly and/or disabled people. Their work focused on developing a lateral stability control for four-wheeled rollators allowing users to move in more smooth trajectories. Such smart rollators can improve the mobility of elderly and disabled people significantly and contribute to their overall physical and mental health. Also Jin et al. [45] describe the development of walking assistive devices for elderly people. However, in their case the assistive device is a soft robotic suit. They demonstrate that such robotic suits have positive long-term effects by helping improving gait characteristics of elderly people when using these suits. Furthermore, such robot-assisted tools could also help elderly people during gait rehabilitation when recovering from bone and/or joint surgery.

Adiputra et al. [46] described the results of a preliminary study focusing on a passive controlled ankle foot orthosis. The device they developed, aimed at assisting walking during the gait stance phase of people suffering from abnormal gaits, such as weak ankle, spasticity or foot drop, conditions that typically result after stroke. Whereas the previous three studies focused on control applications for assisting/improving walking behaviour, the work of Aramendia et al. [47] studied a robotic arm orthosis to assist arm movements. The authors developed a numerical model of a muscle, arm, and orthosis and used this model for simulating different scenarios. They demonstrated that by optimizing

the controller algorithm, the needed force of the biceps muscle to overcome a load added to the orthosis control system could be reduced to nearly half of the force needed without optimized orthosis control algorithm.

Finally, Dao et al. [48] investigated pneumatic artificial muscles (PAM) as a basis for antagonistic actuators in assistive rehabilitation robots. They developed a discrete-time second order model describing the dynamic characteristics of PAMs and a fractional order integral sliding mode controller to improve the trajectory tracking performance. They demonstrated that the system could be used as a basis for a robotic gait training system, contributing in this way to enhancing human health and quality of life for people suffering from gait disabilities.

3. Conclusions

This SI clusters recent contributions in the field of human health engineering. The contributions demonstrate that research is focusing on different aspects of the monitoring and control engineering scheme (sensors, sensing systems, data analysis, modelling approaches, and control algorithms) as applied to human health. Health monitoring and control applications on both healthy as well as (chronically) ill people are covered and this is in relation to physical as well as mental processes.

Thanks to the (r)evolution in sensors and (wearable) sensing technology in combination with the ever growing possibilities in artificial intelligence, it can be expected that human health engineering applications will become more and more ubiquitous in our society and will increasingly assist people of all ages in living healthy, high quality, and productive lives.

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Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Table A1. Special Issue (SI) reviewer list.

Dean Picone	Shiang-Feng Tang	Mariana Domnica Stanciu	Modar Hassan
Warwick Butt	Angelos Karatsidis	Arcady Putilov	Mikito Ogino
Kurt Ammer	E. Mark Williams	Xinqin Liao	Ghulam Hussain
Johannes C. Ayena	Seungyeon Lee	U Rajendra Acharya	Joo-Young Lee
Raphael Vallat	Munish Chauhan	Roger Ho CM	Pawel Mazurek
Claudia Flexeder	Xiaoliang Zhu	Miguel Damas Hermoso	Cátia Tavares
Chrysovalantou Ziogou	Helen J. Huang	David Bienvenido-Huertas	Venkatraman Balasubramanian
Christina Zong-Hao Ma	Changhong Wang	Ana Belen Ortega Avila	Shahab Tayeb
Walter Franco	Huanyu (Larry) Cheng	Wen-Yu Su	Balaraman Rajan
Caterina Ledda	Derya Akleman	Cheng-Hung Chuang	Elisa Passini
Andrea Viggiano	Aiping Liu	Takao Sato	Ehsan Rashedi
Vincenzo Minutolo	Ibrahim Faruqi	Quy-Thinh Dao	Maryam Panahiazar
Baojun Chen	Mojtaba Yazdani	Roland K. Chen	In Cheol Jeong

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