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Editorial

Movement Analysis for Health and Biometrics

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1. Introduction

The analysis of human movement provides important insights in several fields, such as biomechanics, neuroscience, psychology, medicine, and Artificial Intelligence (AI).

The recent advancements in modeling and analyzing movements are contributing to both the understanding of the neurological and physical principles underlying movement learning and execution [1,2] and the development of new applications in healthcare and biometrics [3,4]. In particular, the availability of low-cost and pervasive devices for recording movements (wearable devices, smartphones, tablets, cameras, etc.), together with machine learning methods for the quantitative and automatic analysis of movement, has put forward the development of systems for user authentication, medical diagnosis, and rehabilitation monitoring.

Studying human movements requires choosing both the motor tasks to be analyzed and the equipment to record movements. These choices are taken keeping in mind which aspects of movement are of interest, and the final application. Different motor tasks are investigated in the literature (gait, reaching movements, handwriting, etc.) and recorded with different devices (motion tracker, tablet, smartwatch, etc.).

The Special Issue "Movement analysis for health and biometrics" includes 10 articles and 1 brief report that highlight how movement analysis and new technologies are innovating the fields of medical monitoring and disease diagnosis, action and therapy monitoring, and injury prevention. The instrumentation adopted in the 11 papers includes a 3D Motion Capture System with Inertial Sensors, wearable sensors, and tablets. The motor tasks investigated are handwriting, push and pull tasks, upper-limb movements, walking and running, standing and turning, and other movement patterns.

The remaining of this editorial is organised as follows. Section 2 resumes the findings of the articles focused on the diagnosis and monitoring of musculoskeletal and neurodegenerative diseases, Section 3 summarizes the findings of the studies aimed at preventing injuries via the analysis of movement, while Section 4 describes the only article on human activity recognition. Finally, Section 5 concludes this editorial by highlighting the perspective of human movement science.

2. Movement Analysis for Medical Diagnosis and Monitoring

The automatic analysis of movements to evaluate the presence of signs related to musculoskeletal and neurodegenerative diseases is increasingly attracting interest [5,6]. In this light, the Special Issue includes some studies on movement analysis for the evaluation of upper limb dysfunctions and the diagnosis and monitoring of the disease stage in patients affected by Parkinson's Disease (PD).

Senatore et al. [7] identify a set of distinctive signs characterizing handwriting movements of PD patients in the early stage of the disease. Their analysis provides evidence that early detection of PD, even when the disease affects mainly the contralateral side with respect to the one used for writing, could be achieved by analyzing specific movement

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features, measured during the execution of specific handwriting tasks. According to the obtained results the authors provide a set of guidelines for the design of a diagnostic tool for the early detection of PD and some suggestions for reducing motor impairments in PD patients.

Guzik-Kopyto et al. [8] develop a novel indicator of upper limb manipulative movements, the Upper Body Index (UBI). The index is constructed by analyzing and comparing the kinematics of the upper limb of two groups, (a) healthy subjects and (b) people that had previously suffered an ischemic stroke. The proposed index enables the discovering of deviations from the standard performance of upper limb movements. Therefore, the index may be applicable to the analysis of any sequence of upper limb movements and used for providing some cues about its dysfunctions for suggesting further clinical investigations.

Kazemimoghadam and Fey [9] investigate the motor performance of individuals with mild stages of PD and healthy subjects while performing non-steady-state circuit trials comprising stairs, ramps, and changes of direction. Applying a linear discriminant analysis classifier and a Long-Short Term Memory neural network, their analysis provides some insights into developing advanced frameworks for healthcare monitoring and lower-limb assistive devices.

Chen et al. [10] investigate the balance in terms of changes in body kinematics and muscle activity. The study involves two elderly participants, a healthy subject and a subject with chronic stroke. The study proposes a novel protocol that tests and validates the hypothesis that training improves gait and balance by increasing joint angles and extensor muscle activities in the lower extremities of elderly people.

3. Movement Analysis for Injury Prevention

The analysis of movement can be exploited to prevent a variety of injuries, as for example those caused by falls, poor movement control, and bad postures [11]. In fact, the possibility of estimating forces at joints by tracking movement, as well as evaluating muscular performance, allows the definition of training programs aimed at correcting postures, movement control and improving sports performance. The Special Issue includes six contributions that investigate the use of movement analysis to prevent injuries.

Linek et al. [12] assess the relationship between two movement screening tools in youth football (soccer) players, which suffer from knee injuries caused by poor movement control in the hip and pelvic region. The Functional Movement Screen (FMS) is the most well-known movement screening tool, designed to assess mobility and stability within the whole-body kinetic chain, but it is not useful to assess the functional status of hip dysfunction. The Hip and Lower Limb Movement Screen (HLLMS) was designed to detect altered movement patterns and asymmetry, specifically of the hip, pelvis and lower limbs. The study includes 41 elite male football players. The correlation between HLLMS and FMS scores is evaluated with Spearman's rank correlation. The study shows that the two tools assess different aspects of movement quality in healthy youth football players. In fact, only 2 out of 7 tasks of FMS are moderately related to the HLLMS score, while the other FMS tasks are weakly related or unrelated to the HLLMS.

Ji et al. [13] investigate the efficacy of digital human modeling technologies when used as ergonomics analysis tools to simulate body postures and estimate the risk of work-related musculoskeletal disorders. In particular, the authors evaluate the accuracy of a commercial full-body dynamic simulator in estimating the posture of subjects that pushed and pulled a 40 kg load and the resulting compressive and anterior/posterior shear force at the L4/L5 lumbar spine. The authors compare the postures estimated by the simulator to the actual human movements captured by a motion tracking system. Their analysis shows that joint angle deviations directly led to a significant difference in the estimated forces. Furthermore, it shows that individual factors (such as body height, body weight, trunk and hip flexion, shoulder movement, and muscle strength between genders) directly affect the adopted postures during task execution. As a consequence, these factors must be taken into account by full-body software simulators to perform a robust ergonomics analysis.

Khobkhun et al. [14] investigate the effect of a change of direction on whole-body coordination and stepping in healthy old and young adults. Turning kinematics and stepping variables are recorded using Inertial Measurement Units when subjects execute standing turns on level ground at three different amplitudes and at their own pace. The authors notice that an increase in turn amplitude causes changes in turning kinematics, stepping characteristics, and turning speeds both in young and old adults. However, step duration and turn speed do not significantly differ between the two groups. The results of the study suggest that turning amplitude is a critical factor for the maintenance of balance and stepping movement control. Consequently, it must be taken into account when the turning characteristics of elderly people are assessed to evaluate the risk of falling or when exercises for fall prevention are designed.

Kowal et al. [15] evaluate the impact of whole-body cryotherapy, a treatment used in prevention and post-injury therapy, on the risk of injury in trained subjects. The authors compare the bioelectric activity of the rectus femoris muscle, measured with surface electromyography, and the parameters of the countermovement jump test, measured with an inertial sensor. The study involves 24 subjects executing vertical jumps before and after a 3 min long whole-body cryotherapy. The results show a statistically significant reduction in the elasticity of muscle and an increase in the eccentric force parameter after the treatment. Both the variations indicate an increase in the risk of injury to the soft tissues of the musculoskeletal system, therefore the study suggests that using whole-body cryotherapy may have a negative effect on muscular strength and power.

Ortiz-Padilla et al. [16] summarize the literature in the field of video-based biomechanics, highlighting that studies are mainly focused on the analysis of kinematics measurements, whereas few studies explore the dynamical forces in the joints. The estimation of forces generated by athletes during physical activity is crucial to improve their performance and prevent injuries and fractures. The authors propose three case studies where forces are estimated by videos of athletes performing swimming, taekwondo, and football. In particular, they use a software to manually track the positions of human joints in video frames and then estimate the desired kinematics and kinetics variables.

Candela-Leal et al. [17] adopt a Long Short-Term Memory neural network to estimate the 3D forces exerted by runners on a treadmill by tracking the 3D position of markers placed on runners' joints. The position of markers is tracked by a video camera. The authors evaluate the performance of the proposed framework by a public dataset containing kinematics and kinetics measured from 28 runners.

4. Movement Analysis for Human Activity Recognition

Human activity recognition (HAR) can be referred to as the ability to identify activities using AI techniques from the gathered activity raw data. This field involves the use of various devices, including wearable sensors, electronic device sensors, such as smartphone inertial sensors, and camera devices such as Kinect, closed-circuit television, and some commercial off-the-shelf equipment. The use of different sources makes the HAR an important support for multifaceted application domains, such as healthcare [18].

Usually, the learning-based techniques for effective human behavior identification focus only on fundamental human activities. Nevertheless, postural transitions can play a critical role in implementing a system for recognizing human activity.

Mekruksavanich et al. [19] present a hybrid deep residual model for transitional activity recognition utilizing signal data from wearable sensors. The developed model enhances the ResNet model with hybrid Squeeze-and-Excitation (SE) residual blocks combining a Bidirectional Gated Recurrent Unit (BiGRU) to extract deep spatio-temporal features hierarchically, and to distinguish transitional activities efficiently. To evaluate the recognition performance, the experiments are conducted on two public benchmark datasets (HAPT and MobiAct v2.0), achieving classification accuracies that outperform the state-of-the-art.

5. Conclusions

The advances in methods for the capture and analysis of movement have brought human movement science into a new era. The papers published in this Special Issue show how the body of knowledge in kinesiology and motor control, together with machine learning and computer science tools, bring to the definition of experimental setup and systems for the medical diagnosis and monitoring of musculoskeletal and neurodegenerative diseases, the prevention of injuries and the recognition of human activities.

The current trends in human movement science suggest that in the next years, the connection of movement science with AI will open new research possibilities on neural correlates of behavior allowing the understanding of how the brain learns and controls movement and unveiling how the sensorimotor system works.

Conflicts of Interest: The authors declare no conflicts of interest.

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