Biomechanics for understanding movements in daily activities

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Abstract

We discuss biomechanics and its use in studying human movements especially in sports and exercise events, and how sensor information from the devices such as acceleration sensor, gyroscope, force plate, and motion capture system can be effectively used to gain a greater understanding of human movements in every-day activities and communicative situations as well. Using AI and IoT technology, we propose to apply the approach to collect, analyse, and annotate motion data in common activities.

Keywords: biomechanics, movement, gesturing, everyday activity analysis

1. Introduction

In language communication, interlocutors effectively accompany their speech with gestures and body movements. These movements range from unconscious moving to intentional gesturing, and they have various functions such as giving rhythm to one's speech, indicating engagement in conversation, pointing, coordinating interaction, and of course, performing certain physical actions. Until recently, studies have been based on video analysis and manual annotations (cf. Allwood et al. 2007, Jokinen 2011). Several annotation tools such as Praat (Boersma and Weenink 2009) for speech and Anvil (Kipp, 2001) and Elan (ELAN) for video data can be used for detailed analyses. However, it is time-consuming and often difficult to manually annotate timing and amplitude of the various actions and activities accurately, and so advance video analysis has been used to extract movements of conversational participants using OpenCV toolkit (Bradski and Koehler, 2008), see e.g. Vels and Jokinen (2015) who experiment with bounding boxes, and Jongejan (2016) who provides a plugin to include velocity and acceleration of head movements from video analysis to Anvil-annotations. Sensor and tracking technology has been developed especially in medical domain, and used to analyse e.g. non-verbal behavior (Philippot et al. 2003) and measure movement in Parkinson disease (Galna et al 2014). The Human Communication Dynamics framework (Stratou and Morency, 2017) aims at a unified approach to address challenges in multimodal behavior analysis, and to jointly analyse the participants' language, gestures and social signals for efficient computational perception algorithms in behavioral sciences and real world applications.

In this paper we present a new methodological approach to study movement in human conversation and daily activities, based on Biomechanics. We follow the approach of Human Communication Dynamics, but differ from this in that we especially aim to study human movements and motor learning in everyday activities where the movement analysis is not necessarily used to infer communicative intentions of the participants, but to perform certain actions better, as when instructing learners how to move their body in a correct way in DanceSport, care-taking, etc.

We explore biomechanics in automatic detection and analysis of human motion, and the results of our experiments show that the joint use of various sensor data enables us to achieve accurate perception of human motion. It is thus possible to achieve a better understanding of the different aspects of human motion and to study how they function in everyday communication and signal the participants' engagement in interactive situations. The data can be used in various practical applications developed for the health and well-being of the people.

Another important contribution of the paper is the new methodology that can be used in human-human and human-robot interaction studies. Sensor information allows us to observe human motion and gesturing in everyday activities, and we can then analyse it automatically using machine-learning techniques. Using IoT possibilities to share the sensor information with a communicating robot, the data can be directly used in the control and coordination of the interaction between the human and the robot. If the robot is equipped with the knowledge of the motions in general, e.g. annotations and ontologies of the motion data, it is possible to explore how a robot agent can learn common activities by imitation and explicit instruction.

The paper is structured as follows. We will first briefly introduce biomechanics and the sensors used in the motion and gesture analysis in Section 2. We will then describe the experiments in motion data collection in Section 3. Finally, we discuss methodological issues concerning the application of biomechanics and sensory data for the understanding of the human every day activities in real life.

2. Biomechanics

The new technology on sensors has been significantly advanced in the recent years. Various robust high speed and sensitive devices, such as the acceleration sensor, gyroscope, electromyography, force plate, and motion capture system, have been developed to measure motion and body posture with high accuracy and precision. Information from the sensors can then be effectively used to collect and analyse data on human movements.

Biomechanics is a study of human movement. It applies the laws of mechanics and physics to human performance and aims to explain how and why the human body moves as it does by analysing the forces acting on the body (kinetics) and the movements of the body (kinematics). It is used especially in sport and exercises, with two main purposes: to improve physical performance, and to prevent injuries. Besides human movements in sports and exercises, biomechanics can also be used to study daily activities such as walking, sitting and lifting. Using AI and IoT technology, we propose to apply the biomechanis approach to collect, analyse, and annotate motion data in common daily activities, including language communication.

In biomechanical experiments, sensor technology is widely deployed, and a motion capture system and force plates are frequently used (Figure 1). These instruments can quantify the human movements from dynamics. The motion capture system is used to measure the position data of body segments, while the force plates are used to measure ground reaction forces. The data is interpreted with respect to knowledge about the human anatomy and physiology, and inverse dynamics is used to compute the turning effect of the anatomical structures (muscles, ligaments) in joints, which is necessary to perform the particular motion.

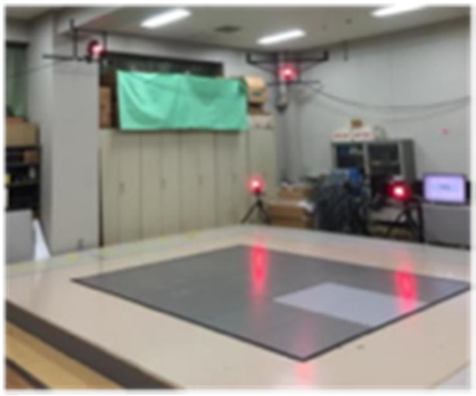

Figure 1 Force Plate and Motion Sensors.

Figure 2 shows a snap-shot of a motion tracker system depicting a person balancing on a force plate. The force plate is a device that measures the three components of a force (along x, y, and z axis) applied to the surface, as well as the vertical moment of force. It is used to measure acceleration, work, and power of locomotion, and can also measure the angle and distance of a move such as a jump. Combined with kinematics of the joint angles, it is possible to determinate torque, work and power for each joint to study movement e.g. for robotics and sports applications.

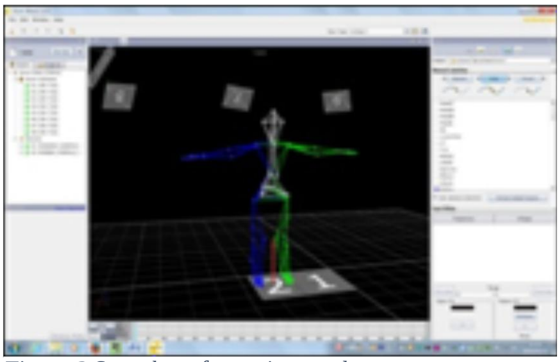

Figure 2 Snapshot of a motion tracker system.

According to Hooke's law, force is directly proportional to extension distance on a linear spring: $F = -kX$, where k is a constant factor and characterizes the stiffness of the spring. Besides the linear force that pushes and pulls an object, movement can also be twisted by a rotational force called torque or moment of force. Torque is defined as the rate of change of angular momentum of an object, and it is directly proportional to angle of rotation on torsion spring (Figure 3). Torque is measured in Newtonmeters (Nm).

Previous studies have shown that muscles have elastic function (Komi 2000). Research about human and animal locomotion have used the spring-mass model to explain the interdependency of the mechanical parameters that characterize the movement, especially running and hopping. The spring-mass model is a simple model that represents the mass of the actor as a single point mass, and the musculoskeletal system as a spring. During running and hopping, lower extremities can be modelled by a linear spring (Farley and Morgenroth 1999), while lower extremity joints can be modelled by torsional spring model (Hobara 2009; Hobara 2010).

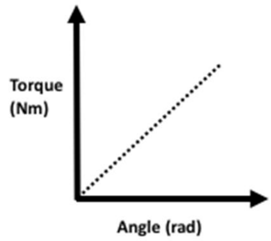

Figure 3 The relationship between torque and angle based on Hooke's law.

Although the actual body is a complicated set of muscles, bones, tendons, and ligaments which act across and upon joints to produce movement, the spring-mass model describes and predicts the mechanics of the movements in an accurate manner. It can be concluded that the individual elements of the musculoskeletal system are integrated in a way that allows the overall system to behave like a simple spring during running and jumping. It is also possible to adopt the spring model to study joints and body parts in various other activities as well, besides running and jumping (see below). Furthermore, it is possible to represent the body's movement ability, or stiffness, by the spring constant k, and much research has focused on determining this constant.

3. Experiments and applications

Development and increased stability of motion trackers as well as sensor technology provide help in quantifying movement. In this section we summarize our research on daily activities, such as walking and dancing, using this information. The purpose of the studies has been to analyze whether the torsion spring model can be applied to the axial twisting movements in ballroom dancing and other activities. We also present Axis Visualizer, a mobile phone application to visualize motions.

3.1 Axis twisting experiment

Axial twisting movements along the longitude axis occur frequently. For instance, during walking the upper body and lower body rotate in opposite direction. We used a motion capture system to measure angle for rib cage, and a force plate to measure torque. The correlation between the angle and torque was calculated and compared with the spring model predictions. The setup of the experiment is as shown in Figure 4. Participants had to do axial twisting

Figure 4 Setup for the axial twisting experiment.

movement sitting on the force plate. After a short practice, the experiment started with a minimum of 10 seconds axis twisting in two conditions: in a slow, relaxed condition, and in a fast, intensive condition. The results are shown in Figures 5 and 6. The smooth harmonic curve and the linear correlation between torque and the angle show that the repetitive axis twisting movement can be modeled using the spring model (more details in Yoshida et al. 2018).

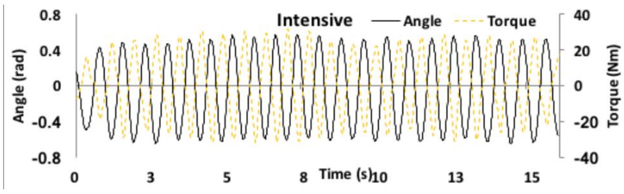

Figure 5 Visualisation of torque and angle in an intensive axis twisting movement. From Yoshida et al. (2018).

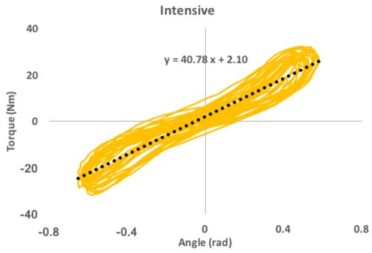

Figure 6 Relation of torque and angle in an intensive axis twisting movement. From Yoshida et al. (2018).

3.2 DanceSport

One of the popular dancing styles in the world is ballroom dancing, nowadays called DanceSport. Dancing can effectively help in fitness and wellbeing, and the exercise effects of DanceSport have already been proved. For instance, Rehfeld et al. (2017) consider the effects of a long (18 months) dancing intervention on elderly people's fitness and well-being, and how it can be efficiently used to enhance motoric capabilities of the elder people thus preventing injuries that stem from inaccurate or fragile motor control.

Dancing is also a good example of a movement which requires balance and smooth locomotion over a large area. Moreover, it requires coordination between two persons. Biomechanical analysis can provide a detailed analysis of the timing, amplitude and speed of the joint movements by the dancer's, allowing accurate quantitative measuring of the coordination in dance configurations. In the preliminary experiments with the Japanese professional dancers, we have noticed e.g., that the amplitude of the joint movements is less compared with the same movements performed by the individual dancer alone (showing the dance movement without the partner), while the rotation speed is slower in individual dancing. We will continue analysing the data from the All Japan Ballroom Dance Competition, to get a clearer understanding of the dance movements. The results can be used for learning and practise purposes, and to train competitors for better individual performance.

Biomechanical data can also be used to investigate human coordination in general, e.g. in joint tasks like cooking, assembling devices, or communication. In particular, since language communication is a cooperative activity whereby interlocutors use gesturing and body posture to coordinate

Figure 7 Axial twisting movement for Axis Visualizer.

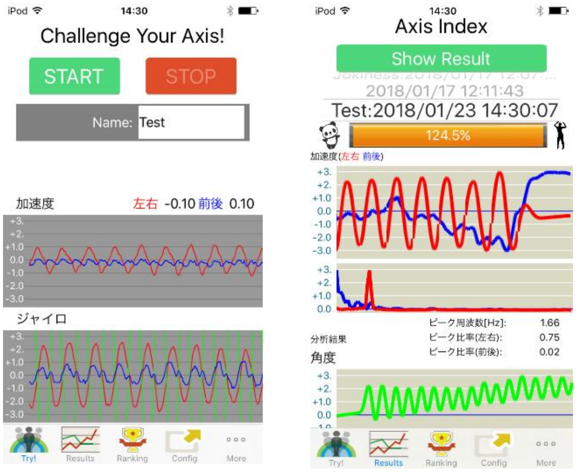

Figure 8 Two screen shots for Axis Visualizer.

the flow of interaction, such accurate measurements of the movements can be used to study engagement in interaction, i.e. to investigate how the interlocutors pursue their communicative goals while simultaneously pay attention to the partner in order to understand the partner's intention. Biomechanical measures allow us to calculate correlations between timing and location of the individual movements, and also include body rotation and speed of the movements as parameters to understand the posture of participants.

3.3 Axis Visualizer

Many people use activity trackers and smartwatches to measure various activities of their daily lives. As a practical application of the biomechanical information for everyday use, we developed an easy-to-use application for mobile terminals which allows the user to assess smoothness of their axial twisting exercise. The application is called Axis Visualizer and it is meant to function as a quick and simple assessment tool. The application deploys iOS Sensors for acceleration, while gyro inside the mobile terminal is used to analyze the spring model (see Section 3.1). The app can be used by simply attaching the mobile terminal to one's chest and doing the axial twisting movement for a short time, as shown in Figure 7. After the exercise, the system analyses the motion, and calculates whether the movement was harmonic. Two screenshots of the app displaying the result of an exercise are shown in Figure 8.

4. Discussion

Accurate biomechanical information has been mainly used for medical testing and rehabilitation tasks as well as for advanced studies on neuro-cognition and biomechanical feedback. We propose to apply the approach to collect, analyse, and annotate motion data in common everyday activities to increase understanding of human behaviour in real situations and to be able to build models for their computational assessment. We provided two examples of this kind of research and discussed an axis twisting experiment and DanceSupport.

Biomechanics data can also be collected using portable devices. This opportunity provides an interesting option for researchers who aim at studying interaction in real-life situations. So far, the participants' movements have been studied from video recordings or by using specific motion-tracker devices, which require the data collection to take place in laboratories. However, for ecologically valid data, it is important to be able to measure everyday activities in real-life situations, using simple devices and easy-to-use interface. The mobile application, Axis Visualizer, can be considered as the first step in this direction, since it exhibits the possibility to use a mobile phone to record motion and get an overview of the person's real-life activities.

In natural multimodal communicative situations, the connection from the visual scene to cognitive interpretation and appropriate conversational responses is important to understand the relevant mechanisms for human-human communication and for interactions between human and robot agents (cf. Jokinen and Wilcock, 2013). Hand and head movements are effectively used as signs that e.g. point to an object of interest, coordinate turn-taking by mutual gaze, and accompany the speaker's speech with beat movements (Kendon 2004, Paggio et al. 2010, Jongejan 2012, Jokinen 2011).

An interesting area of research is simultaneous timing of hand gestures, eyes, and nodding. The eyes and hands are used together in many everyday tasks, and it has been shown that the eyes generally direct the movement of the hands to targets: the eye-gaze is about one second ahead of the action start (Land 2006). Furthermore, the eyes provide initial information of the object (its size, shape, and possible grasping locations) so that the human can determine the motion of the hand, the hand shape and force to be used in the fingertips in order to exert suitable level of force and coordination to perform a task. The complexity of the coordination of eye and hand to perform everyday tasks is an interesting challenge for studies in cognition and neural control of eye and hand coordination, but it is also important in clinical work concerning disorders and impairments. For instance, in older adults, eye-hand coordination has been shown to decrease especially in tasks involving fast and precise movements, e.g. such everyday tasks as picking up a pen or making tea can become difficult. Having technology which enables training and assistance in such situations is useful for improving independent living and wellbeing. In various sporting performances, computer games, typing, etc. feedback through biosensors and biomechanics can give accurate information about how the task is progressing and what kind of changes in the task procedure are necessary to improve the system design and logistics of the interaction.

Given that the new technology allows several different data flows to be recorded and analysed, a unified approach to data model is necessary, cf. Human Communication Dynamics framework (Stratou and Morency, 2017). Some discussion can also be found in Hall and Llinas (1997), and more recently in Blaauw et al. (2016), from the sensor integration point of view, and we aim at exploring with the Fusion Model to enhance our understanding of gestures and movements in communication, to build models for the conversational rhythm and for the interlocutors' interest and involvement in the interaction and to better estimate human engagement in smooth communication. Moreover, combined with the knowledge of actions and activities, it is possible to experiment with automatic learning, i.e. to learn to recognize gestures and action sequences automatically. In attempts to teach a robot agent to perform certain tasks, e.g. pick up a pen, data about the correct movement patterns is necessary, and the proposed method can be an efficient way to collect accurate data.

Considering the IoT context of intelligent homes and public places, the use of biometrics and sensor data brings in a possibility to record everyday activities in real situations in the ubiquitous environments. The data can be immediately shared with other devices, e.g. with robots, which can thus learn about human motion and be able to provide assistance that is relevant in a given context. For instance, in elder care scenarios, a fall of an elder person onto the floor, irregularities in sleeping patterns or toilet use, wandering around the rooms, or not being able to find keys, can be noticed by a ubiquitous system which can then act in an appropriate manner (call for human help, suggest a keyring location, etc.)

The approach also brings in questions about the reliability of the information which depends on the technology. For instance, force platforms can be inexpensive off-the-shelf consumer products which makes it easy to conduct experiments. However, if used in exercise and health-care applications for measuring a patient's balance and mobility performance, their adoption should be carefully checked, and manufacturing should be in accordance to quality standards as established by ISO.

Like any data collection nowadays, the use of sensors needs to be considered with respect to some ethical aspects. Biomechanics allows people to be accurately identified by their physical features and typical behavior, so it will be possible to uniquely identify people. Data collection thus requires extremely careful consideration and planning and brings in questions about data storage and re-use. Statistical methods allow models for anonymous data source, and the data can be deleted after the analysis, but the issues related to building general models or individual models for certain physical and behavioral characteristics remain. Also, high-quality technology can enable attackers and people may give away information without their consent or knowledge.

5. Conclusions

Biomechanics is an area of research widely used in sport and medical domains for rehabilitation and improving performance. In the context of language communication, we expect that it will be possible to use the same approach to collect data, and through modeling, simulation and measurement gain a greater understanding of performance in everyday tasks and communicative events.

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