10th International Workshop on Innovative Simulation for Healthcare
18th International Multidisciplinary Modeling & Simulation Multiconference

ISSN 2724-0371 ISBN 978-88-85741-65-2 © 2021 The Authors.
doi: 10.46354/i3m.2021.iwish.011

Postural Evaluation and Symptom Acquisition Based on IoT-Driven Multi-Sensor-Fusion

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Abstract

The Internet of Things (IoT) is enabling more and more new applications, especially in the field of biomedical systems. Such IoT-systems can not only use an existing infrastructure, but also build an individual network for data exchange. By linking several distributed sensors, complex interpretation of data and identification of scenarios can be realized based on sensor-fusion. As a result, new correlations can be captured and interpreted.
Driven by the increase in pandemic-related work from home, this paper describes an IoT-based and sensor-fusion-enhanced posture monitoring and evaluation. Based on specific sensors, microscopic events are identified that can be placed in a macroscopic context. Using humanoid models, postures and corresponding sensor positions are evaluated and corresponding scenarios are described. The selection of different sensor types can be realized in an application-specific manner using the flexible IoT-platform, representing a toolbox.

Keywords: IoT-platform; sensor-fusion; model-identification; simulation

1. Introduction

Embedded System platforms in biomedical applications and health care offer new perspectives in many applications and disciplines. In particular, the Internet of things technology offers a wide range of possibilities to capture, evaluate and analyze data in a holistic context. The mobility of the Internet of things applications also makes new applications with a long-term character possible and thus also opens an evaluation of complex correlations.
The architectures and systems used here are integrated into an overall platform that has been extended to include such Internet of Things (IoT) (Ahmed et al. (2017), Al-Fuqaha et al. (2015)) systems to correlate movement information from a person's arms or legs with peripheral nerve signals (Klinger (2017)). The variety of possible applications of IoT systems extents the application horizon and enables new approaches for gait analysis, based not on force-related sensors (Klinger (2016)).
This paper focuses on an aspect that is certainly driven by the current pandemic: The monitoring and improvement of posture when working in the home office. Posture can be defined as the position of the body in a specific environment or mode. Some examples of specific postures are sitting, standing, walking, or leaning forward. Posture is based on the position of the spine and all joints of the musculoskeletal system. Postural assessment or analysis consists of evaluating a patient's posture through a series of appropriate tests and measurements. It is part of the branch of physical therapy called kinesiology, which involves the study of the anatomy and physiology of body movement. Good or normal posture is theoretically defined as an imaginary straight line connecting the earlobe, the cervical vertebrae, the acromion (bony outgrowth on the scapula), the lumbar vertebrae, and a series of points behind the

hip and slightly in front of the knee and ankle.
In this paper we will introduce a postural evaluation and symptom acquisition based on IoT-driven multi-sensor-fusion.
At first, we will introduce and define sensor-fusion. We then briefly show the underlying IoT- system and then demonstrate the system's requirements, goals, limitations, and possibilities using specific applications.

2. Sensor-Fusion

According to Steinberg et al. (1999) the process of data fusion is defined as follows: "Data fusion is the process of combining data or information to estimate or predict entity states."
In the following subsections we will introduce the basics of sensor-fusion, some specific applications and an abstraction based on events and behavior-based management (Hall and McMullen (2004)).

2.1. Basics

The general term entity is used, which describes an abstract object to which information can be assigned. In this paper, information refers to different aspects, on the one hand to the determination of body position and body movement, on the other hand also to the monitored disease symptoms. The focus is on the estimation of the body position from whose change on the posture and on possible necessary movement triggers is concluded. The body position of an object is understood in the control-technical sense (e.g. position, velocity, trajectories).
In symptom identification, a distinction is again made between detection and classification (Klein (1999)). In the context of detection, it is decided whether certain symptoms are present; in classification, the set of symptoms is assigned to a predefined class of diseases. The primary objective of data fusion is to combine data from individual sensors in such a way that strengths can be combined in a profitable way and/or weaknesses are reduced. Here, primarily 6-axis sensors (acceleration for x-, y- and z-coordinates and angular velocity for x-, y- and z-axis) for motion recording are used; a later expansion to include other sensors, for example CO2, is planned (Klinger (2020)).

The following aspects can be distinguished (see also Lou and Kay (1991)):

Redundancy. Redundant sensors provide information about the same object. This can improve the quality of the estimation can be improved. The dependence of the measurement errors must be considered in the data fusion and identification. A danger is the multiple introductions of artefacts and misinterpretations into the fusion process (see below). Redundancy can also increase the fault tolerance or availability of the system. On the one hand, this refers to the failure of individual sensors, e.g. caused by the failure of radio communication, although it must be assumed that the system can still be seen with sufficient quality even without the information from the failed sensor (robustness). On the other hand, this relates to artifacts or or misinterpretations of individual sensors. Redundancy can reduce the influence of a single error on the overall system reliability by providing several mechanism, e.g. like a model-based sensor supervision and a plug-and-play sensor replacement.

Complementarity. Complementary sensors bring different, complementary information into the fusion process. process. On the one hand, this can be done from a spatial information of the same sensors with different fields of view. On the other hand, it can be data that refers to the same object but providing different properties, for example by using more than 6-axis sensors, for example with additional magnetic field or position sensors. The use of different sensor technologies increases the robustness of the overall system (Mitchell (2012)) with regard to the detection of specific system states which cannot be reliably identified with a single sensor technology.

Temporal aspects. The acquisition speed of the overall system can be increased by a fusion approach. Through increased accuracy or the introduction of complementary information, the dynamics of the dynamics of the estimation can be influenced.

Costs. When designing any sensor system, the cost is a decisive factor for the practical feasibility of any sensor system. By using a fusion system, the costs can be reduced compared to a single sensor. But the costs of a sensor-fusion system are significantly influenced by the fusion system itself, influenced by the architecture of the system (Hall et al. (2017)).

Behavioral-Driven Development. The IoT-based platform can be seen as a hierarchical system of modules. Functions that can be experienced by the user are often provided by the interaction of several modules that are configured, managed and operated independently. With a mixed top-down and bottom-up approach, an abstract behavior-driven model description enables an scenario-based modeling of functional requirements and environment contexts. Based on use cases, the modeling of functional requirements can be driven by verification patterns. This combination of behavioral-driven development and scenario-based requirements modeling allows an abstract system view comparable to automata.

The architectures and systems used here are integrated into an overall platform that has been extended to include such IoT-systems to correlate movement

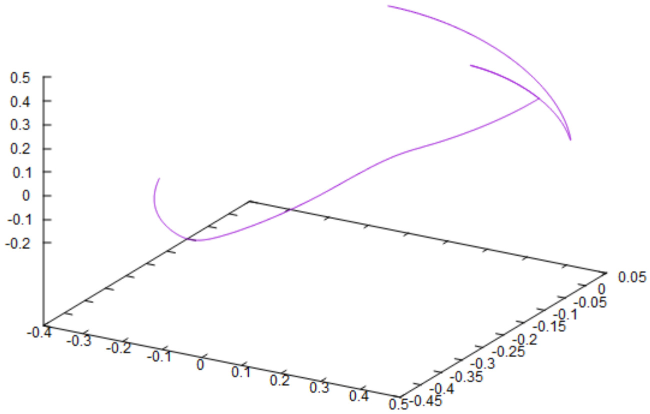

Figure 1. (All units of measurement in m)

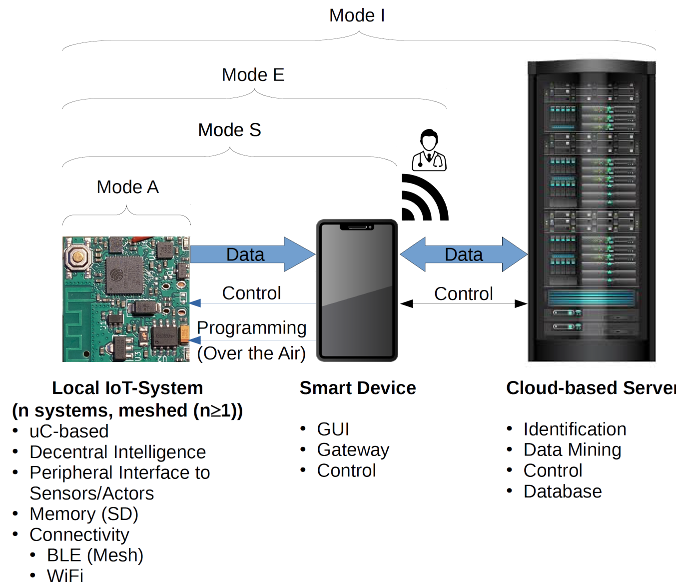

Figure 2. Architecture of the IoT-platform-based multi-mode system (Klinger and Bohlmann (2020))

information from a person's arms or legs with peripheral nerve signals (smart modular biosignal acquisition, identification and control system (SMoBAICS), Klinger (2017)). The variety of possible applications of IoT-systems broadened the application horizon and also enabled systems for other applications, for example gait analysis.

2.2. Event-Based Superposition and Inverse Kinematic

Sensor-Fusion can also be based on features that can already be derived from the raw data. Already in Klinger (2019) and Klinger and Bohlmann (2020), coughing could be identified without doubt from the data of acceleration sensors. Through this hierarchical processing of data, specific features can be collected and transferred to a more abstract feature level. Analogously, this case applies to different symptoms, like courses of fever, etc..

These methods can also be applied to postural scenarios and therefore abstract features can be abstracted and used, especially for behavioral modeling. Furthermore, trajectories can be derived very efficiently from accelerometer and gyro sensor data using inverse kinematics methods (Corke (2017), TheMathWorks,Inc. (2021)), which can be applied very well to body motion by fitting them to a model of a humanoid. Thus, corresponding movements of the trunk or extremities can be identified very well from the sensor data. A well-known example is the recognition of correct hand washing procedure by several smart watches. In figure 1 a trajectory of a hand is shown, computed from micro-electro-mechanical systems (MEMS)-data acquired at the wrist.

3. System

The system architecture used is the same we have introduced in Klinger and Bohlmann (2020). All levels of the architecture, essential for the application described here, are depicted in Figure 2. This architecture acts as our IoT-platform and supports the four different modes and their corresponding scenarios shown in Figure 2) (Espressif (2019)). These modes allow transparent processing of the data and permit General Data Protection Regulation (GDPR)-compliant data management. This special feature with regard to data protection places the individual's right to privacy at the center of data collection and puts the decision on whether to share or process the data in the hands of the respective user. Therefore the acquired data are stored on the IoT-system (mode A: Autarkic), on the gateway system (mode S: Supervision), events are sent to medical staff or doctors (mode E: Event) or used for model identification and data-mining algorithms (mode I: Identification). In Figure 3 the mobile prototype of the new sensor node is shown, providing CO_2-sensor, MEMS, electrocardiogram (ECG) and temperature. This prototype is not yet integrated, therefore the is high shrinking potential for further applications.

4. Applications

Here, some applications are shown, starting with the postural evaluation and its various use cases. The following applications show the integration of this sensor into an integrated system for combined symptom-evaluation, based on multi-sensor-fusion. Finally, an extension with a CO_2-sensor is introduced, providing additional information about risk of infection, used in the pandemic context.

Figure 3. Modules for IoT-features, ECG, 6-dim MEMS (acceleration and angular velocity), temperature, CO_2-measurement and LiPo-accumulator without housing in smart box ($62 \cdot 35 \cdot 12\ mm^3$)

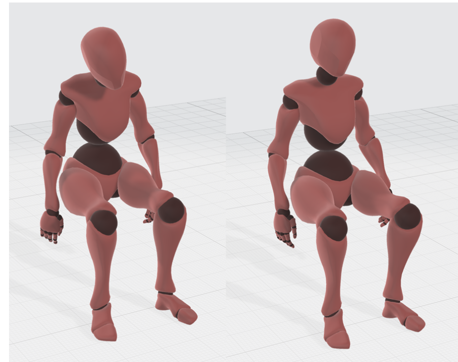

Figure 4. From left to right: Optimization of the sitting posture

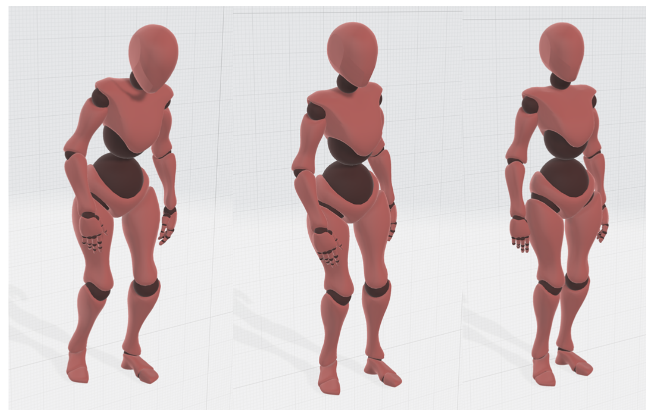

Figure 5. From left to right: Optimization of the standing posture

4.1. Postural Evaluation

Good posture is the end product of a complex combination of mechanical, neurological and psychological factors, including muscle strength and flexibility, vision, sense of touch, balance, self-esteem, kinesthetic awareness (a sense of the position and movement of muscles and joints) and a well-functioning vestibular system (inner ear) (Goodman and Fuller (2015)). Good posture is desirable when sitting and standing, as well as when walking and running (Bullinger et al. (2013), Heidenfelder (2011), Ito (2008), Hartmann et al. (2013)). Because of the number of parts and functions involved in good posture, a postural assessment can serve a variety of purposes:

- As part of the musculoskeletal assessment of a balance. Postural abnormalities often affect an older person's sense of balance and their ability to respond quickly to Respond to loss of balance.
- As a step in the differential diagnosis of chronic pain syndromes. In particular, chronic neck and back pain often results from poor posture that causes muscle contractions, alters blood flow to the spine and leads to deformation of the connective tissue in the spine and neck.
- As part of a physical examination in sports medicine. Deviations from normal posture increase the risk of certain types of sports injuries and can affect athletic performance.
- In the assessment of work-related postural problems and repetitive strain injuries, long periods of sitting at a desk and in front of a computer, naturally play a dominant role. This is especially true in the current pandemic situation.

The first thing to do here is to identify and become aware of any postural problems. A movement triggered by this can be used to optimize the respective posture. This focus is triggered by the pandemic situation, too: Lots of hours in home office reduce the movement possibilities for compensation and aggravate all posture problems.

In figures 4 and 5, the unity-based humanoid models (see UnityTechnologies (2021)) are shown to illustrate the problem of poor posture; starting from poor posture on the left to good posture on the right (sitting: Figure 4., standing: Figure 5). A major challenge is the calibration of an approximately individual perfect posture. What is needed is an absolute positioning, which cannot be achieved with the MEMS-sensors. Here, only cameras can be used, which, however, can also provide incorrect results due to the clothing. Currently, the calibration is performed by a set of motion prescriptions (Krankenkasse (2008)), which are supplemented by various stretching movements of the arms and movements of the upper body and head.

The SmartBoxes and their specific sensor systems are listed in Table 1. The corresponding position on a sitting humanoid is shown in Figure 6. Based on simulations, the position of the mobile sensor-systems (SmartBoxes) has to be further evaluated. In the following subsection the focus is on the combined evaluation of several sensors to provide a good assignment of

Table 1. Types of SmartBoxes

Term	Sensors	Position	Description
CS 1	CO_2, ECG, MEMS, temperature	neck, left	This combined sensor provides not only MEMS-functionality but additional systems, like temperature- and CO_2-sensor. The CO2-sensors are now mobile ones, so stationary sensors are saved and thus necessary infrastructure is reduced.
MEMS 1	MEMS, temperature	lower lumbar spine	
MEMS 2	MEMS, temperature	restraints	The frontend to interface the force sensors, used in Klinger (2016), is not yet available.

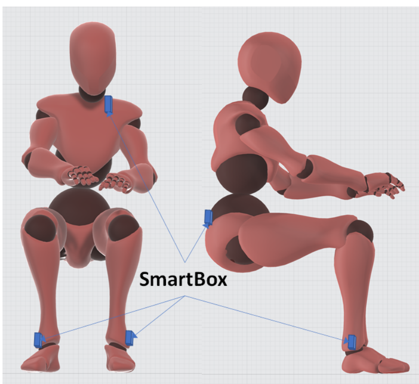

Figure 6. Position of the SmartBoxes

sensor data to corresponding scenarios.

4.2. Combined Evaluation

All sensor data are available as time series. There are clear correlations between individual sensor values and corresponding reactions. For example, a too high CO_2 value triggers a ventilation event (see section 4.3. For example, if the acceleration values of the SmartBoxes CS 1 and MEMS 1 are nearly constant over a long period of time during a sedentary activity, a motion initiation must be generated. This is because a very big danger in sedentary activities is motionlessness. Employees often adopt a forced posture for hours at a time when sitting continuously in the office. As a result, muscle groups atrophy, tenseness occurs, tendons become inflamed, etc.. If changes occur in the data from several sensors in a specific situation, these correlations between the sensors can indicate certain scenarios. This is not only true in the identification of medical conditions through the detection of various symptoms, but also in postural evaluation, certain movements and their concrete sequences can both indicate anatomical problems and initiate a certain sequence of movements to prevent negative effects and postural damage. These include, for example, hunched shoulders, incorrect use of mouse and keyboard, and crossed legs.

The relationship between the individual sensor values, events derived from them, a sequence of events up to a probability of occurrence are already known or can also be newly understood and modeled. Behavioral methods in particular help here, as the hierarchical formulation and sequence of events makes it possible to easily grasp relationships, for example also through a domain-specific language.

4.3. CO_2-Measurement for Reducing Infectiousness of Indoor Air

As mentioned in Klinger and Bohlmann (2020), indoor carbon dioxide comes from the exhaled air of the people who are indoors and have a decisive influence on the room-related CO_2 content. The exhaled air therefore contains not only CO_2 (0.3 liters/minute) but also aerosols which, due to their size, can float in the air for a long time. If the person in question is infected with the virus, these droplets can also contain virus particles. These aspects are better understood since last year (Kiwull (2017)), van Doremalen et al. (2020)). Based on the model of the correlation between CO_2 concentration and infection rate (Rudnick and Milton (2003)) the risk of indoor airborne infection transmission can be estimated from carbon dioxide concentration. Good ventilation should be a matter of course when a larger group is gathered. The Federal Environment Agency has drawn up general guidelines on the health assessment of carbon dioxide in indoor air, which we will use as a guide in the following. According to Federal Environment Agency guidelines, a concentration of < 1000 ppm is hygienically harmless. A concentration between 1000 and 2000 ppm is classified by the guideline as questionable and anything above this level as unacceptable. A detailed discussion of the airborne transmission pathways of SARS-CoV-2 can be found in Morawska and Cao (2020). While using fixed CO_2-sensors in a room (see Figure 7), the CO_2-content in the room air is significantly changes during a lecture. In Figure 8 the CO_2- concentration, temperature and humidity for 4.5 hours within a auditorium with a test-taking rate of only 20 % of students are shown. Two ventilation breaks reduce the proportion significantly and show a corresponding air exchange. After the second ventilation event, the participants leave the auditorium, and the CO_2-content stagnates.
To monitor low CO_2-levels in each individual, the fixed assignment of CO_2 sensors in a room is extended by a measurement system, positioned on the body. This measurement is made by the sensor CS 1 and allows everyone to provide appropriate ventilation in any room

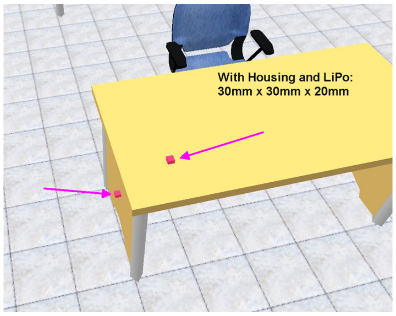

Figure 7. Application of gas sensors

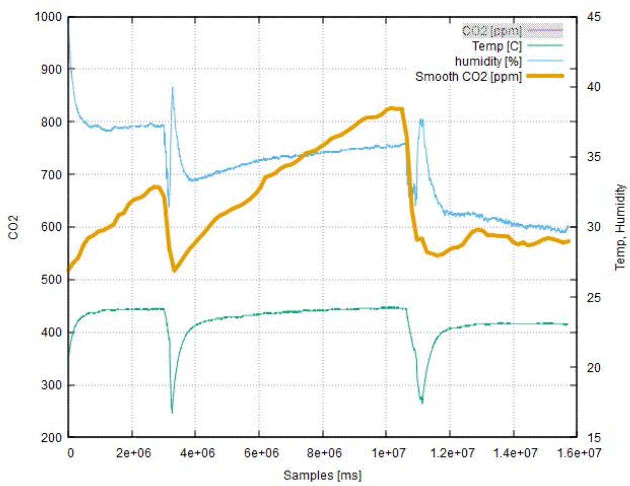

Figure 8. CO_2-content in auditorium

conditions.

5. Summary and Further Work

The IoT-platform enables the integration of a variety of sensors and has a high flexibility to implement specific requirements. The use of multi-sensor-fusion expands the scope of application by superimposing and supplementing individual sensor values to form an overall picture. This overall picture, which is characterized by a hierarchical event definition both in time and in the expression of specific characteristics for individual scenarios, has great potential. Figure 9 shows the fusion and identification of events and scenarios in an abstract way. The acquisition of data and the fusion of different time series from individual sensors and their specific aggregation into events and/or scenarios is shown. The main block contains different algorithms for detecting specific events, aggregating events to scenarios and symptoms and uses inverse kinematics to generate events related to posture.
In Figure 10 the raw data from the accelerometers of the SmartBoxes CS 1 and MEMS 1 are shown. Already

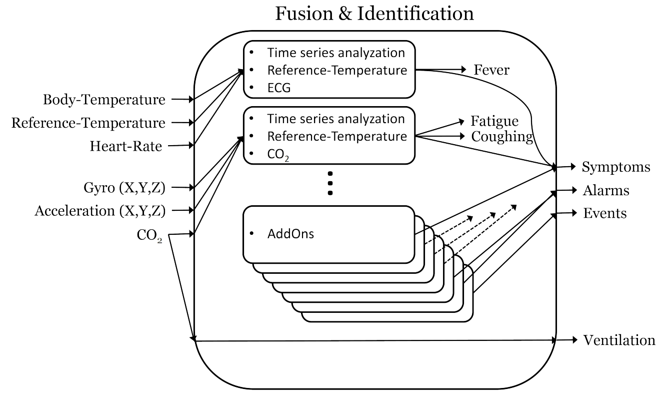

Figure 9. Sensor-fusion and identification of events and scenarios

here a very good assignment of the sensor data to the corresponding motion sequences can be recognized.
The posture evaluation introduced in this paper enables an individual support of the respective posture and can thus prevent consequential damages by identifying posture deficiencies.
The further work has the following key aspects:

- Improvement of sensor-fusion and elaboration of improved verification concepts.
- Higher integration density of the systems to allow easier application.
- Deployment of new housings that meets medical requirements.
- Ongoing tests to improve the sensor-fusion and to verify additional use cases based on the platform architecture.
- Evaluation of power consumption and optimization characteristics to optimize the mobile data fusion.

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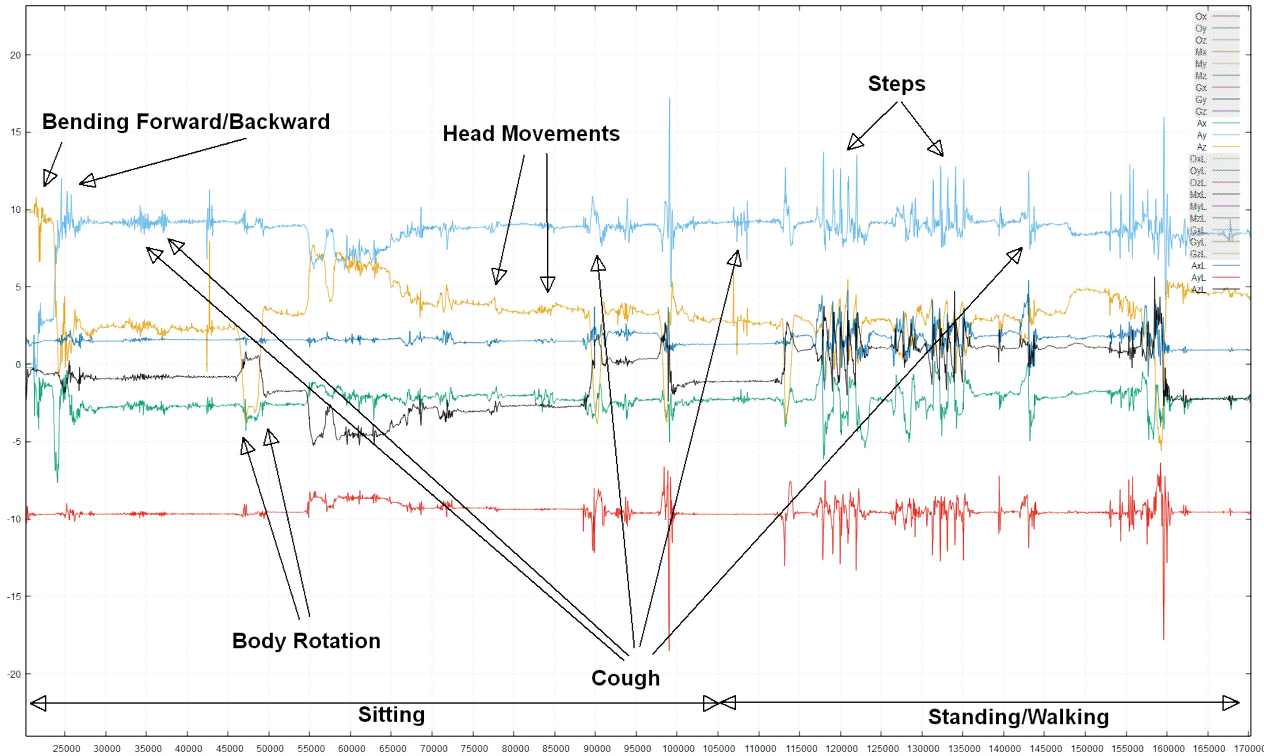

Figure 10. Assignment of individual sensor data to microscopic events

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