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Application-based IoT-system for Pandemic Prevention Based on Platform-Approach

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Abstract

For the quantitative description and prognosis of pandemic propagation processes, simulations and methods of theoretical biology, such as the SIR model (susceptible-infected-removed model), are used. Important in all these methods are models and data. These describe cause-and-effect relationships on the basis of which the models can be developed and improved. However, data collection and data correlation in particular are costly and often complicated against the background of data protection. Within the framework of a project on electroneurogram (ENG)-based prosthesis control, work is already underway on a data-based system identification for model generation; in this context, a hardware-/software-platform has been developed that also has a Internet of Things (IoT) extension and can be used for the required sensor fusion. These methods can be used within the existing framework. The flexibility of the platform is also demonstrated. Part of the platform are not only new approaches to modelling based on agent-based evolutionary methods, but also a concept that transparently secures personal rights in different modes of operation. The aim is not only to further investigate microscopic relationships of the pandemic, but to evaluate in particular macroscopic relationships within a set of scenarios, i.e. to establish cause-and-effect relationships more precisely between different symptoms and an infection.

Keywords: Hardware-/Software-Platform; Data-Driven Methods; Modelling; Simulation: Sensor Fusion; Model Identification

1. Introduction

Embedded systems and the IoT enable new procedures, measurement and analysis methods in the field of biomedical systems. This includes not only the measurement of data, but also a multitude of new approaches in diagnosis, prevention or rehabilitation. Within the framework of a project on the ENG-based control of prostheses, a platform was developed, smart modular biosignal acquisition, identification and control system (SMoBAICS). As described in Klinger and Klauke (2013) and Klinger (2014), SMoBAICS is a modular system with the objective of ENG-based motion identification and prosthesis control. Based on the acquisition of action potentials via ENG, the information of the peripheral nervous system is used to identify movement patterns. A microelectro-mechanical systems (MEMS) used during the mobile operation of the prosthesis control (mobile phase Klinger and Klauke (2013)) and/or camera system (learning phase Klinger and Klauke (2013)) is necessary to get information about the movement trajectories and about plausibility. To integrate the MEMS, an IoT-module was designed to improve flexibility and to simplify the integration of different sensors using wireless connection. This platform can also acquire and process electrocardiogram (ECG) and electromyogram (EMG) signals by adaptation (Yang et al. (2018); Ryser et al. (2017); Wu et al. (2018)).

In addition, the platform has been extended with

IoT-systems in order to be able to integrate necessary information into the platform by means of additional sensors. The IoT-systems are also designed on the basis of the platform approach, which increases the overall flexibility of the system architecture Klinger (2019).

This paper evaluates against the background of the current COVID-19 pandemic whether the existing platform can be efficiently adapted or extended to an application with completely different requirements and boundary conditions.

What is the motivation behind this adaptation of the platform? There are several reasons for this.

First of all, the occurrence of modern pandemics and the increasing probability that such pandemics will occur again more frequently. The return of the epidemics has to do on the one hand with the adaptability of the pathogens and on the other hand with various constantly increasing trends of globalization. Pathogens are constantly evolving and can develop complex survival strategies, for example against antibiotics. In addition, however, it is in particular the enormous increase in the mobility of people and goods, rapid global population growth, urbanization and the ongoing destruction of the environment that have given the spread of infectious diseases a huge boost and increased their geographical spread. The rapid global spread of COVID-19 shows how quickly a disease can travel around the world in the highly interconnected 21st century, and in its early stages probably goes unnoticed for weeks. For pandemics of this kind, it is valuable to be able to identify symptoms quickly, to have a precise knowledge of the disease-specific symptom chains and to try to draw conclusions about an infection as early as possible.

Secondly, the symptom-determined change in physiological parameters and the occurrence of specific symptoms, such as coughing or sweating, can also be used to identify an infection, with the aim of treating them as quickly and as well as possible and keeping the radius of infection as small as possible.

Last but not least, of course, it is an opportunity to investigate the correlation between certain physiological parameters, such as outside temperature, body temperature and the stress on the cardiovascular system, using continuous data recording over hours and days.

Based on an analysis of use cases it is examined which characteristics, advantages and disadvantages a use of the existing platform brings with itself.

First the platform is briefly introduced, then the requirements and use cases are discussed on the basis of scenarios.

2. Platform-based IoT-Platform

The Internet of Things creates new opportunities to link sensors, actuators or intelligent decentralized systems either with each other or with other systems Bassi et al. (2013). The IoT-Roadmap promotes new technologies and, therefore, new challenges. Based thereon the availability of technologies and components offers good conditions for a platform-based system such as SMoBAICS. The extension or adaptation of the system may then, depending on the application, benefit from existing developments and/or modules.

The SMoBAICS platform (Klinger and Klauke (2013); Klinger (2014)) and its enhancement using IoT-modules (Klinger (2019)) is used to acquire EMG- and ENG-signals and to provide a data-based identification of movements and trajectories. The identification method is model-based and uses simulation for the continuous model improvement and for verification purposes. The data of the external sensors, here especially of the 9-axis MEMStracking device, are essential for the model- and simulation-based identification method.

First we introduce in the following the general properties of IoT-systems, used for the pandemic prevention platform, subsequently we give some details regarding hardware and software of these systems.

2.1. IoT Characteristics

An analysis of different use cases shows the need of an integration of additional sensors in the acquisition and identification platform. This includes the MEMS-device, which is needed to provide motion data of the prosthesis. The connectivity is here one key factor. Lots of smart devices, like smart phones or tablets, provide a communication- and computing- infrastructure. Based on this the flexibility and scalability of the platform can be increased significantly. In addition the number of intelligent components rises within the scope of the IoT rapidly Bassi et al. (2013). Thus intelligent sensors can be integrated to the platform. This decentralized periphery extends the application spectrum of the platform considerably.

Nevertheless, some key aspects have to be taken into consideration using IoT-modules:

- The core platform is an essential part. It enables an efficient and powerful integration of different modules and provides smart services.
- The modular character of hardware and software and their platform characteristics is of particular relevance. The platform paradigm provides a flexible partitioning and relocation of functions and services on specific hardware and software modules. Especially the open system gateway initiative (OSGI)is one of the key features realizing

the software platform.
- Connecting more than one or two devices, the Smart-Device and/or the CPU-module of SMoBAICS has to provide gateway functionality. Based on new Bluetooth-(mesh) or WiFi- (802-11ah) standards, the communication environment with these characteristics can be realized.
- The service orientation of the interface is an essential aspect due to the integration of IoT components. An efficient linking and communication require a defined quality-of-service level to realize a seamless integration of services and modules.
- Using IoT-modules security aspects are a further key point. Without secure data transfer and a secure module interconnection an IoT-based system is applicable in a limited way. Every connection has to be secured using pairing based or certificate-based strategies.

The base functionality of an IoT-module contains an actor/sensor element (A/S) , and processing (P), memory (M) and connectivity (C) features, adapted to the specific application. For example, the connectivity may be based upon a wireless or wired connection. Moreover, all modules are designed regarding low-power strategies providing an autonomously operation. Here, energy harvesting is one of the main future topics for IoT-systems.

Figure 1 shows different specifications of IoT-systems designed for specific applications. For example, in Figure 1 the processing features (above) or connectivity (below) are more pronounced than other features. Based on the platform paradigm every IoT-system can be designed according its specific project requirements.

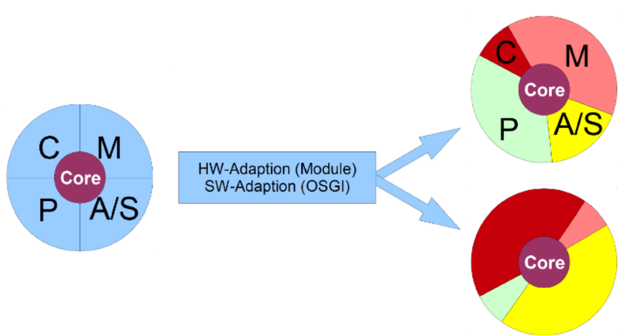


Figure 1. IoT instances based on an IoT-platform

2.2. Hardware

The hardware part of the project includes the partitioning between the different printed circuit boards (PCBs). The architecture of the IoT-device is realized according the platform paradigm, too. The microcontroller (µC)-board is designed as a stand-alone board that can be run independently from the presence of an application specific front-end. Such an assumption forced the designer to include several components on the board. The key constraints for the design are defined by the four basic characteristics of an IoT-system Klinger (2016): Connectivity, processing, memory, sensor/actor integration.

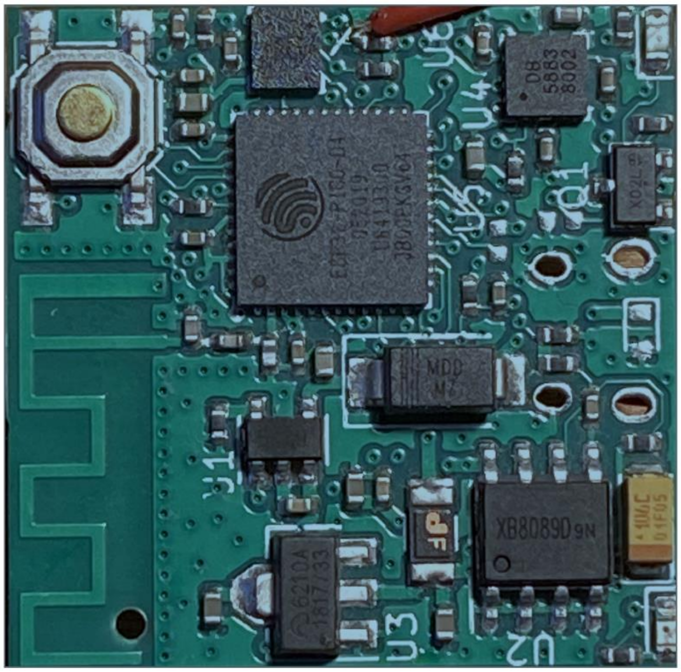
The µC-board acts as the central component of the system and is based on an ESP32 Espressif (2019). This EPS32-based device is a dual-core System-on-a-chip device. It is primarily intended for use in the IoT area, but in contrast to a single-board computer, such as a Raspberry Pi 4, it requires much less power. Its size is also only a fraction of that of a single-board computer (80920 mm^3 as opposed to 1080 mm^3 (1.3%)). Thanks to its many interfaces, including BLE and WiFi, it is ideally suited as a IoT module. These aspects make ESP32 the preferred choice for all wearables and all systems worn on the body, including those described in this paper.

On the µC-board directly an acceleration sensor and a temperature sensor is placed. All other sensors are swapped out on specific PCBsand are connected to the microcontroller via connector to form a module system. Figure 2(a) shows the microcontroller board and Figure 2(b) an unassembled module for recording the ECGsignal. The ECG-board is smaller than the µC-board because of the antenna.

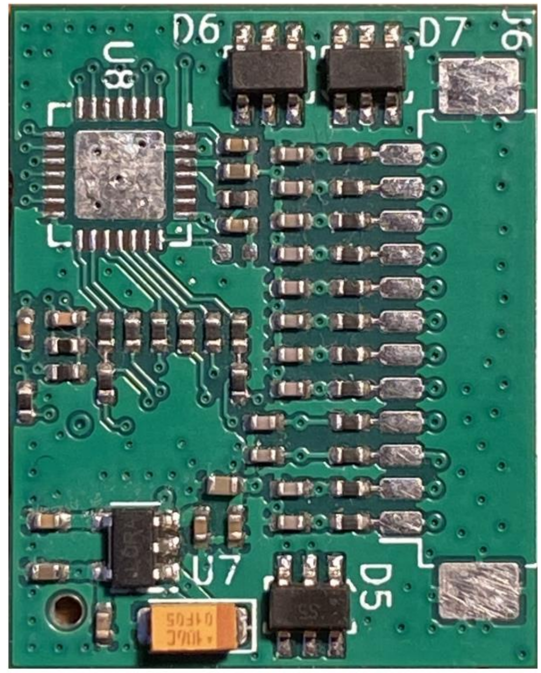
2.3. Software

The software platform provides an operating environment, or an operating system under which other smaller applications can be executed. Regarding the platform paradigm, different types of software has to be implemented, embedded software for the µC for an Android smartdevice, and for the identification environment.

After application and platform are initialized, an automatic Bluetooth Low Energy (BLE) connection is established to provide connectivity between all IoT-devices and with the smartdevice, if mode S, E or I is selected. The BLEconnection is using BLEmesh networking standard based on Bluetooth Low Energy that allows for many-to-many communication over Bluetooth radio. It operates on a flood network principle, based on the nodes relaying the messages. The measurement results can be saved in the internal RAM. The µCsoftware can be subdivided in application software and BLEstack software, both composed with help of an integrated development environment (IDE). The application software is running on a real time operating system (RTOS) providing services and handling of the different tasks, like BLE communication, sensor data acquisition, data processing and other services. According to the Bluetooth specification, the device acts as a GATT (Generic Attribute Profile) server. The µCESP32 has two processor cores, providing rather high computing power, which has sufficient power for the acquisition of sensor values in the range of seconds or minutes and a corresponding model calculation. The IoT-



(a) Microcontroller-modul (Dimensions 25 · 25 mm²)



(b) Unassembled EKG-modul (Dimensions 25 · 20 mm²)

Figure 2. SMoBAICS-IoT-Device

platform is based on this µC, which provides both, WiFi and BLEconnectivity, which creates a flexible connection infrastructure for all modules up to the smartdevice, the gateway.

3. Application Scenarios

There are a variety of possible scenarios, based on standalone µC-IoT-modules and based on a network of these modules. Therefore, to somehow visualize the range of application, some use cases are presented subsuming in Table 1.

The scenarios were divided into different categories:

- Symptom-related

  The symptoms are corresponding data that are determined by the respective individual. These include, for example, in the task at hand, COVID-19, body temperature, ECG, coughing frequency and oxygen saturation. In general, the acquired data are stored as time series. This makes it possible to identify certain curves and to put their specific changes into an overall context.

- Air quality-related

  Parameters of the surrounding atmosphere are recorded here. For example volatile organic compounds (VOC). A large number of solvents and other chemical-organic substances can be determined. These include irritants and odorous substances such as butyl acetate, styrene, hexanal, which can be emitted from a wide variety of materials and pollute the air in the room. For the present focus, however, only the CO_2 saturation is determined.

- Combined

  Use of all sensors for a broad basis of correlation possibilities.

The system supports 4 different modes in addition to the various measurement scenarios. These modes allow transparent processing of the data and permit General Data Protection Regulation (GDPR)-compliant data management (DSGVO). This special feature with regard to data security places the individual right of the individual at the center of data acquisition and places the decision on whether to pass on or process the data in the hands of the respective user. The following list describes the different modi. The architecture of the system, providing these modi is shown in Figure 3.

- Mode A: Autarkic

  In autarkic mode, only the wearables are active and perform basic signal identification and sensor fusion. Here, optical (LED) and/or acoustic signals can be used to indicate corresponding results. This includes, for example, a temperature increase or a corresponding deterioration of the ambient parameters (e.g. CO_2). The collection of data and the evaluation are carried out exclusively locally and are therefore unproblematic in terms of data protection (GDPR).

- Mode S: Supervision

The supervision mode extends the autarkic mode by a graphical user interface, which allows a view of the corresponding time series as well as a configuration of the system. Current and historical values can be viewed here and the corresponding triggers (optical, acoustic) can be defined. In addition, data analysis and data identification can be carried out here that goes beyond the already identified relationships of the identification system. Here too, all functions are executed locally and are therefore unproblematic in terms of data protection. The contribution of the identification system is limited to corresponding signal correlations, signal patterns and derived relationships for the sensor-related fusion of data.

- Mode E: Events

Events are designed to leave the local data world and to trigger corresponding events. Such events can, for example, be information for a treating physician who can give an assessment of the current state of health. Of course, it can also be the care and rehabilitation or prevention in connection with a known cardiovascular weakness thatrequires adequate treatment. In this case, therefore, information is passed on to medical personnel, naturally under the cloak of medical confidentiality. This is also where a further opening can take place and the data which, for example, provide information about an infection with a certain probability, can be passed on to a central register. This can be done either anonymously or non-anonymously, depending on the level of data protection of the respective office.

- Mode I: Identification

The identification, which is based on a multi-level evolutionary algorithm, has been implemented in the context of the ENG-based identification of motion data and the prosthesis control based on it (Bohlmann et al. (2012, 2017); Klinger (2017, 2018)). The transferred data of the different sensors are analysed and transferred into a model that contains the interrelationships. On this basis, mutual information and the corresponding effects of individual data on an interconnected behaviour or infection can be transferred.

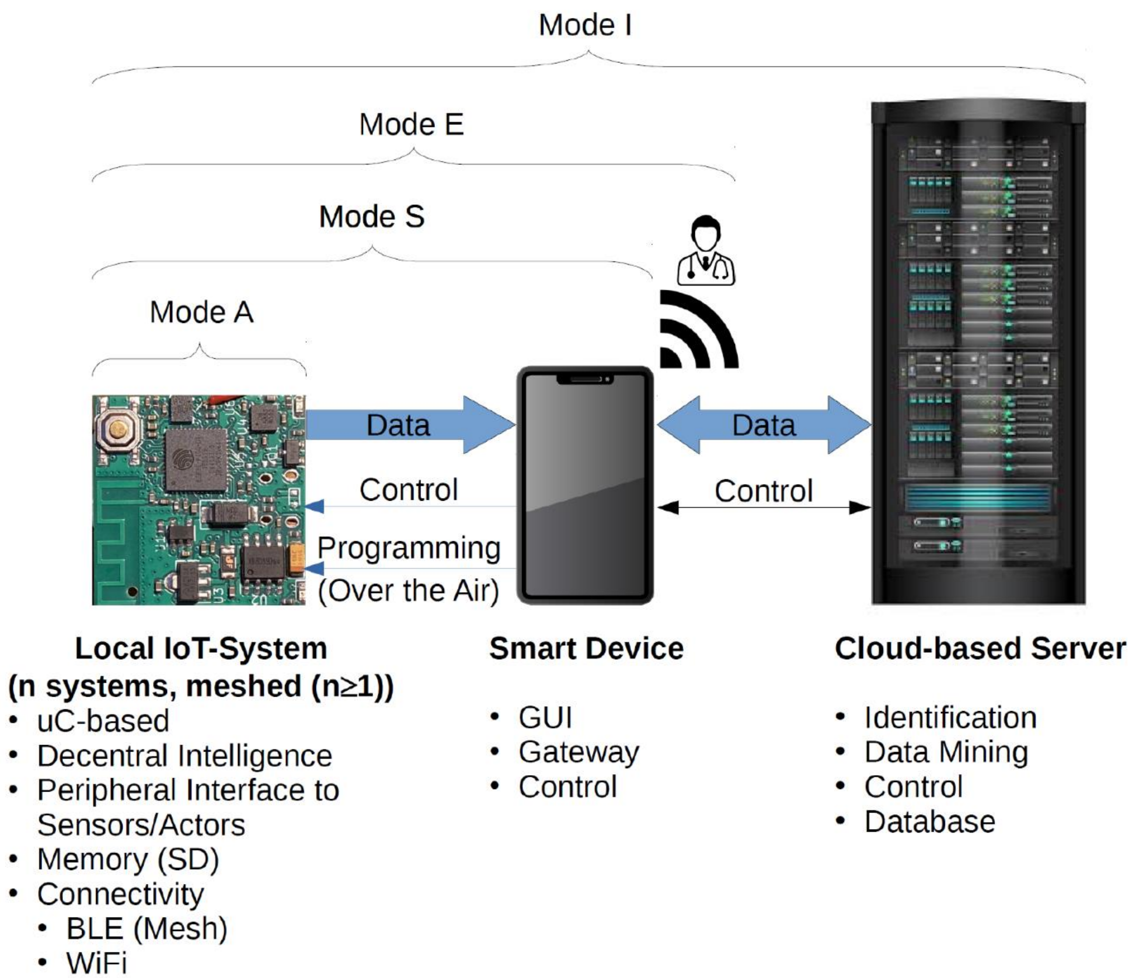


Figure 3. Architecture of the IoT-platform-based multi-mode system

The generated model can then be transferred to the underlying clients (smartdevice, µC-IoT) and, depending on its complexity, can be used there in a simplified or complete way to fuse all sensor data. The identification can be continued on the basis of the further transferred data to map new information and correlations accordingly in an improved or updated model. It can be decided in each case which data is to be used, i.e. clearly configured which data is to be used for identification.

Against the background of the individual scenario categories and modes of operation, the following section presents the individual scenarios, which are already summarized in Table 1. The positions, where the IoT-systems are worn on the body, are shown in Figure 4.e.

3.1. Symptom Analysis and Disease Identification

Simple Diagnosis (SD). The simple form of diagnosis consists in measuring the temperature. Elevated temperature, long known as fever, allows conclusions to be drawn about infections. However, it is not very helpful to measure temperature only selectively, because only the fever curve provides information about the cause of the disease, depending on whether the cause of infection is bacterial or viral. The expected level of fever and whether the fever rises suddenly or gradually is also significantly related to the type of disease. There are a total of six forms of progression, which always pass through four general phases. These phases, P1 to P4, and forms of progression, which are only briefly summarized below, can be recorded and evaluated by the microcontroller.

P1 Fever increase

P2 Fever height

P3 Fever decline

P4 Exhaustive sleep and regeneration

Depending on the type of infection present, the course of the disease describes different course curves under which five main course forms are distinguished (Abele-Horn (2010)):

1. Continuous fever

2. Recurrent fever (variety of bacterial and viral infections,but is particularly typical of inflammation of the upper respiratory tract.)

3. Intermittent fever.

4. Undulating fever.

5. Biphasic fever (frequently occurs in connection with viral infections, with organ-specific symptoms in the second phase show.)

Table 1. Application scenarios related to COVID-19 Pandemic

Use Case	ID	Sensor	#IoT Systems	Position in Fig.4	Mode (A,S,E,I)	Description
Symptom-related						
Simple Diagnosis	SD	Body temperature	1	a, b	A, S, E, I	System detects the fever curve and logs it. Depending on the curve progression, min and max values and the daytime in event is written. Depending on the mode there is a local alarm or trigger sent to a physician.
Correlated Diagnosis 1	CD-FH	Body temperature, ECG	2	b	A, S, E, I	Acquisition of fever curve and ECG. Objective is the fusion of data to record the body temperature depending on the state of stress and to obtain an improved fever statement.
Correlated Diagnosis 2	CD-FHC	Body temperature, ECG, acceleration	2	b, c	A, S, E, I	Additional extension of the symptom list to include the detection of dry cough. Here a further data fusion is performed to make the prediction more precise.
Correlated Diagnosis 3	CD-FHCO	Body temperature, ECG, acceleration, oximetry	3	b, c, e	A, S, E, I	Another addition to the list of symptoms is the measurement of oxygen saturation. This value can be a central value for the confirmation of an infection.
Air quality-related						
Air quality 1	AQ-CO2	gas	1	d	A, S	The Air quality is based on the CO_2-content of the ambient air. Using a model (see subsection 3.1), the focus here is on ventilation recommendations.
Air quality 2	AQ-CO2D	gas, distance	1	d	A, S	The CO2-measurement of the own sensor is extended by the CO2-measurement of other participants in the room. Based on this, a local recommendation is added and a distribution of people in the room is recommended.
Combined						
Combined	CDE	Body temperature, ECG, acceleration, oximetry, gas, distance	4	b, c, d, e	A, S, E, I	Scenario is based on the use of all available sensors.

Here, continuous data recording in particular helps to obtain more information about the specific course of fever in a COVID-19-infection. Correlated Diagnosis 1 (CD-FH). It is known from sports science that humans have an elevated body temperature during intensive sporting activities. During a marathon run, for example, the body temperature rises to about 39◦C. Since cooling the body during physical exertion is associated with high energy consumption, in competitive sports there is a systematic attempt to cool down the body temperature before the competition and possibly during the breaks (including half time). Conversely, an increased body temperature is also a prerequisite for peak physical performance. Warming up, combined with an increase in body temperature to 38.5 to 39◦C, improves various physiological processes. After a systematic warm-up of 15 to 30 minutes, especially before speed performances (e.g. sprint, basketball) and sports with maximum use of power (rowing, weight training), 4 to 7 % higher performances have been observed. The risk of injury is also reduced.

Based on this information, the body temperature has to be correlated with the heart rate to identify specific sporting events that do not involve fever in the strict sense. To realize this, a ECG-sensor is integrated, providing a correlation between physical activity and body temperature.

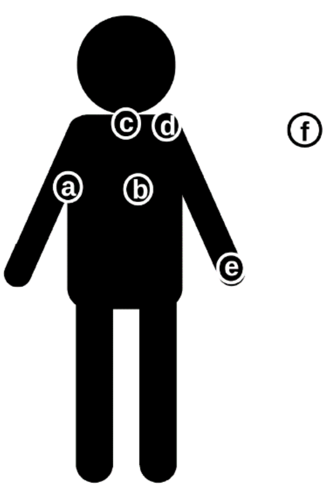


Figure 4. Overview of IoT-module locations (possible positions): Wearables (a-e) and ambient (f) IoT-systems

Correlated Diagnosis 2 (CD-FHC). Targeting COVID-19 requires an analysis of the most common symptoms. In RKI (2020) it was found that dry cough in particular indicates a corresponding infection in 49% of all cases. In order to be able to detect this symptom as well, the system will be extended by an additional sensor. An acceleration sensor is ideally suited for recording coughing events. In Figure 5 the coughing events are clearly highlighted and can be easily detected. With a corresponding increase in coughing events, an acceleration sensor can be used in accordance with the identified model, an increasing probability of infection can be determined. However, caution is advised here! The analysis carried out so far make a clear identification based on these symptoms difficult. Here, further investigations are necessary to improve the identification of an infection by additional sensors.

In Figure 5 coughing events are shown, acuired during rest and race condition of a human being by the acceleration sensor module, placed at the sternum. The signal is in no way conditioned by preprocessing and postprocessing, but it can already be seen that coughing events can easily be recorded and thus be considered for a cause-and-effect relationship related to symptoms.

Correlated Diagnosis 3 (CD-FHCO). In this scenario, a further sensor is added to enable measurement of oxygen saturation (oximetry). This can also be used as an indication of a consequence of an infection. A worse gas exchange can be detected early by this measurement as another component of the symptom space.

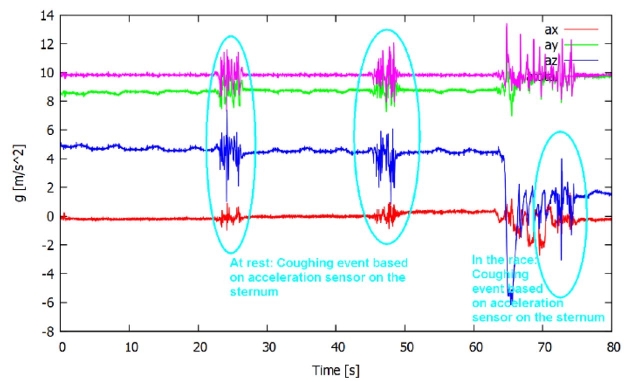
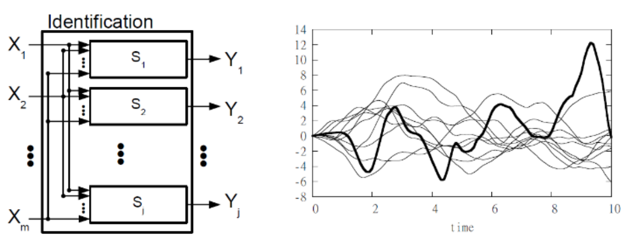


Figure 5. Coughing, acquired during rest and race condition

Air Quality 1 (AQ-CO2). The question of the infectiousness of indoor air is certainly one of the most exciting ones of all. The current state of knowledge is that the infection is not so much a smear infection but rather one caused by aerosol. By neglecting plants in a room, the CO2 concentration can be used to estimate how much air has already been exhaled by other people in the room. Of course, there is then only a risk of infection if there is an infected person among them. However, the CO2 concentration can also be used as an opportunity to ventilate the room accordingly. If you assume that there are infected persons in the room, you can make the following assumptions.

Indoor carbon dioxide comes from the exhaled air of the people who are indoors. Each person exhales about 8 litres of air per minute, which has been in intensive contact with the lung tissue there. The exhaled air therefore contains not only CO2 (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. The range of the droplets depends on their size. With aerosol sinking rates between 0.1 m/h (particle size: 1 um) and 11 m/h (particle size: 10 um) (Kiwull (2017)) and a decrease in virus-infection activity with a half-life of 2.7 hours (for SARS-CoV-2, van Doremalen et al. (2020)), the air in the room remains polluted for a longer period of time. If a healthy person breathes in these contaminated droplets and the number of virus particles contained in them exceeds a minimum infectious dose, the disease is transmitted. A detailed discussion of the airborne transmission pathways of SARS-CoV-2 can be found in Morawska and Cao (2020). Based on the model of the correlation between CO2 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 these 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.

Air Quality 2 (AQ-CO2D). The use of the CO2-sensor in scenario AQ-CO2 is characterized by a strong locality. If other CO2-sensors of other users are added via the BLE connection, or environmental CO2-sensors are used, a more differentiated picture results. This can also be achieved by distance measurement via Received Signal Strength Indication (RSSI) of the BLE-protocol.



(a) Black Box: Input and output

(b) Input and output data series output

Figure 6. Identification

Combined (CDE). This scenario combines the various sensors to correlate a large number of parameters. In the course of the identification of the individual correlations and cause-effect relationships, it will certainly be possible to set accents with regard to the primary and secondary influencing factors and thus also sensors.

4. Summary and Further Work

The flexibility of the IoT-based system is very high. Due to the interchangeability of the sensors and the flexible and easy integration of different sensors into the system, the focus can be changed and adapted to a very wide range. A major strength of the system is the integrated ability to determine correlations of the individual data series using databased identification. This problem corresponds to the situation in Figure 6(a), where a black box abstractly represents the correlation between m input signals and j output signals. This is related to the Input Sequences by functional relationships $f: \mathbb{R}^m \longrightarrow \mathbb{R}^j$:

$$f_1((x_1)_t, \dots, (x_m)_t) = (y_1)_t, t \in \mathbb{N}$$
$$\vdots$$
$$f_j((x_1)_t, \dots, (x_m)_t) = \left(y_j\right)_t, t \in \mathbb{N}$$

In Figure 6(b) an example for m=10 and j=1 is shown. The automatically found dependency is shown by the bold line, which is the result of the 10 thinly drawn lines. The identification has the objective of finding this relation, where we only know values of $(x_1)_t, \dots, (x_m)_t$ (thin lines) and $(y)_t$ (thick line) for a very limited set of $T \subset \mathbb{N}$ of time indices, which may be different for each sequence (Bohlmann et al. (2010)). Preprocessing is followed by a multi-agent-based learning strategy using evolutionary-memetic algorithms with a focus on multilevel evolutionary strategies.

In the concrete application case, the challenge is to know the initial function $(y)_t$ (thick line), which here actually means “infection”. The task is to find out whether an infection has occurred, and the corresponding correlation of all sensor data for this case is sought. Due to the protection of personal data and the fact that patient data generally require special protection, the information that an infection has occurred is not available. For this reason, a three-stage procedure is necessary here:

1. Equipping people with platform devices to cover different scenarios.
2. Interdisciplinary cooperation, in order to be able to allocate the data anonymously on the one hand, and only together with a physician on the other.
3. Verification of the predictive power of the found model in relation to an infection with COVID-19.

In any case, the use of the sensor data in the various scenarios does not provide 100% information that an infection is actually present. There will also be false alarms. However, the continuous acquisition of different sensor data can significantly improve the knowledge about the probability of an infection. Data-based methods can also help to obtain better models for the infection processes.

The further work has the following key aspects:

- Equipping the IoT-modules with a new housing that meets medical requirements.
- Ongoing tests to improve the sensor fusion and to verify additional use cases based on the platform

architecture.
- Comparison of different implementations of a local identification method ESP32-based µC-module.
- Evaluation of power consumption and optimization characteristics to optimize the mobile data fusion.

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