Health@Hand A Visual Interface for eHealth Monitoring

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Abstract—The digitization within the healthcare sector is an extensive topic for multiple ICT technologies, such as Cloud Computing, Internet of Things (IoT), and Artificial Intelligence. Over the past years, there has been an increasing interest in the storage, evaluation and visual representation of medical data. This led to a substantial amount of independent eHealth technologies, that are primarily concerned with information gathering and management. However, the multitude of existing tools makes it is difficult for the user to understand global relationships between different management systems. Therefore, we present Health@Hand an IoT system for monitoring vital and administrative data in the digital twin of an intensive care unit (ICU). The main goal of our system is to summarize and process real-time data in order to assist medical experts such as physician, head-nurses or controllers in their daily tasks. Health@Hand achieves this by providing a visual interface for the management and analysis of different medical data sources.

Index Terms—eHealth, Internet of Things (IoT), Assistive Technology (AT), sensor data analysis, visual interface, vital data monitoring, activity recognition, anomaly detection, position tracking, wearable devices

I. INTRODUCTION

The progressing digitization of the healthcare systems is advancing rapidly, so that we are now facing a variety of applications and key systems. Novel approaches such as *Telemedicing* and the *Internet of Things* (IoT) are changing the healthcare domain just like Industry 4.0 technologies are influencing the industrial domain. However, with these advancements follows a multitude of problems for the seamless integration of new eHealth technologies.

- a) Processing of Big Data: The growing amount of IoT infrastructure leads to a processing problem as multiple devices monitor the health state of a patient in relatively short time periods. The evaluation of this big data needs to be fast and consistent in order to provide immediate feedback. This is where most systems lack in performance.
- b) Interoperability of heterogeneous systems: The technological infrastructures in hospitals or care facilities are highly fragmented when it comes to technical support for health processes. New eHealth applications are challenged by technological isles, e.g. for the monitoring and storage of health records, due to a strong dependency on medical equipment manufacturers. Although, there are technical advances

such as HL7 [7] that aim to close the gap between different healthcare systems and applications, efficient work processes for medicine are still being detained by interoperability issues and missing integration [12].

c) Representation of Information: The visual representation of information is a very important aspect for the interpretation of medical data. Medical experts need to make fast decisions based on big amounts of data, which would be nearly impossible with tabular data sets. Therefore, options must be provided to assist the user in understanding the data and changes in the data.

Obviously, it is hard to satisfy all of these requirements. This is why most of the existing systems try to resolve some of the challenges separately. In this paper we present a visual approach for integrating heterogeneous health monitoring technologies in a combined presentation and operation layer on top of existing healthcare infrastructures. Our developed <code>Health@Hand</code> system represents data as well as analysis tools in a digital twin of a hospital or care facility. The goal of our application is to simplify the monitoring processes of an ICU station to detect faults or anomalies immediately and thus make it possible to intervene at an early stage.

II. STATE OF THE ART

The digitalization in the healthcare sector is primarily concerned with the storage and analysis of data. A popular example would be the exchange of laboratory values and personal record data on digital systems such as local databases and secured cloud systems. Hence, we look at both the current state of the art for data management as well as real-time monitoring in modern medical institutions.

A. Healthcare Management

The digitization of the healthcare sector started with topics such as storage and exchange of laboratory health records via digital file systems. As a result, there are clinical information systems (CIS) [20], picture archiving and communication systems (PACS) [5], radiological or laboratory information systems (RIS/LIS) [13] or electronic health record systems (EHR) [11] that are generally accepted and widely used in

health facilities today. In clinical practice, additional specialized tools are being used by these systems. The goal of these medical applications is to portrait a comprehensive picture of the reality to a domain-expert such as an physician.

B. Real-time Monitoring

Another important aspect in eHealth systems is the monitoring of real-time patient data. Chronic diseases require repeated and frequent treatment in medical facilities intensive care units (ICU) in order to maintain stable vital parameters [14]. In hospitals, this is usually done by attaching sensors of a stationary machine to the patient in order to assess various signals. However, less critical health states are already observed with mobile blood pressure monitors [1] and mobile ECG devices [4]. This offers the patients more freedom as data can be captured during their daily routines without the need of in-patient observation.

Today with Health 4.0, there are several devices available for the gathering and evaluation of data, such as smartphone, smartwatches or even smartpatches. These wearable devices either use their internal sensors to measure and store individual patient data, or use connected external sensors, respectively. The rich sensor technology simplifies the situation and activity recognition, and enables therefore the detection of different health conditions. Furthermore, there are novel approaches towards wireless body area networks (WBAN) that combine wireless communication technologies and miniature size wearable sensors in order to maximize the energy-efficiency of wearable devices [18].

III. HEALTH@HAND

Our *Health@Hand* system engages the previously mentioned challenges by providing a visual interface for the supervision of ICUs. It includes solutions for data storage and linking as well as representation of medical information.

A. Data Model

The *Health@Hand* data model is structured similarly to the *Plant@Hand* framework [2], which is used for the monitoring of manufacturing data. We chose this framework for the integration of medical data management systems, because it offers a wide accessibility for databases, web services and local file systems. Our data model is based on four major components described in the following section (and illustrated in figure 1).

We define the previously mentioned medical data management systems, such as PACS [5], LIS [17], and EHR [11] as so called *data storage systems*. These systems are the foundation for the subsequent processing of medical data, as they are used within *Health@Hand* to create different self-defined data sources.

A *data source* is thereby a set of elements that are extracted from the underlying storage systems. For example, the data source for the patients vital data includes elements such as pulse, blood pressure, heart rate variability, and respiration rate. This display can be enriched by switching to data

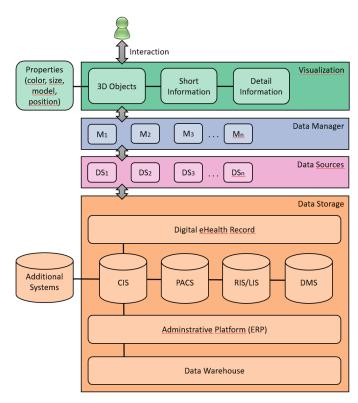


Fig. 1. Structure of the *Health@Hand* Model, which connects popular medical data storages with a visualization. Information is either shown as *short information*, *detailed information*, or implicit as overview information in a 3D model of the ICU.

sources that visualize multiple interfering factors such as the temperature, humidity, or noise level in the room.

Each of these *elements* is regarded as a modular component that contains information of the corresponding 3D objects in the scene. The connection between the data sources and the 3D objects is established by a so-called *data manager* that uses unique identifiers to match the data with the corresponding upper layer visualization. This data manager can thereby use single or multiple data sources for the computation and representation of information.

B. View Model

The visualization for <code>Health@Hand</code> uses the underlying data model illustrated in figure 2 to gather and provide information in the 3D model of the ICU. This digital twin contains <code>3D objects</code> which represent rooms, patients, staff, and inventory, each at their current position. The conceptual approach for this was introduced by Alm et al. [3]. The data behind these 3D objects is displayed as either short information or detailed information. The <code>data source</code> can be changed by interacting with the <code>data manager</code>, which is accessed over the main menu at the bottom of the screen.

The **short information** is displayed in smaller panels which are located next to the corresponding element. We use color coding for each panel to emphasize health states for the shown values. Furthermore we apply semantic zooming [6] as an interaction technique, so that the user can hide irrelevant

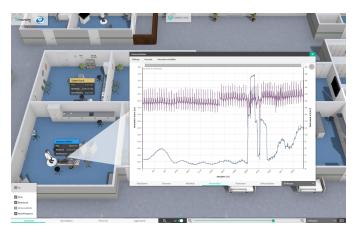


Fig. 2. Visualization of the *Health@Hand* tool, where *short information* are shown over the patient beds, while *detail information* can by displayed in advance.

information in the billboards without losing the context due to the color coding scale. It is also possible to hide or show additional information over the selection menu.

The **detailed information** is accessed by interacting with the short information panel. The detail information window can thereby contain more information on the patient or specialized tools. We currently use the following tools for the analysis of patient data:

- The *eHealth Record Browser* provides a digital copy of the patients personal record data. This data includes values like name, age, gender, weight and height.
- The *Image Viewer* supports the analysis of imaging techniques by providing a view that either shows images or visualization tools for clinical findings.
- The *Shimmer Monitor* presents an overview on the patients activity data in a superimposed bar chart that is based on a certain time interval.
- The *Vital Data (VD) Dashboard* visualizes all vital parameters such as pulse, blood pressure, heart rate variability, respiratory rate, blood sugar or oxygen saturation.
- The Cardio Anomaly (CA) Detector offers a function that calculates an anomaly factor based on the patients vital data. Afterwards, the view can be switched to a scatter plot diagram of the heart rate and heart rate variability in order to identify outliers.

The presented tools can either be used *independently* or *combined* in a coordinated workflow based on lightweight coordination [16]. This is especially interesting for repetitive examinations. A representation of this workflow-oriented interoperability is showing in figure 3, where a selection in the shimmer monitor induces a linked selection in the VD Dashboard.

IV. INFORMATION GATHERING

We already discussed that we want to integrate digital records, clinical findings and real-time vital and activity data from the existing data storages and stationary ICUs. However, we have also shown that it is possible to use additional

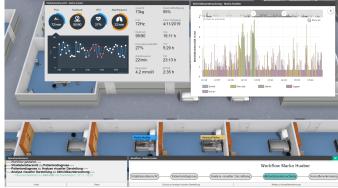


Fig. 3. Visualization of the workflow-oriented data analysis, where an analytical process is structured according to different workflow steps (shown at the bottom right) and executed in order to find cardiovascular anomalies. The data is linked between the *Shimmer Monitor* (shown at the top right) and the *VD Dashboard* (shown at the top left) by using Brushing & Linking mechanisms.

sensing devices such as wearables to gather information for medical equipment, staff and patients. These devices can be connected to a cloud-based repository to feed data into the aforementioned tools (e.g., in order to identify cardiac anomalies in patient data or analyze patients activity). For now we focused on *activity recognition*, *anomaly detection* and *position tracking*.

A. Activity Recognition

Data that is visualized within the *Shimmer Monitor*, is recorded with wearable inertial sensors. The recorded raw data is then passed through an activity recognition chain. Within the recognition chain, subsequent steps such as 1) pre-processing (e.g., de-trending, filtering) 2) segmentation 3) feature extraction and 4) classification are performed. In previous work, we analyzed the recognition of activities of daily living, by attaching several wearable sensors to the human body: 1) wrist-worn smartwatch; 2) smartphone in trousers pocket; 3) head-worn smartglasses [10]. The resulting system recognizes 7 tasks (resting, being active, walking, running, jumping, cycling, office work) with a recognition rate of 86.13%.

B. Anomaly Detection

Anomalies such as cardiac diseases (e.g., atrial fibrillation), can be identified by applying anomaly detection tools. The aforementioned *Cardio Anomaly Detector* serves this purpose. The tool applies Long-short Term Memory (LSTM) Neural Networks to compute anomaly scores for anomalous sections within the recorded raw data. The scored data is afterwards classified with a J48 decision tree. In previous work, we discussed opportunities of wrist worn sensing devices in the context of anomaly detection [8], [9], [19]. The proposed use cases for the smartwatch-based anomaly detection included the recognition of sleep apnea, epileptic seizures, fall, stress level and cardiac anomalies.

C. Position Tracking

In order to provide a fast intervention, it is necessary to know the position of staff and medical equipment like anesthesia machines, c-arm x-ray devices, or ward physicians etc. Furthermore, material flow and automated device identification optimize processes. Current tracking solutions are based on optical or radio frequency identification techniques [15]. Very common are Bluetooth low energy (BLE) beacons [21] that are small (size of a coin), long lasting (battery lifetime 2-7 years) and provide a high accuracy for the positioning within a room. The visualization of the localized items is an important part of <code>Health@Hand</code>. The staff and medical equipment are displayed at the current location and the observer can track the position change over time.

V. CONCLUSION

The digitization of the healthcare sector is a multi-layered subject that needs new ICT technologies. Our <code>Health@Hand</code> offers different approaches for healthcare management and data monitoring to support this tasks with multiple IoT devices. <code>Health@Hand</code> uses different tools to cross-check the vital and administrative data in the digital twin of an existing ICU ward. Although we support the integration of multiple sensors and data sources, there are still limitations due to different coding standards. The automatic integration of tools is only done for web services. Other tools need to be integrated manually. Furthermore, we are still missing a cooperation partner to evaluate the performance our system in a real hospital scenario.

In the future, we want to use the possibilities of artificial intelligence and deep neural networks for an anomaly detection algorithm based on the patients vital data. We hope that this will improve the recognition of unknown clinical states in order to find new solutions in the medical field. Moreover, we want to provide more detail information about the work schedule or responsibilities of the staff, the cleaning or disinfection logs of the rooms and the medication ingestion or equipment usage for the inventory.

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