Data Reliability in Home Healthcare Services

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Abstract

Home healthcare services are emerging as a new frontier in healthcare practices. Data reliability, however, is crucial for the acceptance of these new services. This work presents a semi-automated system to evaluate the quality of medical measurements taken by patients. The system relies on data qualifiers to evaluate various quality aspects of measurements. The overall quality of measurements is determined on the basis of these qualifiers enhanced with a troubleshooting mechanism. Namely, the troubleshooting mechanism guides healthcare professionals in the investigation of the root causes of low quality values.

1 Introduction

Recent advances of ICT had a major impact on the healthcare domain, especially on the home healthcare services [5]. These innovations, however, introduce several security issues, whose resolution is fundamental for the acceptance of the new services. One of the most critical issues is the trust that end-users, both patients and healthcare professionals, have in such services. In particular, data reliability and more precisely the quality of medical measurements is of utmost importance for building trust.

In home healthcare systems, patients are remotely monitored at home using a variety of small mobile and wearable devices. In particular, patients may be required to take medical measurements such as their blood pressure. These measurements are used by healthcare practitioners to evaluate patients' health condition and therefore as the basis for necessary advice such as changes in the treatment scheme. Thus, healthcare providers have to rely on the measurements taken by the patients in order to evaluate their health condition and decide the appropriate treatment.

Decision support systems have been proposed to assist healthcare professionals in evaluating the quality of patient measurements. Existing solutions evaluate the quality of measurements based either on the reputation of patients or on data qualifiers. Both approaches, however, are not satisfactory. Approaches based on reputation are very subjective. They assume that a patient with high reputation always provides high quality measurements. On the other hand, data qualifiers are used to evaluate a number of quality aspects of measurements related, for instance, to device accuracy and timeliness of measurements. However, these aspects are usually analyzed individually and thus they do not provide an insight of the overall quality. Moreover, data qualifiers may not have a unique interpretation. In particular, low quality indications can be also caused by the deterioration of patients' condition. An automated decision support system may misinterpret the reasons of low quality indications, leading to incorrect decisions.

This work presents a semi-automated approach for assessing the quality of medical measurements. The proposed system uses a number of data qualifiers to evaluate quality aspects of measurements. To evaluate data qualifiers and determine the overall quality, a troubleshooting mechanism is employed. In particular, the troubleshooting uses a set of rules to identify the root causes of low quality indications and reason on the overall data quality. To improve the quality of measurements and therefore of the provided service, the system gives patients advice on how to provide better measurements based on the identified root causes. We demonstrate our approach using the system designed by Roessingh Research and Development for the gathering of activity data [1] as an illustrative example.

2 Approach

In this section, we present an architecture for the evaluation of the reliability of patients' measurements in home healthcare services. The architecture (Fig. 1) consists of four components: *data qualifier*, *quality indicator*, *troubleshooting mechanism*, and *feedback system*.

Patients receiving home healthcare services usually take medical measurements by themselves at home. The collected measurements are used by healthcare professionals to evaluate their health condition. To assess the quality of

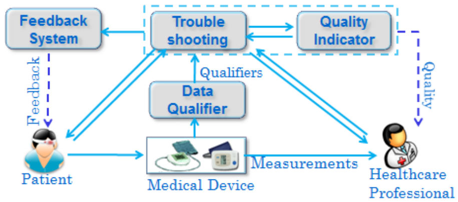


Figure 1. System architecture

the received data and therefore to decide whether healthcare professionals can rely on them, measurements are checked through the data qualifier component. This component employs *data qualifiers* to evaluate different aspects of a measurement's quality (e.g., stability, timeliness of data).

To assess the overall quality of measurements, data qualifiers are aggregated. However, aggregation is a complex task as qualifiers might differ in their nature. For instance, device and time specific qualifiers evaluate different aspects of a measurement and thus they cannot be quantified in the same manner. The aggregation is performed by the quality indicator component using a rule-based approach. In particular, rules capture the relationship between the qualifiers and their influence on the overall quality of measurements.

The aggregation process, however, cannot be fully automated. A patient may provide unstable measurements due to the deterioration of her health condition, which can be characterized as low quality by data qualifiers. To discriminate these situations, the root causes of low quality indications are identified through the troubleshooting mechanism. In particular, this mechanism interacts with patients and/or healthcare professionals to evaluate the data qualifiers for a measurement and thus determine its overall quality.

The last component of the architecture is the feedback system which aims to improve the quality of the provided service. This component provides advice to patients based on the evaluation of the submitted measurements.

In the remainder of the paper, we demonstrate the approach using the system developed by Roessingh Research and Development (R&D) as an illustrative example.

Example 1 *Roessingh R&D has developed the Continuous Care & Coaching Platform (C3PO) [1], a remote monitoring and treatment platform for assisting elderly and patients with chronic disorders. The platform monitors patient activity and provides advice on how to improve their activity behavior. Patients are equipped with a sensor that captures patient movements. Raw activity data are processed and aggregated to form activity measurements. Activity measurements are sent to the C3PO central server along with a timestamp indicating the time at which data have been collected. Based on the collected data, C3PO evaluates patients' activity throughout different phases of the day (morning, afternoon and evening) and provides them feedback.*

ID	Description	Source
Q1	**Stability**	
Q1.A	*Range Check* indicates whether data are within the logical bounds defined by the type of measurement.	[2, 3]
Q1.B	*Expected Value* measures the distance of a measurement from the expected value.	[3]
Q1.C	*Variance* measures the statistical variation of a series of measurements.	[2]
Q2	**Data Timeliness**	
Q2.A	*Freshness* measures how recent the measurement is.	[2]
Q2.B	*Timing* measures the difference between the time at which the data were taken and the time at which they should have been taken according to the treatment plan.	[3]
Q3	**Device Accuracy**	
Q3.A	*Precision* measures the detail in which a measurement is expressed.	[3, 4]
Q3.B	*Conformance with Standards* indicates the standards (e.g., ISO/IEEE 11073) which the device specifications and measurements comply with.	[4]
Q3.C	*Device Calibration* measures the time lapsed since the last calibration.	[3, 4]
Q3.D	*Power Supply* indicates the level of electrical power supply at the time the measurement was taken.	[4]
Q3.E	*Age* measures the age of the sensor.	[3]
Q4	**Sensor Application** measures to what extent a device or a sensor is correctly applied.	[3, 4]
Q5	**Data Authenticity** evaluates the authentication mechanisms adopted to guarantee data provenance.	[2, 3]
Q6	**Fault Checks** evaluates the mechanisms employed to ensure data integrity.	[2, 3, 4]

Table 1. Data Qualifiers

3 Data Qualifiers

Different issues may affect a measurement's quality: for instance, a device malfunction or an error during data transmission can lower the quality of data and, therefore, decrease the reliability of measurements. We have identified a number of data qualifiers for assessing data reliability (Table 1). It is worth noting that these qualifiers intend to be general. The actual qualifiers to be used to assess the quality of a measurement depend on its type, the device used to collect it, and the treatment scheme followed by the patient.

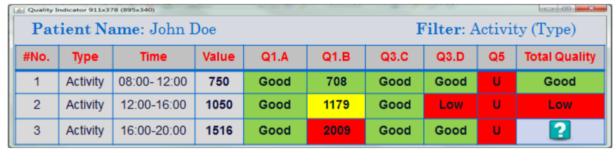
The first group of qualifiers in Table 1 captures aspects related to the stability of measurements (*Q1*). For instance, *Q1.B* compares the value of the measurement against the expected value. Timeliness is also an important aspect of data quality. For instance, diabetic patients determine their insulin dose by measuring their glucose level. If the glucose level is high, the insulin dose has to be increased. However, the level of glucose in the blood changes frequently over time. Therefore, the measurement should be fresh to be used to determine the current insulin dose. Time aspects are captured by the qualifiers that belong to *Q2*.

Device accuracy qualifiers (*Q3*) are used to measure aspects of the device that may affect the closeness of measurements to the true value. In particular, the device should support the technical characteristics needed to capture the measurements defined in the treatment. Device maintenance should be also evaluated to assess the quality of measurements. For instance, devices can malfunction if they operate under abnormal power supply such as exhausted batteries. This aspect is measured by *Q3.D*.

The quality of measurements may be also affected by other aspects such as sensor application (*Q4*), data authenticity (*Q5*), and fault check (*Q6*). For instance, a blood pressure measurement device has to be placed at the patient's arm according to device specifications. As the distance from the defined place increases, the accuracy of measurements may decrease. Moreover, patients should be properly authenticated to assure the provenance of measurements. Different authentication methods provide different level of authentication and reliability. *Q5* is used to measure the level of authentication provided by the device based on existing taxonomies of authentication methods. Similarly, *Q6* employs existing taxonomies of fault checking methods to measure the level of integrity provided by the device and network infrastructure.

Example 2 *To evaluate the quality of activity measurements, a subset of the qualifiers presented in Table 1 can be used. For instance, the activity that can be performed (and recorded) in a given time interval is limited by physical constraints. This quality aspect is captured using qualifier Q1.A which verifies whether raw data are within a defined logical bound. In addition, C3PO evaluates the quality of data against a predefined reference value which is based on the treatment prescribed to the patient. This quality aspect is captured by Q1.B. Device characteristics that are affected by usage such as calibration (Q3.C) and power supply (Q3.D) are also considered for the evaluation of the data quality. In contrast, the age of the sensor (Q3.E) is less significant in the application scenario due to the fact that devices are directly distributed to patients by the hospital. Data authenticity (Q5) has also an impact on the reliability of data due to the nature of the mobile device. In particular, the sensor do not support any authentication mechanism: data authenticity is assumed by possession of the device.*

Data qualifiers indicate which aspects are relevant for assessing the quality of a given measurement. To determine the actual quality of a measurement based on those qualifiers, we introduce the notion of *quality level* for data qualifiers. The quality level measures the quality of a measurement with respect to a given data qualifier on the basis of thresholds. Intuitively, thresholds define boundaries for data quality. It is worth noting that thresholds depend on the type of measurement as well as on the patient and his health condition. For instance, the acceptable time difference (*Q2.B*) of a blood pressure measurement differs from a patient performing a routine check and a patient suffering from hypertension.


Quality Indicator 911x378 (895x340)

Patient Name: John Doe — Filter: Activity (Type)

#No.	Type	Time	Value	Q1.A	Q1.B	Q3.C	Q3.D	Q5	Total Quality
1	Activity	08:00- 12:00	750	Good	708	Good	Good	U	Good
2	Activity	12:00-16:00	1050	Good	1179	Good	Low	U	Low
3	Activity	16:00-20:00	1516	Good	2009	Good	Good	U	?

Figure 2. Data qualifier component

Example 3 *An application of the data qualifiers is shown in Fig. 2. A patient's activity measurements are presented along with the used qualifiers. Each measurement is represented by a row in the table. Each column provides information about the measurement. For example, the second column shows the type of the measurement (e.g., blood pressure, activity); the third represents the time of the day (morning, afternoon or evening) in which the measurement have been collected; and the fourth contains the overall activity value for the specified time frame expressed in IMA (i.e.,* $counts \times min^{-1}$*). Others columns specify the level for each qualifier and for the overall quality of the measurement. The quality level can be either high (green), medium (yellow) or low (red) depending on the defined threshold.*

4 Data Qualifier Aggregation and Feedback

To evaluate the impact of the data qualifiers on the overall quality of measurements, we propose a troubleshooting mechanism. In particular, the troubleshooting aims to investigate the root causes of poor data quality indications. To this end, we classify qualifiers in three categories. The first category includes qualifiers that have a unique interpretation and directly affect the overall quality. In particular, a measurement with a low value on one of these qualifiers is considered unreliable. This category includes data timeliness (*Q2*) and sensor application (*Q4*) as well as device calibration (*Q3.C*) and power supply (*Q3.D*). The second category includes qualifiers for which low quality indications do not have a unique interpretation. Indeed, they may reflect the actual quality of data due to malfunction or improper use of the device, or can indicate a deterioration of patient health condition. Stability qualifiers (*Q1*) belong to this category. The third category includes qualifiers that, although have a unique interpretation, are not sufficient to determine the overall quality of measurements. Data authenticity (*Q5*) and fault check (*Q6*) as well as some device accuracy qualifiers like precision (*Q3.A*), conformance with standards (*Q3.B*) and age (*Q3.E*) belong to this category.

The evaluation of data quality is based on the prioritization of qualifiers with respect to their classification and quality level. Intuitively, qualifiers providing direct evidences of the overall quality have priority over the other qualifiers. In addition, the evaluation goes from low to high quality indications. Accordingly, the evaluation procedure starts by analyzing the qualifiers in the first category. If any

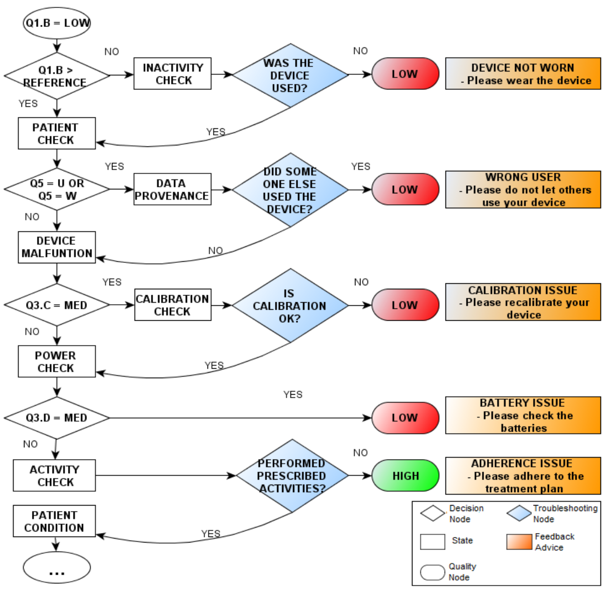


Figure 3. Troubleshooting workflow for *Q1.B*

of these qualifiers indicates low quality, the overall quality is low. Otherwise, if these qualifiers indicate medium or high quality, the qualifiers in the second category are analyzed. If a qualifier in this category indicates low quality, the troubleshooting mechanism is triggered. The troubleshooting mechanism consists of a set of rules for investigating the root causes of the poor data quality indications. These rules examine the status of second category qualifiers in conjunction with the qualifiers of the other categories. The latter qualifiers are used to identify the exact causes of poor data quality indications by suggesting predefined questions. The raised issues should be investigated with the patient to determine the actual data quality. The steps above are then repeated to analyze medium quality indications. Finally, if all qualifiers in the first and second category are high, the overall quality level is high. Notice that the qualifiers in the third category do not have a direct impact on the quality of measurements and thus they are only used to assist the troubleshooting.

We represent the troubleshooting mechanism as a set of workflows. In particular, a workflow is defined for each qualifier in the second class relevant to the measurement. An example of troubleshooting workflow is shown in Fig. 3. Processing steps are represented as rectangles. Decision nodes are represented as diamonds. In particular, light blue diamond nodes denote troubleshooting questions. Finally, oval nodes represent start nodes and end nodes. End nodes indicate the overall quality level.

Example 4 *The last column of Fig. 2 presents the overall quality of the activity data in Example 3. The evaluation of the first two measurements is straightforward: the data qualifiers for the first measurement are all high except for one in the third category (Q5); the quality of the second measurement is low because the level of a qualifier in the first category (Q3.D) is low. The third measurement triggers the troubleshooting mechanism. This is because all data qualifiers in the first category are high and a qualifier in the second category (Q1.B) is low. To identify the root causes of low quality indications for activity data, we have defined together with practitioners at Roessingh Hospital a set of rules that form the troubleshooting. Rules have been prioritized with respect to their likelihood. An except of these rules is presented in form of workflow in Fig. 3.*

To improve the reliability of future measurements, patients should take into account the issues with previous low quality measurements. To this end, the feedback system advises patients on how to improve their measurements based on the quality of the submitted measurements. In particular, the feedback contains an advice related to the root causes of low quality indications found by the data qualifier aggregation (orange rectangles in Fig. 3).

5 Conclusions

This paper presents a solution for evaluating data reliability in home healthcare services. The approach employs a number of data qualifiers to capture different quality aspects of a measurement. The overall quality of measurements is assessed using a semi-automated mechanism based on troubleshooting. This mechanism relies on workflows to determine the root causes of low quality indications for data qualifiers. Finally, a feedback mechanism is proposed to help patients improve their future measurements.

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References

[1] H. op den Akker et al. Development and Evaluation of a Sensor-Based System for Remote Monitoring and Treatment of Chronic Diseases - The Continuous Care & Coaching Platform. In *EHST*, 2012.

[2] M. Petkovic. Remote patient monitoring: Information reliability challenges. In *TELSIKS*, pages 295–301. IEEE, 2009.

[3] M. Shin. Secure remote health monitoring with unreliable mobile devices. *J Biomed. Biotechnol.*, 2012, 2012.

[4] J. Sriram, M. Shin, D. Kotz, A. Rajan, M. Sastry, and M. Yarvis. Challenges in data quality assurance in pervasive health monitoring systems. In *Future of Trust in Computing*, pages 129–142. Springer, 2009.

[5] S. Vavilis, M. Petkovic, and N. Zannone. Impact of ICT on home healthcare. In *ICT Critical Infrastructures and Society*, IFIP Advances in Information and Communication Technology 386, pages 111–122. Springer, 2012.