

The data exchange between smart glasses and healthcare information systems using the HL7 FHIR standard

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Abstract—In this study we evaluated system architecture for the use of smart glasses as a viewer of information, as a source of medical data (vital sign measurements: temperature, pulse rate, and respiration rate), and as a filter of healthcare information. All activities were based on patient/device identification procedures using graphical markers or features based on visual appearance. The architecture and particular use cases were implemented and verified using smart glasses prototypes developed under the eGlasses project and using a reference Health Level 7 Fast Healthcare Interoperability Resources (HL7 FHIR) server. The results show that information about the identified patient can be quickly retrieved from FHIR servers and annotated using voice recognition services. Smart glasses can be used in the measurement of vital signs of the observed patient, providing values of body temperature, pulse rate, and respiration rate by means of non-contact measurements. Such measurements are sufficiently reliable for medical screening and for fast data exchange using HL7 FHIR actions.

Keywords—*smart glasses; face recognition; object recognition; human-computer interaction*

I. INTRODUCTION

In many countries physicians, health care providers and other health care professionals are using smartphones and tablets in their work [1]. According to the *mhealthshare* reports [2] the global revenue projection for m-health applications in 2017 is about \$27 billion. In the USA the professional usage of mobile devices is very high and therefore there are special guidelines considering the use of mobile devices and health information privacy and security [3], especially related to the HIPAA standard [4].

Smart glasses are mobile, wearable devices that can provide valuable information to the user extending human senses and capabilities of information processing. Typically, the near-to-eye display could be used to present graphical information. Such method of information presentation is more confidential than those used for tablets or smartphones. Smart glasses can be equipped with different sensors, communication interfaces, etc. For example, a visible light camera is typically used for image/video recording. In recent years, many devices have been proposed, including Google Glass, Epson Moverio BT-200, Recon Jet, Lumus DK-40, etc. [5]. Many demonstrations of potential roles of smart glasses in

healthcare were presented. For example, Evena Medical introduced a modification of smart glasses to identify veins in a patient's body and to provide the assistance for a nurse e.g. at the time of sample collection or for injections. Short wave IR illumination is used to visualize the internal structure of the skin [6]. Beth Israel has integrated Google Glass locating QR code on the doorway to each emergency patient's room. Using dedicated software Google Glass can retrieve patient ID from the QR code and can instantly call up a patient's electronic medical record [7]. In [8] Philips "simulated the first proof of concept for the seamless transfer of patient vital signs into Google Glass".

In this paper we will focus on the possible role that smart glasses can play in interaction with health information systems (e.g. with a Hospital Information System - HIS). We limited our research to three types of roles of smart glasses:

- smart glasses as a viewer of information (e.g. request information from a healthcare information system),
- smart glasses as a source of information (e.g. vital sign measurements with smart glasses sensors),
- and smart glasses as a filter of healthcare information (e.g. select information from a medical device and add interpretations).

In the presented study prototypes of smart glasses developed under the eGlasses project were used (www.eglasses.eu).

Additionally, we consider the application of the automatic identification of patients and/or devices (e.g. connected to a patient) using either the recognition of graphical markers or the recognition of features based on visual appearance of a person or a device. Using the identifier of the patient or the device, smart glasses can retrieve or add information to the healthcare information system. In this research we analyze the use of HL7 Fast Healthcare Interoperability Resources (FHIR) Specification [9] for medical data exchange. The HL7 FHIR has been recognized as a very promising draft standard for medical data exchange also for mobile applications [10]. The use of RESTful services in mobile processing is especially interesting for Mobile Health Document Sharing [11], Management of Patient IDs, etc.

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The proposed architecture was implemented and tested using prototypes of eGlasses smart glasses platform and using the HAPI-FHIR server hosted by University Health Network (<http://fhirtest.uhn.ca>). This server provides a nearly complete implementation of the FHIR Specification.

The contributions of this paper are as follows:

1. we proposed the design of the system architecture using smart glasses as a node for exchange of medical data using FHIR standard
2. we proposed the use of smart glasses for the estimation of vital signs of the observed patient and describing them using the FHIR notation
3. we proposed a method for interaction between smart glasses and a medical device for simple annotation of medical data represented in the FHIR format

The rest of the paper is structured as follows: Section II presents the proposed system architecture and describes the methodology including experiments. Implementation of the proposed methods is shown in Section III. Results are described in Section IV. Section V presents a discussion of results and concludes the paper.

II. METHODS

We propose the simple system architecture for interaction of smart glasses with healthcare information systems based on the identification of patients or devices. In such architecture smart glasses can show data from information systems or from medical devices, can provide information about a patient to information systems, or can filter information from available sources.

A. The architecture of the system

The system architecture for the proposed interaction methods is based on the multi-tier model (Fig. 1a).

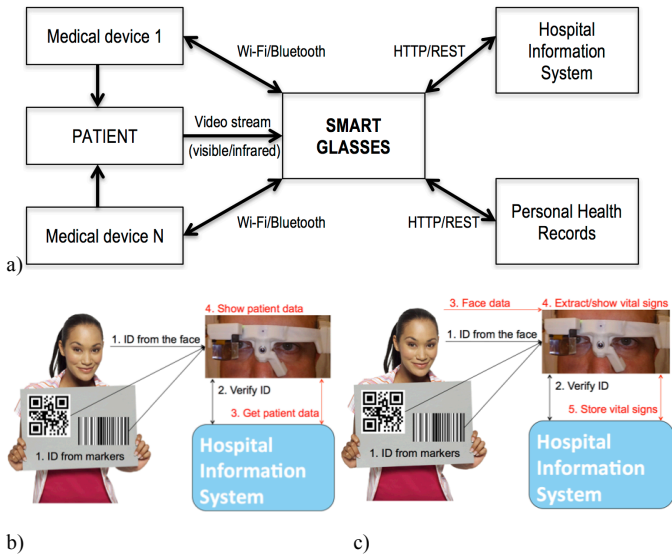


Fig. 1. Interaction of smart glasses with the HIS: a) general architecture of the system, b) retrieval of information about the identified patient, c) vital signs measurements with the updating of the HIS data.

In the first scenario smart glasses are located in the middle between a patient and a healthcare information system (e.g. Hospital Information System, HIS). In this scenario smart glasses are used to identify a patient (i.e. to obtain a patient's identifier, PID) and to manage his or her medical data. We assume that the identification process can use either the recognition of graphical markers (e.g. QR-codes, bar codes printed on the hospital wrist-strap) or face recognition. When the patient is positively identified smart glasses can: provide information from the connected HIS (Fig. 1b) or can be a source of information for the HIS (Fig. 1c). In the second scenario smart glasses are a middle-tier between a medical device, which is connected to a patient, and the connected HIS. It is assumed that the identified device is connected to the identified patient and information about this association is stored in a server (e.g. in the HIS). In this scenario smart glasses provide means for the identification of devices (using graphical markers or features based on visual appearance). It is additionally assumed that when the device is positively identified then it is possible to download information about the device. Using this information smart glasses can connect to the device and execute available actions. For example, it can be assumed that a medical device securely provides information about actual and previous measurements (observations). In both scenarios different security mechanisms should be introduced, but we do not analyze them in this paper. We further propose to use the HL7 FHIR Specification for data representation and data exchange between nodes of such multi-tier system. In the analyzed scenarios FHIR RESTful resources are used describing a Patient, a Device, or an Observation. When the identifier of a patient or a device is recognized it can be used to read information from the HIS/FHIR server using the HTTP GET method. Smart glasses can parse the retrieved JSON or XML message and present chosen information on the near-to-eye display. If smart glasses are used as a source of medical data, such data can be presented on the near-to-eye display (Fig. 2b) and can be additionally exported as the Observation resource to the FHIR-compatible HIS. Smart glasses can also filter any (Patient, Device, Observation) resource to update it with new properties (e.g. adding the interpretation information).



Fig. 2. a) Interaction of smart glasses with a HIS using data from the identified medical device connected to the patient (simulated hospital environment). b) An example of possible data presentation on the near-to-eye display of the smart glasses

B. Identification of subjects and objects

Using smart glasses different methods of the identification of patients or devices can be proposed using markers or patient-based features (e.g. face features). We previously performed experiments related to recognition efficiency of graphical markers using Android-based smart glasses (e.g.

Google Glass, eGlasses) [12][13][14]. Results of those studies were used in this research. To improve the code detection we additionally use the camera zoom (2x/4x) to crop the marker image for better recognition effects. Additionally, the identification of subjects (and objects) based on visual appearance was used as described in [15][16][17]. Regardless of the method of the recognition of an entity the proposed identification method assumes two phases. In the first phase (described above) the identifier of the patient or the device is obtained using the recognition of either graphical markers or features based on visual appearance. However, the accuracy of such methods is usually limited and some false values of identifiers could appear. Therefore, in the second phase, the recognized identifier is used to query the HIS for information about the entity. Such information is presented to the user of smart glasses for the final confirmation (e.g. asking about personal data, etc.). When the identity of the entity is confirmed the next actions can be performed.

C. Smart glasses as a source of information

In this paper we would like to focus on the analysis of the potential use of smart glasses for the estimation of vital signs (e.g. for screening tests). Vital signs are measurements of the body's most fundamental functions. The typical vital signs include: body temperature, pulse rate, and respiration rate. Smart glasses can use different sensors to measure or estimate these vital signs (for the observed person and for the wearer). Here, we assume that body temperature can be measured using infrared sensors (thermometers) and pulse rate can be estimated using videoplethysmography based on video acquisition of face images with a visible light camera. Additionally, respiration rate can be estimated using analysis of thermal image sequences from the nostrils region of a face.

Body temperature

Body temperature could be estimated measuring the temperature of the skin on the forehead. The remote temperature measurements using infrared radiation have been found reliable and enough accurate for medical diagnostics [18]. In this study we used the OMRON D6T thermal sensor embedded in the frame of the smart glasses and additionally two different PIR handheld devices: Tech-Med Infrared Thermoscope TM-F03B (accuracy $\pm 0.2C$) and Microlife IFR 100 (accuracy $\pm 0.2C$). As a reference the Kardioline KL-50 thermometer was used (accuracy $\pm 0.1C$). The D6T sensor was initially calibrated using a reference object with known temperature and the offset value was calculated. This is a very simple procedure and in the future it requires much better solution. However, the goal of this activity was to investigate if measurements performed using the remote D6T sensor are related to measurements obtained using two infrared thermometers. Similar differences should be obtained between temperature values measured using infrared thermometers (forehead) and using the reference thermometer measuring body temperature under the armpit. Each measurement was repeated (after a short break) and results were averaged.

Pulse rate

It was shown by Poh, et al. [19] that pulse rate could be reliable estimated using videoplethysmography. In [20] we

also shown that using fast PCA method applied for the filtered signals obtained from a web camera the pulse rate can be estimated fast enough to implement the method in mobile devices. Such method requires a small delay related to the measurement of at least 3-5 evolution of the heart to reliable estimate the pulse rate value. During the acquisition, a series of images in visible light were collected with sampling frequency from 15Hz to 25Hz. Collected images were acquired directly in YUV color mode and, based on our previous studies, we chose only V frames for further processing. For each frame average values were calculated for the face ROI and for the forehead ROI. The procedure was repeated for each frame producing a digital signal for each ROI. Data were analyzed in short time windows, i.e. up to 20s. Each digital signal was then filtered using band pass filter between 0.67Hz and 4Hz. Next 3 pulse rate estimators ("ePR") were used: ePR_{sp} – frequency value for the dominating peak in the frequency domain, ePR_{ac} – periodicity of peaks locations for the autocorrelation function in the time domain as a function of time lags, ePR_{pk} – number of peaks in the time domain.

For the ePR_{ac} estimator the autocorrelation for different time lags is calculated and the period is determined calculating an average time differences between detected peaks. Another pulse rate estimator was based on the number of peaks in the filtered signal and it estimates the frequency as:

$$f_{PK} = \left(nPK_i(\bar{s}_{fn}(t)) - 1 \right) * \frac{fs}{N_i} \quad (1)$$

where: nPK_i – number of inspiration peaks, N_i – the total number of samples between the first detected peak and the last one. The calculated frequencies were multiplied by 60 to obtain results in beats per minute (bpm , e.g. $ePR_{ac} = f_{pk} * 60$).

Respiration rate

Using smart glasses, respiration rate is estimated based on the continuous measurement of frames from the thermal camera (TAMARISK 320) taken from the nostrils region (camera at a distance 0.4-0.7m). It was assumed, that measurements take place in the controllable environment, where ambient temperature is at least 5 degrees different than the body temperature. In this preliminary study it was also assumed that the subject is not moving (except small rotation movement up to 2 degrees). The multistep procedure is used for the estimation of respiration rate parameters. First, a sequence of frames was captured during the short time period (e.g. 30s windows were used in this experiments). Next, in this preliminary study, the data source region (a rectangle with width = nose width) was manually selected directly around nostrils. The selected ROI was used to calculate the average pixel value inside the ROI. The average value was calculated for each frame. As a result a 1-D signal (time series) was constructed. Time series was filtered using the low pass filter (moving average) and using the 4th order Butterworth high pass filter to eliminate the baseline drift ($f_c=0.1Hz$). Next the respiration rate was estimated using the same estimators (e.g. $ePR_{sp} \rightarrow eRR_{sp}$) as used for pulse rate. The pressure belt (Vernier RMB) was used as a reference to compare respiration signals and respiration rate estimators.

Estimation of vital signs (temperature, pulse rate, and respiration rate) was verified during experiment with the participation of 11 volunteers (mean age: $39.73y \pm 11.98$).

D. Smart glasses as a filter of information

When the patient and the connected device are identified the health professional can retrieve information about the patient from the HIS and from the connected device. Here, we assumed that simple observations (e.g. pulse rate) are presented to the smart glasses user. The user can review them and can add notes as the interpretation. The interpretation can be provided in a structured form (e.g. L - "below low normal" using a chosen coding system) or using free text. When the first form is used the available codes should be provided on the display (e.g. as a scrollable list). The user should be able to use the code and confirm it. It is much more problematic to use free text as it is difficult (and not functional) to use a keyboard for text entry in smart glasses. However, speech to text interface can be used as it was already used for the Google Glass applications (e.g. in [21]). In our study we used Android speech recognizer API. The interpretation is added as a part of the Observation Resource in the HL7 FHIR message.

III. IMPLEMENTATION

Under the eGlasses project (www.eglasses.eu) we have been developing the smart glasses platform to provide an open, experimental platform that researchers and developers can change some electronics, print another cover using 3D printer, add sensors or electrodes, change the display, etc. The current prototype uses OMAP 4460 processor with 1GB RAM, 1024x768 transparent display from Elvision Company, 5MPx camera, WiFi and Bluetooth 4 wireless interfaces, different sensors (accelerometer, gyroscope, magnetometer, OMRON D6T thermal sensor, etc.) and extension slots. The TAMARISK 320 thermal camera was used to record thermal images (resolution 320x240, sensitivity < 50mK, spectral band: 8-14um). The eye tracker embedded in the eGlasses is also under development to provide gaze tracking in the context of the near-to-eye display and in reference to observed scenes. The Android 4.1 OS and Linux Ubuntu OS were tested. Two prototypes of the eGlasses platform have been already developed (Fig. 3). The difference of those platforms is mainly related to the plastic cover and to the display.

In this study class templates with the fixed number of attributes (mapped to JSON properties) were prepared for 3 different types of HL7 FHIR resources: a Patient, a Device, and an Observation. Similarly the GET/POST HTTP methods were used with predefined headers. All functionalities for were implemented using Java programming language for the Android OS used by the eGlasses. The HAPI-FHIR server hosted by University Health Network (<http://fhirtest.uhn.ca>) was used to process FHIR requests. The server provides a nearly complete implementation of the FHIR Specification. The simple mapping between JSON properties and UI widgets was used to present information from FHIR resources (e.g. property name -> a disabled Button, etc.). Due to the limited resolution of the display of smart glasses and due to the limited perception capacity related to the use of near-to-eye display the graphical user interface was limited to only few

data fields in a data presentation form. The example is presented in Fig. 8.



Fig. 3. The eGlasses prototypes with three sources of potential medical data: the visible-light imaging camera, the thermal camera, and the thermal sensor. Below electronic board from the side panel of the eGlasses is presented.

In this study a Medical Device was simulated using software server application running on a PC computer. The JSON notation was used to represent data transmitted from the simulated medical device.

The estimated vital signs and related RESTful based architecture were used to qualitatively evaluate data exchange procedures between smart glasses and the healthcare information system, implemented as a HL7 FHIR demonstration server. All 3 scenarios were evaluated: smart glasses used to obtain data from the server, smart glasses as a source of vital signs, and smart glasses as a filter of information. The accuracy of vital signs estimation with the use of smart glasses was analyzed using calculated absolute error values between the proposed methods and reference methods. The mean absolute error, the standard deviation of the mean, and the mean square error were used as quantitative measures of the estimation accuracy. Additionally, data exchange processing times were measured for two categories of actions: read (GET FHIR resources) and create (POST FHIR resource). The smart glasses were connected to the Internet using WiFi router in Poland, while the FHIR server was located in Canada.

IV. RESULTS

A. Smart glasses as a source of information

In Table 1 parameters describing quality of pulse rate estimation are presented in reference to the measurement performed using the pulse oximeter with the finger probe. The mean value represents the mean absolute error between the pulse rate value estimated using the given estimator and the reference measurement. Similar method was used for the standard deviation. The Mean Square Error represent also mean, squared difference between estimated values and the reference. The coefficient of determination, R^2 , represents the linear correlation (fitting) between distribution of estimated pulse values and reference values. The chart, shown in Fig. 4, presents the distribution of measured reference values and values estimated for the best estimator. In Fig. 5 the autocorrelation values calculated for different time lags are presented together with the detected peaks used to calculate an average value of periodicity (subject No. 1).

TABLE I. RESULTS OF PULSE RATE ESTIMATION

	Face ROI			Forehead ROI		
	ePR _{ac}	ePR _{pk}	ePR _{sp}	ePR _{ac}	ePR _{pk}	ePR _{sp}
Mean	1.23	0.99	3.10	1.07	1.13	2.05
Std. Dev.	1.19	0.67	2.52	0.89	1.08	1.33
MSE	2.80	1.40	15.37	1.86	2.34	5.80
R ²	0.97	0.99	0.89	0.99	0.97	0.99

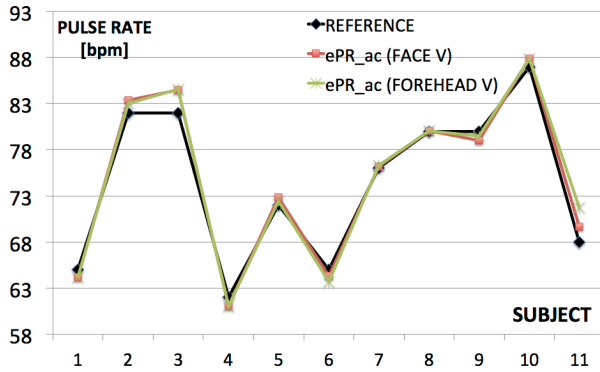


Fig. 4. The distribution of measured reference values (black) and values estimated for the best estimator (ePR_{ac}) for face and forehead ROIs.

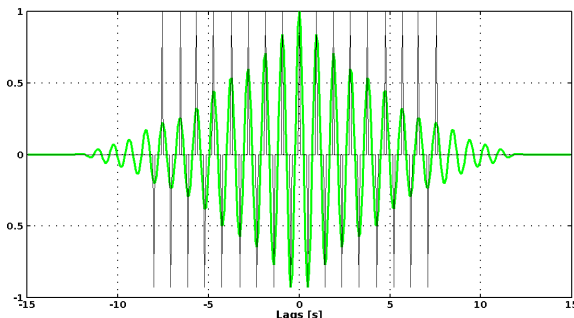


Fig. 5. The autocorrelation values calculated for different time lags together with the detected peaks used to calculate an average value of periodicity

In Fig. 6 an example of the filtered pulse wave signal is presented (extracted for the V component, for forehead ROI, subject No 1). Additionally the detected peaks are presented.

Examples of respiration rhythm signals measured using the described method are presented in Fig. 7. Since the ambient temperature was lower than the body temperature therefore the inhalation period can be observed as decrease of the signal and exhalation as increase of the signal. This can be observed in Fig. 7 (top). In Table 2 parameters describing quality of pulse rate estimation are presented (the same as for pulse rate) in reference to the manually indicated inspiration start events for the measurement performed using the pressure belt. Results obtained for temperature measurements were poor. The mean difference between the temperature values measured using remote infrared thermometers (forehead) and the reference thermometer (under armpit) were: 0.9C (Omron D6T) and 0.4C and 1.1C for other two infrared thermometers. However, there was high correlation ($R^2=0.84$) between measurements performed with remote infrared thermometers.

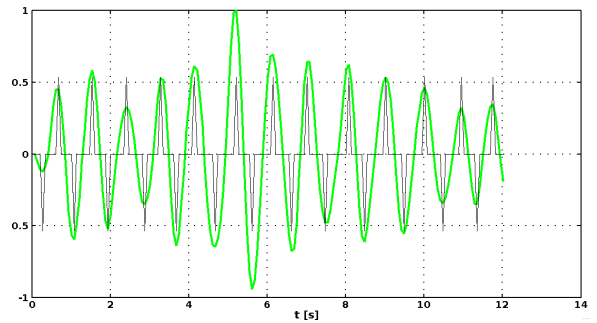


Fig. 6. An example of the filtered pulse wave signal is presented (extracted for the V component, for forehead ROI, subject No 1).

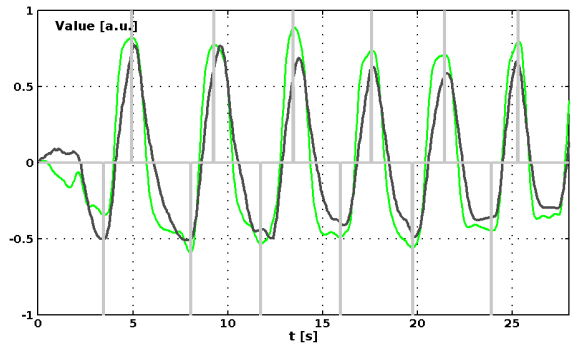
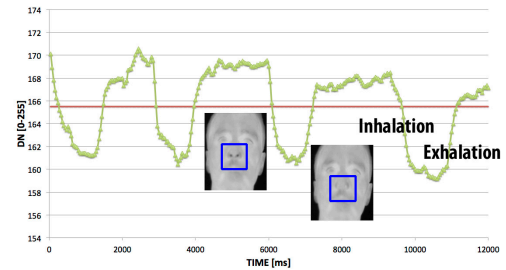


Fig. 7. Top: respiration rhythm extracted from the sequence of thermal images. Bottom: filtered respiration signals for the belt (in black) and for the thermal camera (in green) with detected inspiration starts and ends (light gray)

TABLE II. RESULTS OF RESPIRATION RATE ESTIMATION

	Thermal			Belt		
	eRR _{sp}	eRR _{ac}	eRR _{pk}	eRR _{sp}	eRR _{ac}	eRR _{pk}
Mean	0.93	0.40	0.72	0.87	0.43	0.39
Std. Dev.	0.59	0.38	0.61	0.57	0.42	0.53
MSE	1.17	0.29	0.85	1.05	0.34	0.41
R ²	0.89	0.98	0.95	0.90	0.97	0.97

B. Smart glasses and data exchange using HL7 FHIR

The patient's identifier, recognized using a marker or face features, was used to formulate the GET query for the FHIR server. Vital signs parameters (body temperature, pulse rate, respiration rate) estimated using sensors of eGlasses were used to send POST requests to the server with different Observation resources (separate or as a bundle). The average read (GET) operation time was 6.4ms±3.71ms (server processing time) and the average create (POST) operation time was 12.2ms±3.49ms. The average time of data rendering from the JSON message to the GUI form was shorter than 5ms.

For read operations (i.e. get data for the identified person or the device) the entire process from the start of QR-code scanning to the end of results rendering was shorter than 1s. According to the “Powers of 10” rule [http://www.nngroup.com/articles/powers-of-10-time-scales-in-ux/] when the computer takes more than 0.1 second but less than 1 second to respond, users notice the short delay, but they stay focused on their current train of thought. Finally, introducing simple interpretations to observations depends on the data input method. In this study we used speech recognition. The total interaction time mainly depends on the performance of voice recognition algorithm and the related service. We used the Android speech recognition service using the *SpeechRecognizer* class from the Android API. Several tests were performed for short statements (i.e. up to 7 words, e.g. "below low normal", "heart rate value above normal limit"). The delay, defined as the time period between the end of speech and the time when the related text is presented on the display, was shorter than 2s. We did not evaluate the accuracy of the voice recognition procedure (it has been evaluated by other groups, e.g. in [22][23]). In Fig. 8 an example of the graphical user interface (*VitalSignsViewLayout* class) is presented. It is automatically added as an overlay view above the camera preview after the successful identification of the patient. Data values should be presented when all measurements are completed. Additionally, the text note from the recognized speech can be presented.

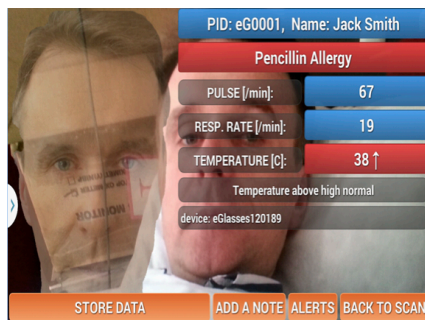


Fig. 8. An example of the graphical user interface

V. DISCUSSION AND CONCLUSIONS

In this paper we presented system architecture and three use cases for the interaction of smart glasses with a healthcare information system. When the entity is identified, information about the entity can be retrieved using query request send to an information system. Using the reference FHIR server we verified simple exchange of data between eGlasses and the server based on recognized patient identifier. The method is simple, easy for the implementation, but provides fast information for healthcare professionals. In this study we limit the number of properties that can be displayed on the smart glasses display. For this task we simply mapped the JSON properties from a Patient FHIR Resource to graphical widgets of the Android API. The typical system response time, i.e. from the beginning of marker scanning to the end of data rendering from the FHIR server, was below 1s. This processing time mainly depends on the entity identification time. Presented results were obtained for the QR-code (4.4cm/4.4cm, camera zoom set to 2x) scanned from the

distance not longer than 1m (incandescent light). Similar results were achieved for bar codes (Code 128, physical width 4.4cm) for the distance up to 50cm. Of course worse results would be probably obtained for scanning from longer distances, using smaller sizes of codes, etc. Related experiments and results were presented in [13][14]. Similar aspects are associated with the identification of entities based on visual features. In real situations a large number of subjects/devices would be used, so the recognition process would require more computation resources. As we shown in [14] the recognition speed for the modified Local Ternary Patterns method was 18ms for a face. Therefore, the identification process for the real HIS should be implemented as a service of the HIS (or a gateway [17]).

In this study we also proposed the use of smart glasses for the estimation of vital signs. Three parameters were considered: body temperature, pulse rate, and respiration rate. Using thermal sensor (Omron D6T) eGlasses can quickly measure the temperature of the skin (e.g. on the forehead), however the obtained accuracy (0.9C) was poor. It is probably the result of the simplified calibration procedure. However, other tested infrared thermometers (clinically verified) showed similar, poor accuracy. Further studies with more subjects are required. The results obtained for the pulse rate estimation shown very good results, practically for all estimators. It is important to underline that the reference measurement performed using finger pulse oximeter provides averaged results of last few instantaneous pulse rate values. So within 20s the presented values are not stable but often differ about 2bpms. The best results of the pulse estimation were obtained *ePR_{ac}* estimator. It is not very complicated to calculate and has not limits of the estimator based on frequency domain analysis (limited frequency resolution). Also for the estimation of respiration rate the same estimator produced best results. The respiration rate can be easily and reliably estimated using the described method. The method has of course limits related to ambient temperature value (should be different that body temperature) but this requires further studies. There are many other methods for remote monitoring of respiration rate proposed in literature. Many of them are based on analysis of video recorded from the chest region [24]. Those recording are typically performed using visible light camera [25] or infrared cameras [26][27]. Some studies also used thermal recordings from face region [28]. In our work we proposed the use of very small thermal camera embedded in smart glasses and we evaluated different RR estimators. Measurements using smart glasses are potentially possible in many practical situations, e.g. when visiting a patient at a hospital ward, at airports for screening, etc. Additional research should be also performed for such situations as nasal congestion, rhinorrhea, etc.

In the presented experiments we used wireless mouse as the input device for the eGlasses. Of course, it is not the optimal solution for smart glasses. Therefore, in the eGlasses project, we are developing three interfaces for data input: optical proximity radar used for hand gesture recognition [29], gaze-based interaction subsystem [30] and the use of smart fabrics. This is currently the subject of further research.

Concluding in this paper we: a) analyzed the potential role of the smart glasses as a medical device for vital signs

estimation; b) designed, implemented and tested the system architecture for data exchange, between smart glasses and healthcare information systems using the automatic identification of patients and devices, and c) designed, implemented and tested the system architecture for data exchange between smart glasses and HIS using FHIR.

Further improvements of the methods based on video recordings can use motion compensation, automatic ROI detection, etc. The technological progress enables the miniaturization of sensors. For example, in the next eGlasses prototype the very small thermal camera will be also used (the Flir Lepton sensor [31]). Integrated and synchronous measurements of different vital signs play important role in many medical applications, for example in sleep analysis [32]. Smart glasses enable to combine measured medical information with contextual information (location, time, etc.). Using the smart glasses system the senses of a doctor could be extended by different sensors. Additionally, knowledge of a healthcare professional could be also extended by the use of connected systems (e.g. knowledge databases, data-mining systems, content-based retrieval systems, etc.). In this paper we showed simple examples of such activities.

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