Fusion of Body Sensors' Data and Video Images in Assistive Technology

Hans-Petter Halvorsen, Karina Kaspersen, Alexander Jonsaas, Saba Mylvaganam
Faculty of Technology, Department of Electrical Engineering, IT and Cybernetics, University of South-Eastern Norway (USN)
hans.p.halvorsen@usn.no, karina_kasp@hotmail.com, alexander.jonsaas@gmail.com, saba.mylvaganam@usn.no

Abstract— **Modern innovations in the design of sensors and the convergence of computing, cognition and communications have led to many new possibilities in incorporating AI-techniques in Assistive Technology (AT) for elderly people. Combining wearable sensors (body sensors) with sensors and computing capabilities of smartphones, a set of experiments were performed to test various AI-algorithms for the detection of critical events such as accidental falls, prolonged stationary states and going astray from residence of "Elderly Living Independently At Home, (ELIAH)". Selected results from studies related to both critical and trivial events are used to test different AI models (threshold, Artificial Neural Networks (ANN), Support Vector Machines (SVM), k-Nearest Neighbors algorithm (kNN). The AI models are versatile enough to identify clearly fall from non-fall events. After selecting suitable features based on sensor data fusion, AI model using only wrist-based sensors flawless detection of events related to fall. A proposed system architecture for implementing these detection models in an application software for smartwatch and smartphone can serve to alert accidental faults as well as going astray of ELIAH. Data fusion with video images is also discussed.**

Keywords—ELIAH (Elderly Living Independently At Home), Wearable sensors, body sensors, AI, Smartphones, fall detection, sensor networking, threshold, ANN, SVM, kNN

I. Introduction

Assistive technology (AT) deals with the usage and development of assistive, adaptive, and rehabilitative devices for people with disabilities, covering also the elderly living independently at home (ELIAH, our own acronym), in the context of this paper. When caring for ELIAH, most often, a critical event is that event indicated by a monitoring system in the form of alarms. Critical events must be handled often by emergency services alerted by specific alarms and frequently followed by subsequent actions by dedicated care personnel. Due to accidents involving falls under varying circumstances in bathrooms, on slippery roads during winter, or stumbling, about 9000 persons fracture neck of the femur (upper part of the thigh bone) every year in Norway alone. About 60% of these injured persons die within five years. In 2017, 400 persons with fracture of the femur died due to ensuing complications. These data show that some measures have to be taken to reduce this number of accidents and possibly to eradicate them completely. These data are found in various sources in the media as well as in the reports available in the archives of public health, [1] and [2].

II. Falls and their significance for Eliah

According to a recent Norwegian study, fall is the most frequent critical event encountered by ELIAH, [3]. According to [4], AT should promote self-dependency, allow community dwelling, increase the elderly user's participation in ICT-based assistance and provide insightful data to health professionals, caregivers, family members etc. in our case ELIAH. Safety alarms and relevant action by care personnel are proper for ELIAH.

Fig. 1 shows common problems encountered by ELIAH and how welfare technology can lead to some improvement of their angst situations. This paper addresses the "safety- and security technology for creating a secure framework around the user". An important aspect regarding IoT and healthcare solutions is that we need to have focus on data security, cyber security and data privacy, including the new GDPR directive.

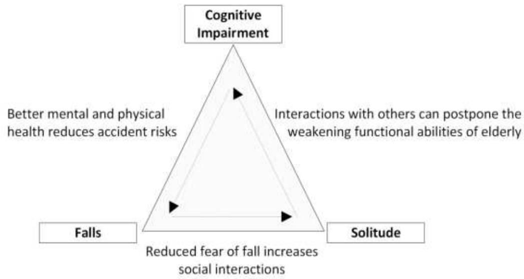


Fig. 1. Cognitive impairment and the angst for falls as discussed in [5].

To illustrate the state of the art, it is interesting to refer to the technology push in this sector, in Norway by the Telenor as illustrated in Fig. 2. Telenor is a Norwegian Telecommunication company providing tele, data and media communication services. Data acquisition platforms are commonly the link between ELIAH, the alarm central, relatives and other relevant actors. "Telenor Objects", Telenor's digitalization platform within the health and welfare sector, has created a generic data acquisition platform called 'Shepherd', which manages the communication and data transmission between the user's house and the other actors involved, as shown in Fig. 2. Some of these functionalities are offered by providers of alarm systems/security technology based on sensor networking with some aspects of push messages using mobile telephones and email.

In the context of safety and security of ELIAH, an intelligent and unobtrusive wearable sensor package along with the ubiquitous smartphone as schematically illustrated in Fig. 3, may offer one possible solution, when the user is not expected to be an expert in the technological aspects of these devices. Given that a scenario of sensors is available, the technology provider can cater to the handling of critical events, using an architecture for sensor fusion shown in Fig. 4. Most of the systems have their own DCUs (Data Collection Units).

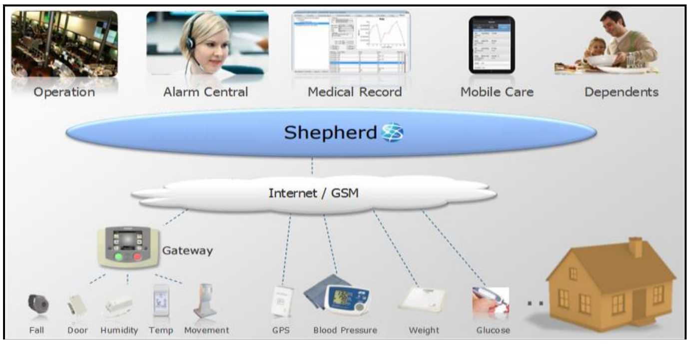


Fig. 2. Shepherd solution currently under development by Norwegian Telecommunication Company Telenor with possibilities for handling data from devices from different vendors [6]

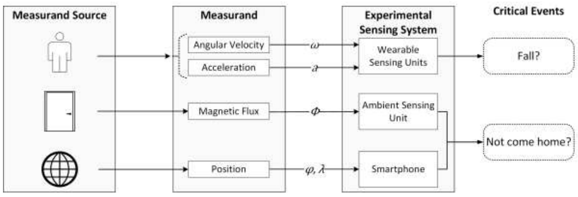


Fig. 3. Measurands logged in with wearable sensors and smartphone

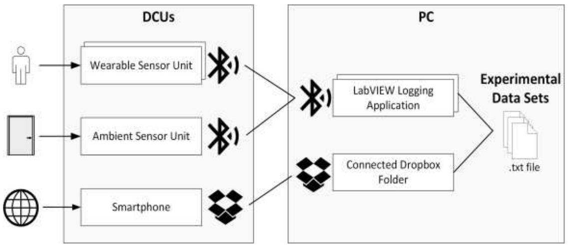


Fig. 4. Fusing sensors' data for unobstrusive supervision. PC section can be an embedded algorithm in a dedicated intelligent unit such as the one indicated in Fig. 2. Ambient sensor unit consists of temperature, magnetic flux, IR etc. As the title suggests, only body sensors are considered in this paper. DCU (Data Collection Units)

An idea of the measurands involved and their ranges can be seen in the TABLE I below. Threshold for acceleration values along 3-axis are calculated by simulating different fall conditions. The threshold values are shown in Table I. Above these values, the system detects fall. The range of acceleration is [-2g 2g], g being the acceleration of gravity. An increasing advancement in communication technology, especially wireless protocols such as Wi-Fi, ZigBee and Bluetooth and recently 5G and the extension of services with IoT, [7], enables monitoring systems to expand in terms of usability and range for remote measurements.

Depending on the sensor placement on the body, the sampling rates obviously vary, e.g. upper arm 32 Hz, waist 0.2 – 1.0 Hz, waist or wrist 30 Hz, ankle 128 Hz, chest, thigh and feet 32 Hz as typical values. In our studies, the sensors with 16 bits resolution were mounted on the wrist and chest.

An increasing advancement in communication technology, especially wireless protocols such as Wi-Fi, ZigBee and Bluetooth and recently 5G and the extension of services with IoT, [7], enables monitoring systems to expand in terms of usability and range for remote measurements, as shown in TABLE II. An updated version of the Bluetooth protocol (Bluetooth Core Specification v5.1) allows for positioning at centimeter level. Bluetooth can already be used in conjunction with indoor positioning systems, but with Bluetooth 5.1 there is a very accurate functionality to find the direction as well. Applications can be in indoor navigation and location services.

TABLE I. MEASURANDS WITH THEIR RANGES. BPM – BEATS PER MINUTE

Sensor No./Measurand	Low	High
1/ Acceleration-x	-2g	2g
2/Acceleration-y	-2g	2g
3/ Acceleration-z	-2g	2g
4/BPM/ number	55	110

TABLE II. CHARACTERISTICS OF SOME WIRELESS NETWORKS (TYPICAL VALUES MAY VARY FROM VENDOR TO VENDOR).

Technology	Range	Speed	Power	Description
Wi-Fi 802.11ac	Short	1300Mbs	High	Communication used by PCs and Smartphones
Bluetooth 5	40-400m	2Mbs	Low	Latest Generation, Low Energy, High Accuracy, Ready for Internet of Things (IoT)
ZigBee	10-20m	250Kbs	Low	Used for Data Transmission from Sensors
4G	Long	100Mbs	High	Todays Mobile Data Communication
5G	Long	10Gbs	High	Launched in Kongsberg, Norway on 8th Nov. 2018

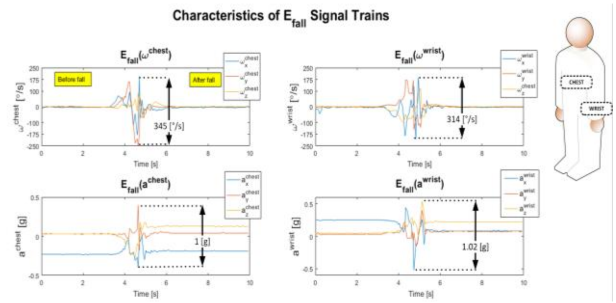
III. EVENTS RELATED SIGNAL TRAINS

Based on the angst scenario portrayed in Fig. 1, the relation between falls, cognitive impairment, and solitude for elderly, and how one disability can provoke another leading to the elderly being prematurely moved into care-homes. AI models can help to detect falls and alert if a user has not returned home. TABLE III shows the different experiments conducted to log in data from wearable sensors shown in Fig. 3.

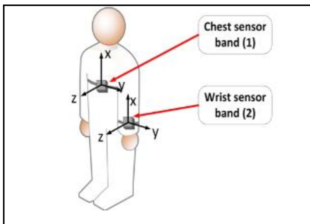
TABLE III. EXPERIMENTS CONDUCTED WITH WEARABLE SENSORS

Experiments	**Experimental Categories**		
	Fall	***Non-fall***	***Comments***
Fall & non-fall indicating various scenarios	E_{fall}=E_{1-56}	Transition: $E_{transition} = E_{57-108}$ Sedentary: $E_{sedentary} = E_{109-120}$ Walking: $E_{walking} = {}_{121-130}$ Running: $E_{running} = E_{131-140}$	Exp. 1-56 falls 57 – 140 different non-fall scenarios

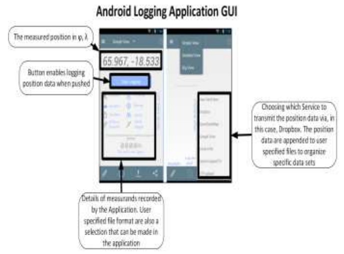
The fall and non-fall experiments were performed using different types of landing grounds and furniture commonly found in all home environments. Bed, sofa, chair, and an exercise mat representing the floor, were utilized when recording falls and non-fall experiments. Non-fall experiments include transitional motion like standing to sitting, sedentary motion like sitting and lying and continuous motion like walking and running. Fig. 5 and 6 show some signal trains obtained during the experiments.



(a) Signal trains from sensors mounted on chest and wrists



(b) Body sensors at wrist and chest with their respective orientations.



(c) Android position data for ELIAH

The absolute values of the coordinate distance or [°] from the home coordinates $(\varphi,\lambda)^{home}$. The user-defined radius, $\varnothing_{thresh}$, are determined before utilizing the unobtrusive monitoring system for elderly

$$F_{geo} = (\varnothing_{\varphi} \wedge \varnothing_{\lambda}) > \varnothing_{thresh}$$

Where:

$$\varnothing_{\varphi} = |\varphi^{home} - \varphi|$$
$$\varnothing_{\lambda} = |\lambda^{home} - \lambda|$$

The user is:

- outside geofence if $F_{geo} > \varnothing_{thresh}$
- inside geofence if $F_{geo} \leq \varnothing_{thresh}$

(d) Geofence activation based on GPS threshold levels

Fig. 5. (a) Signal trains from wearable sensors obtained during events involving falls. (b) Acceleration and angular velocities from wearable sensors on the wrist and chest (c) Android unit used in position data collection (d) Geofence for ELIAH based on GPS threshold values.

IV. FEATURE EXTRACTION

After characteristics of the E signal trains shown in Fig. 5 and Fig. 6 the experimental data sets are processed for feature extraction. The data sets $E1{-}140$ (fall and non-fall) from the wearable sensors need to be preprocessed before using them in the AI models. The final feature matrix $\mathbf{F}(E(130)xF(80))$ does not have the same order of the E's as E_{1-140} indicate, because of variable name handling in MATLAB. Feature extraction is shown in the flow diagram of Fig. 7. The activities involved in data processing and feature extraction of E_{1-140} data sets are illustrated in Fig. 8, where $\mathbf{F}$ is the feature matrix involving all the experiments, E, and features F, based on statistical, correlation and neural network processing.

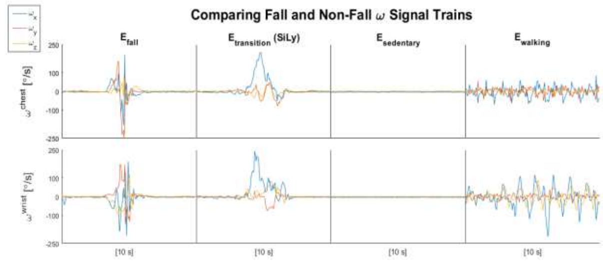


Fig. 6. Events involving fall, transition to sedentary followed by walking characterised by wearable sensors. Angular velocity sensor outputs from wearable sensors

In Fig. 7, interval extraction involves extracting the necessary time intervals from the signal trains such as those shown in Fig. 5 and 6. Feature extraction involves determining the features of all E_{1-140} and construct the feature matrix $\mathbf{F}$. Normalization is applied to all parameters involved in $\mathbf{F}$. Some of the E's are removed during outlier removal, as these E's did not represent the data good enough to create AI models for fall detection, which could possibly affect the training process.

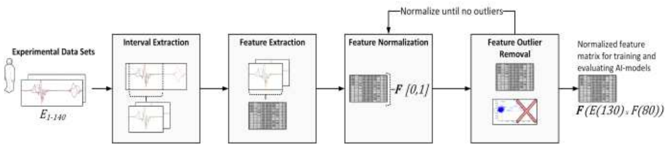


Fig. 7. Graphical overview explaining the flow of activities involving interval and feature extraction as well as feature normalization and feature outlier removal.

Relevant features, F, are extracted from the experimental data sets based on the domain knowledge obtained by studying the characteristics of the signal trains such as those shown in Fig. 5 and Fig. 6. Initial features are generated into a feature matrix, $\mathbf{F}(\mathrm{E}(l\ =\ 140)xF(n\ =\ 80))$ representing all features for $E1{-}20$ (samples), were l is number of experimental data sets E and n is number of features F. Feature category used in this study is summarized in TABLE IV. Among different features used, one of the features correlation is shown in Fig. 8 for different "events", such as running, sedentary, falling etc. Fig. 9 shows one tool for preprocessing the data for outlier removal indicating the removal of the data associated with the event "running", which in the present context is a non-critical event.

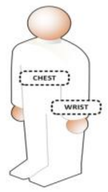
TABLE IV. FEATURE CATEGORY AND NUMBER OF FEATURES F IN EACH CATEGORY OF E

Feature Category	No. of Features of the Feature Categories
Peak Features	$F_{noOfPeak} = F_{1-12}$ $F_{S(noOfPeak)} = F_{13-16}$ $F_{thPeak} = F_{17-28}$ $F_{S(thPeak)} = F_{29-32}$ $F_{S(diffPeak)} = F_{77-80}$
Percentile Features	$F_p = F_{34-60}$
Wavelet Features	$F_c = F_{61-64}$
Cross-Correlation Features	$F_{xcorr} = F_{65-76}$

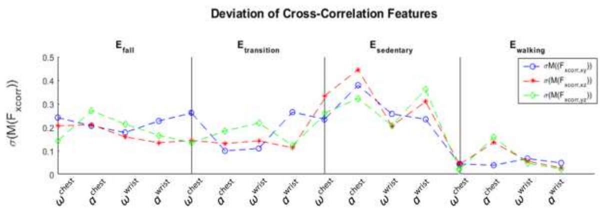
Using Fig. 8, the techniques used in finding the different states of the person based on data fusion is illustrated. The number of tests run in this particular experiment is also shown in Fig. 8.

In Coviu, [6], video consulting is proposed for the elderly. Using video images, as applied in [8], but with focus on orientation of the trunk of the person, in the context of current study, for information on the person's posture (horizontal, vertical etc.) along with the body sensors' data will help to ascertain the seriousness of the fall.

Comb. No.	Evaluation	Placement on Body	No. of Sensors	No of $F(j)$
1	Placement	Chest and Wrist	Gyroscope and Accelerometer	80
2		Chest	Gyroscope and Accelerometer	40
3		Wrist	Gyroscope and Accelerometer	40
4	Sensor	Chest and Wrist	Gyroscope	40
5		Chest and Wrist	Accelerometer	40



(a) Number of falls and the signals logged in with the respective sensors for AI processing.



(b) Using correlation to detect conditions of fall, sedentary/walking etc.

Fig. 8 Details of the fall experiments and results from one type of test using cross-correlation (a) Sensors used with the respetive number of tets runs (b) Signals during falls, in transition compared with those during sedentary and walking conditions.

V. Performance of the fall detection with AI models

Based on the optimal feature subset $F_{testopt}$ for each sensor type, on both chest and wrist placement, the performance in detecting the right event was assessed. A total number of 143 different experiments were performed, consisting of $E_{fall} = E_{1\text{-}56}$, $E_{transition} = E_{57\text{-}108}$, $E_{sedentary} = E_{109\text{-}120}$, $E_{walking} = E_{121\text{-}130}$, $E_{running} = E_{131\text{-}140}$, $E_{door} = E_{141}$, $E_{position} = E_{142\text{-}143}$, out of which 140 experiments were fall related. The AI algorithms resulted in a experiment-feature matrix F of size 140x80, which was used in different analysis. In this study 80% of the data were dedicated to training and 20% for testing. TABLE V shows the success rate for sensors in all placements.

VI. The System Architecture:

The system described in this paper for ELIAH is unobtrusive and user friendly. Due to the size and the possibility of combining with smartphone and smartwatch, the modules are fashionable and less stigmatizing. However, the design expects availability and reliability of battery used in the wearable devices.

TABLE V shows the success rate of the event detection using the system developed in this study.

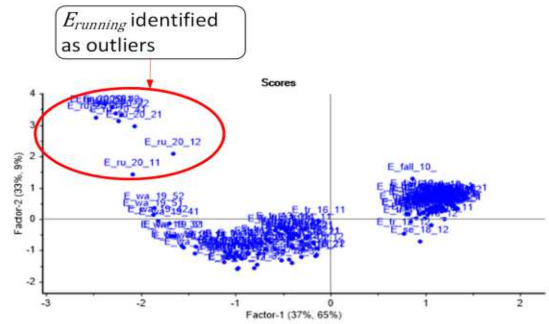


Fig. 9. Outlier removal using PCA. Score plot generated after performing PCA on $\boldsymbol{F}$ in Unscrambler. The $E_{running}$ experiments inside the red circle, is identified as outliers, and will be removed from $\boldsymbol{F}$ before training AI models for fall detection.

TABLE V. Performance of the data fusion models in detecting the events.

All Placements		
AI Model	**Gyroscope**	**Accelerometer**
ANN	92 %	92 %
SVM	96 %	96 %
kNN	92 %	100 %

VII. Alerting Health/Rescue Personnel

In a pilot study, a data fusion approach was developed to test the possibility of using existing data from sensors to alert health and safety personnel. The technique was based on data fusion from selected sensor modalities including video images, extending the work described in [5] and [8]. Some results are presented in [9], from which the data flow diagram is reproduced in Fig.10, in which MPU 6050, inertial sensor module for monitoring motion is used.

The data flow for the pilot system is shown in Fig. 11. The flow diagram in Fig. 12 gives some of the details behind the alert activation based on the position of the person, e.g. vertical, supine etc. in different time segments. Different programming languages were used in the pilot study referred to in [9], to facilitate usage of existing machine learning software to implement the algorithms.

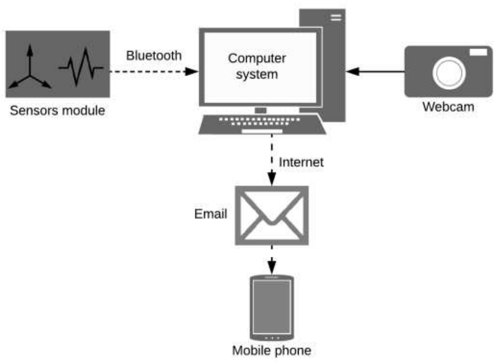


Fig. 10 Simplified system for emergency alert using data from sensors and video images, leading to alert messages to health and safety personnel, e.g. ambulance, emergency admission in hospitals with MPU 6050, inertial sensor module for monitoring motion, [9].

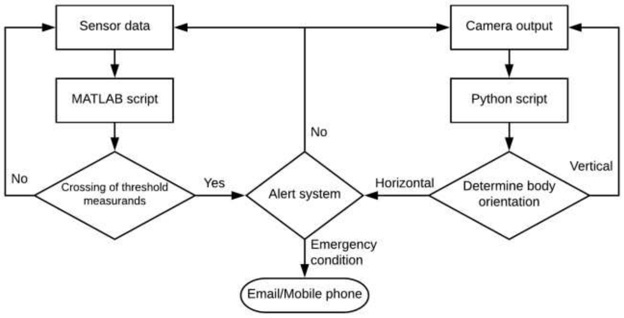


Fig. 11 Data flow for the pilot system based on diverse sensor data and video images, [9].

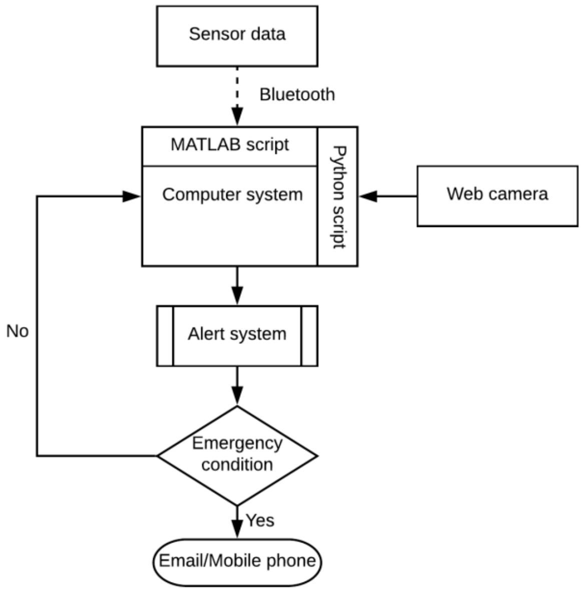


Fig. 12 Alert system overview based on fusion of information from sensor data and video images, [9].

There are systems with body sensors, which detect changes in height and orientation with respect to a horizontal reference line. The Coviu method uses video images to detect these changes in posture and a variant of the method was tested along with the body sensors' signals, which have also information on position, mobility/immobility and hence with a countdown mechanism can activate a push message for rescue operation. Recently, many solutions have been presented for such functions with smart watches.

Recently, in Japan a research group using video images and humanoids with cameras, has implemented a similar system using a set of body sensors and cameras mounted in the room occupied by the person. The cameras on roof within the movement area of the person under observation and on the robot along with an array of sensors on the floor detected the supine position over an unusual length of time, the sensors on the floor effectively emulating a touch pad. In another application using push messages and cloud services for data flow, a system developed at USN in collaboration with the Telemark Hospital and local municipalities, is operating in Norway to alert people on air pollution levels exceeding limits stipulated by the authorities, [8]. A simplified representation of the system is given in Fig. 13. Ultimately, the involvement of health care personnel will be important for any elderly person. However, such technical HW/SW used in these supporting surveillance and assistance, "*ease the burden on nursing staff and boost the autonomy of people still living at home*", according to Hirohisa Hirukawa, director of robot innovation research at Japan's National Institute of Advanced Industrial Science and Technology, as presented in [10].

VIII. CONCLUSIONS

A fusion of these evolving technologies and usage of reliable programming platforms will help to realize a system to implement the unobtrusive supervision of elderly living independently at home. An example of a sensor-networking scenario with various sensors in a typical living environment of an elderly living alone is schematically presented in Fig. 13.

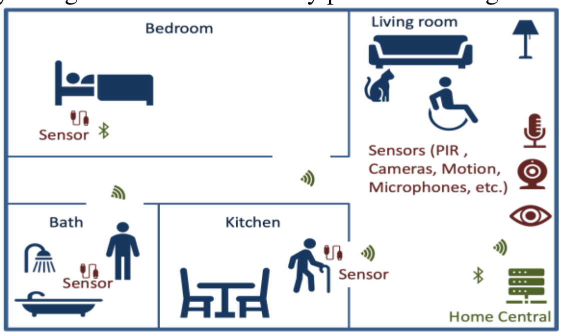
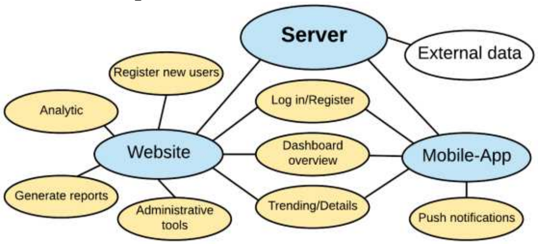


Fig. 13. Example of a sensor-networking scenario with various sensors in a typical living environment. Home Central can communicate with other services and actors as shown in Fig. 14.

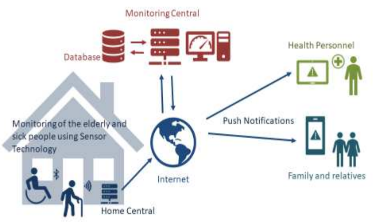
A system for alerting contact persons/relatives in case of emergencies may be configured according to the schematic shown in Fig. 14 (a). The system for alerting needs a web browser functioning properly and reliably. The HW/SW ancillaries for the system are shown as developed for monitoring and surveillance of the levels of gaseous and particulate pollutants in different Norwegian cities, [11]. The alert system with push notification in the context of ELIAH is schematically illustrated in Fig. 14 (b), which is a variant of Shepherd shown in Fig. 2 of Telenor Objects.

The results from our studies and developments in Japan indicate that it is possible to realize an unobtrusive service for supervising elderly with push notifications to relevant healthcare personnel. Diverse data from the living area of the elderly along with those from the body sensors can be successfully fused to improve the living conditions of the elderly by addressing cognitive impairment and the fear for falls as well as reducing the detrimental effects of solitude and dementia.

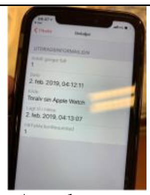
At the sensor data level, the system which has been tested and in operation for environmental alert using push services described in [11], can be modified as shown in Fig. 15 to alert health personnel/relatives in case of emergencies discovered by sensors' and video data fusion. Figure 14(c) shows the push alert to rescue personnel on 02.02.2019, which saved the life of a 67-year old man in Norway, [15]. Smartwatches typically have all or some of the following communication protocols and sensors: Bluetooth, Wi-Fi, NFC (Near Field Communication), GPS, accelerometer, gyroscope, ambient light sensor, microphone speaker, heart rate sensor, ECG, blood pressure, etc.



(a) Push notification in atmospheric emission alerts



(b) Push Notification in ELIAH



(c) Actual successful rescue operation with 4G on 02.02.2019 with fall detection using SMART watch in Norway, [15].

Fig. 14. (a) Push notification for environmental pollution monitoring as an example for the current study. The sytem uses Microsoft Azure for data storage, running programs and push alerts. More details in [11]. (b) Schematic represenation of push notification in ELIAH with the sensor-networking scenario of Fig. 13. (c) A successful rescue operation in the context of ELIAH at 04.14 AM on 02.02.2019.

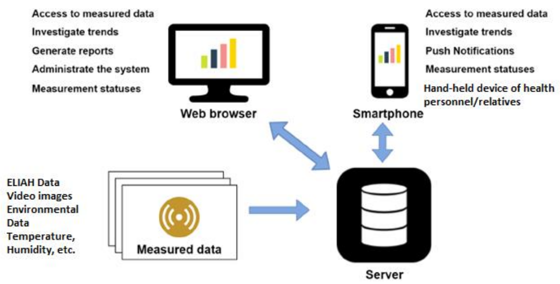


Fig. 15. The four modules, ELIAH data from sensors/video, server, web browser and personal device such as smartphone, for alerting health personnel/relatives in case of emergencies, adpated with modifications from [11].

In the system described in [11], data and algorithms were all handled and executed in Microsoft Azure platform. Different platforms are available for this type of application from many vendors. The selection of this service will be determined by its reliability and conformity with the stipulations from the authorities. Some interesting scenarios with IoT in such applications are presented in [12]. IEEE-11073 deals with the standardization of telemonitoring with sensors, data from them and associated systems meant for ELIAH, [13]. A good review on wearable sensors is presented in [14].

Ambient sensor unit may consist of temperature, magnetic flux, IR etc. As the title suggests, only body sensors are considered in this paper. Using GPS coordinates or the updated version of the Bluetooth protocol v5.1, a geofence could be defined and in the context of ELIAH, for persons with dementia moving out of the geofence, a push signal can be sent to alert relevant people with the information of the actual position of the person for "rescue" operations, [5].

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