assisted living,
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pervasive computing

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ASSISTED LIVING INFRASTRUCTURE

Assisted living applications are commonly understood as technical environment for disabled or elderly people providing the care in the user-specific range. We are going to present the data capture methodology and design of a home care system for medical-based surveillance and man-machine communication. The proposed system consists of the video-based subject positioning, monitoring of the heart and brain electrical activity and eye tracking. The multimodal data are automatically interpreted and translated to tokens representing subject's status or command. The circadian repetitive status time series (behavioral patterns) are a background for learning of the subject's habits and for automatic detection of unusual behavior or emergency. Due to mutual compatibility of methods and data redundancy, the use of unified status description vouches for high reliability of the recognition despite the use of simplified measurements methods. This surveillance system is designed for everyday use in home care, by disabled or elderly people.

1. INTRODUCTION

1.1. TECHNOLOGY FOR OR AGAINST THE HUMAN

When I recall my first memories of kindergarten, I remember the drawing competition about Poland and the world in the year 2000. Because the date seemed so far away, the expectation of substantial change was evident. To be honest, some people were wearing antennas on their heads, but almost all our sketches were about space conquest and not about human life. We were young and not even thinking about getting older or disabled.

Now this magic date is behind us, and we — the children of the '60s — were right in having predicted the communication era for the year 2000; but we are not children anymore. Now, as engineers, we are responsible for the communication era. It manifests itself by the numerous applications of communication technology that exist, first in military and then in civilian life. Digital television and voice telecommunication, the Internet, global positioning systems, and global reference of time are the most common examples. We, the consumers of the early 21st century, are witnesses of the communication era. And we are much more concerned by the age and health problems.

Once more we — the children of the '60s — were right… unfortunately. In the communication era there is much attention on entertainment, on commerce and publicity, but still there is very little concern about human life. Who are we? The civilization that cares more about the primitive shows and worldwide games than about our health? Are we really responsible or are we still in our childhood?

Fortunately, the communication era already made its first marks in healthcare as well. We are witness to the triumphal spread of the idea of telemedicine all around the world. The future success of telemedicine in home health care depends on the conditions treated, the technology implemented and the use of scientific outcomes studies.

Before the 20th century, almost all illnesses were cared for in the home setting. During the 1900s, a shift to institutional-based medicine occurred, coincident with the rise of specialization. Now, 100 years later, the site of healthcare is returning home. However, by the last decade, only 2 percent of personal physician-patient contacts in the U.S. occurred at home.

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The renewed emphasis on home care is rooted in two separate dynamics:

- continued and mounting pressure to reduce medical costs,
- emerging telecommunication technologies.

The re-emergence of home care is also fueled by a third factor that has never changed: Sick people would rather be cared for at home. This remark is the foundation of human-centered technologies described as "assisted living".

1.2. BETWEEN THE SURVEILLANCE AND HOME CARE

Due to substantial progress in electronic technologies, making any device smaller, smarter and less energy consuming, many healthcare devices were transformed in their mobile and some even in wearable counterparts. Besides complying to the postulate of providing the health care at home and making the services faster and more accessible, current solutions extend the diagnostic capabilities by two important aspects:

- increasing the monitoring frequency, some solutions provide continuous data logging,
- increasing the monitoring reliability, by strict observing the metrological principle saying that the measurement should have minimum influence for the observed object; this prerequisite means keeping the patient as much as possible in his or her everyday living conditions and discreetly recording the physiological response to all activity he or she normally undertakes.

The latter remark suggests that the telediagnostics (being a part of home care) has a common meaning with remote surveillance and motivates the hope for possible use of intelligent surveillance systems to monitor health aspects of outpatients. Such systems, usually composed of a grid of interconnected intelligent audio-visual sensors are able to recognize objects (e.g. people, animals, luggage), to follow their motion, to identify sounds (e.g. gunshot, glass breaking, scream etc.) and indicate direction to their source. However their typical applications are automated security systems in airports, bank offices etc., they also have been found useful in medical institutions such as hospitals, hospices and nursing homes. Accordingly to the application, these monitoring systems have extended functionality and support emergency alerting as well as integration with selected patient health sensors. Similar infrastructure may easily be adopted as a part of the patient's (or an elderly person's) home, providing a reliable improvement of personal security with easily configurable health professionals or relatives alerting options [1]. The use of wireless communication, although raises additional privacy issues, makes the assisted living infrastructure easy to setup and maintain [2].

Three classes of systems for medical surveillance of people may be distinguished based on their functional principle:

- dedicated sensors with messaging service,
- multimodal programmable supervisors,
- interactive stimulators with assessment of action-dependent reaction.

Nowadays, systems belonging to the first category are well developed and commercialized. People with certain disabilities may be monitored through the specific parameter values, which are assessed automatically by the local software or transferred to the surveillance center for a contextual or human-supported evaluation. Such systems are designed as embedded – being part of the building infrastructure of the house or office or as personal, which recently also have a wearable form, and accompany the supervised human in motion. The focus on predefined parameters and close architecture, although facilitate the design and increase the reliability of the outcome are main factors limiting the lifestyle analysis or research for behavioral coincidences.

Using multimodal programmable supervising systems enables the monitoring aspect to be selected flexibly from the available parameters in context of their relevance, reliability and availability. This category includes distributed sensor networks (partly embedded and partly wearable) cooperating as an intelligent network towards a consistent description of human behavior with use of geometric, acoustic and health parameters-base description of the subject. The purpose of the artificial intelligence is to provide a realistic classification of human actions, to transform the action sequences to subject specific behavioral patterns and to predict the potential danger from the pattern inconsistency.

Most sophisticated assisted living infrastructures, although not yet emerged from their conceptual stage assume stimulation of a particular behavior and assessment of the human reaction as representative to certain health aspects.

1.3. FREQUENT APPLICATIONS OF ASSISTED LIVING TECHNOLOGIES

Brief survey of the most popular assisted living technologies certainly should notify: personal glucometers for diabetics, asthma episodes detectors and cardiovascular monitors.

Although diabetes is a complex disease requiring monitoring of multiple parameters, all persons with diabetes share the need for regular blood glucose measurement to optimize glycemic therapy. Data transfer of **glucose levels** can be accomplished in a variety of ways. The most straightforward approach is to directly sample glucose levels from blood drawn by the patient or caregiver, then enter the read-out into a personal computer connected via the Internet to a central monitor. Although technically simple, this approach needs a significant patient involvement, which increases the potential for measurement and data transmission errors. Another indirect method involves glucose measurements with use of transcutaneous biosensors, which then transmit the data to a central monitoring computer through the Internet. While less prone to human error, this measurement of glucose is also less precise.

Objective measurements of airway obstruction are the most important part of modern **asthma therapy**. The most important parameters: peak expiratory flow, forced vital capacity and forced expiratory volume in one second can be measured with use of a portable spirometer interfaced with a palmtop computer. The data is transferred via a Web-based system to a central computer for storage and analysis, followed by immediate feedback in the form of treatment instructions.

Cardiovascular pathologies are measured by electrical activity and blood pressure parameters. While external ECG-derived data, as instantaneous heart rate and its variability belong to the well known techniques, blood pressure and oxygenation are now recognized as less prone to artifacts. The most sensitive physiologic indices of heart failure are pressures within the heart itself. An implantable device has been developed that continuously monitors cardiac function by providing measurements of intracardiac pressures and heart rate. Outcome studies of treatment decisions based on this data may prove that early intervention may prevent episodes of congestive heart failure, costly hospitalization and even death. Other area of cardiovascular monitoring is **hypertension**, which itself is a major risk factor for many other illnesses, including heart failure, coronary disease, stroke and kidney failure. Despite availability of highly effective medications, blood pressure is adequately controlled only in about 25 percent of persons with hypertension. Wearable pressure monitors enable daily Internet transmission of home-measured blood pressures to central processors, with immediate feedback.

Significant number of reports refer to video-based assisted living technologies applied in **psychiatric disorders**, in which measurement of physiologic or biochemical parameters is generally not key to diagnostics nor management. Instead, treatment decisions and monitoring are usually based on personal interaction with a psychiatrist or psychologist. Two Way Live Video has been reported to offer an effective means for interactive psychiatric interventions in select populations, such as prisoners. Another domain of great social significance is **neonatal care** that consumes more healthcare funds than any other expenditure in developed countries' hospitals. Care demanding (e.g. low birth weight) infants place significant emotional strains on families after discharge. Assisted living solutions, based on digital video transfer, may allow some infants to be discharged directly from the neonatal unit to the home, rather than to an intermediary unit. Telemedicine also provides support to families who care for these infants after discharge.

2. A MULTIMODAL SYSTEM PROTOTYPE

2.1. SYSTEM DESIGN

The survey of the present applications of assisted living technologies [3] led us to an idea of more complex, multimodal intelligent system suitable for two separate tasks:

– continuous supervision of the subject's health with use of medical and behavioral description,
– home automation with intelligent recognition of commands from the subject.

The seamless health monitoring and command recognition have the common subject's interface and the system identifies the intentional commands by subject's position and occurrence of a specified behavioral sequence. The system uses artificial intelligence to learn the gestures corresponding to commands from video sequences of the body, face and eye motion. The system also learns the subject-specific behavioral pattern for particular time of the day from a set of sequences previously recorded and qualified as safe. The use of artificial intelligence is mainly justified by the desired system adaptability do the user-specific lifestyle and limitation, but also allows for distant modification of the monitoring following the health changes the patient may subject with time.

As the main purpose of the monitoring is the subject's safety, selected health parameters are monitored in a seamless way with use of unobtrusive smart sensors [4]. The sensor set was selected arbitrarily as targeted at an ageing person with some insomnia problems, but the system design allows for an easy integration of other sensors when necessary. The health parameters (in our case: heart rate, body motion, snoring episodes) are monitored continuously and contribute to identification of the subject action. The sequence of actions with their temporal markers form a behavioral pattern which is qualified by the software as typical, atypical, suspicious or dangerous.

Various actions may be programmed as the consequences of the behavioral pattern qualification. These range from modification of the recorded parameters set, through enabling real-time video streaming to alerting of subject's relatives or medical assistance [5, 6].

For the sake of usability, being here of primary importance, following the proposal of [7] the set of wearable sensors [8] was limited to an electrocardiogram monitor, three axes accelerometer and an optional SpO2 sensor. Remaining parts of the system (cameras, microphones and bed sensors) were embedded into a smart home infrastructure [9]. Accordingly to a personalized medicine paradigm, both components are dynamically customizable by software settings.

2.2. SYSTEM INFRASTRUCTURE

In general, personal and residential monitoring systems are intended for different usage, what implies the application-specific design of communication interfaces:

– personal (wearable) systems commonly use wireless interfaces, allowing for a virtually unlimited operation range at the cost of high energy required for the omni-directional radio wave propagation and long-range transmission (GPRS, satellite, etc.),
– residential (home care) systems use wired, relatively cheap wideband connections, however this limits their operation range to the in-house patients.

Accordingly to the specification of example subject, the prototype of the personal cardiac monitoring system was designed as a cardiology-oriented monitor including MW705D GPS receiver (Mainnav), Aspekt500 12-leads ECG recorder (Aspel), TeleMyo 2400 G2 Telemetry System (Noraxon) and PXA-270 portable evaluation kit (Collibri) powered from the 4800 mAh 7.2V Li-Ion rechargeable battery pack [10]. These four components were organized in a wearable body sensor network (BSN) and interconnected via Bluetooth class II interfaces.

The personal part of the monitoring system provides two communication interfaces for short-range and long-range bidirectional connections (fig. 1). The use of short-range connection requires a building-embedded gateway to a wired access to the Internet. The role of data transfer service (DTS) may be fulfilled by a regular wireless local area network (WLAN) often already present in offices, or by the residential part of the monitoring system. In the latter case, the infrastructure of intelligent house contributes to personalized interpretation of behavior of the health-monitored subject. The bandwidth of a short-range DTS allows to send all 8 ECG channels, and with a maximum speed of 500 kbps the BSN is able to update all the information stored during a connectionless monitoring period within less than 160 seconds. In case the subject leaves the residence, the wearable part of the system remains active thanks to the long-range wireless connection, however the GPRS throughput limits the datastream to 2 ECG channels (upstream link of max. 16 kbps). Accelerometers placed on subject's upper and lower limbs provide a quantitative motion estimate but also precise kinematics parameters [11]. These data are particularly useful for semantic description of human outdoor activity and for discrimination of motion patterns.

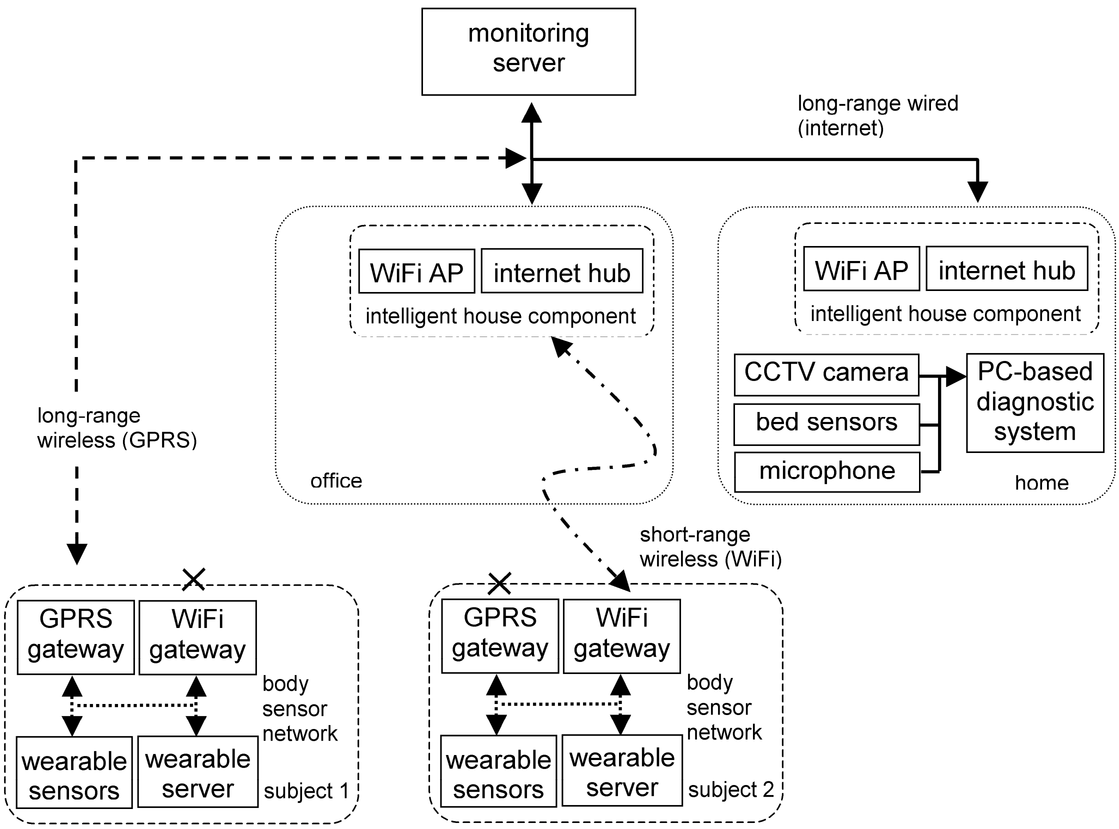

Fig. 1 Data transfer services in the compound personal and residential health monitoring infrastructure [12].

Audiovisual monitoring of daily activities is limited to the subject’s residence and relies in division of the supervised living area to smaller regions differing by specification of most common type, intensity and time duration of the human activity. Any deviation from the usual behavior with regard to specified spatial or temporal assumptions is categorized and implies alerting. The subject's state is identified in real time as a result of motion quantification (quantity and variability) of whole human body or its selected segments, especially upper and lower limbs. The body posture is recognized with use of selected features of vertical and horizontal projections calculated on histograms of the segmented subject's silhouette. For the motion monitoring, we use monochrome CCD (charge-coupled device) PAL system camera of resolution 720 by 576 pixels and additional set of nine infrared diodes placed around it. In this arrangement, the illuminators help to achieve an uniform exposure in the whole area of frame. Due to lower noise and wider analyzed volume, cameras are usually located in parallel to the longer dimension of the room. Measurement of the acoustic signal for fall and snoring detection is performed with the sample rate of 44100 Hz using a microphone.

The residential video-based presence detection and motion tracking system was designed as a component of the intelligent house infrastructure. It uses the wired broadband internet connection supporting the real-time motion picture transmission (standard datastream of 1800 kbps). This system also provides a WiFi-compatible interface to accept the external (non-video) data. Therefore, as long as the subject is within the connection range, the personal part is integrated in the monitoring infrastructure, which embeds the personal data into the packets, separates it at the recipient and redirects to the independent (i.e. cardiac) system server. This solution provides not only wider transmission bandwidth whenever possible, but also substantially reduces transmission costs and extends the personal part autonomy time by reducing its energy consumption.

2.3. BEHAVIOR AND HEALTH INTERPRETING SOFTWARE

The software of the prototype assisted living system consists of three parts depending on the function performed:

– smart sensor embedded software – designed to provide quantitative parameters contributing to the assessment of subject's health and behavior,
– integrating software – providing a semantic description of behavioral patterns with respect to the temporal context, subject's position, parameters' reliability etc.,
– intelligent messenger – generating alerts based on distance of current pattern and the set of patterns described as 'safe', updating and verifying the patterns etc.

The software embedded in smart sensors is expected to provide highly reliable low-volume description of the subject. Particular sensors types (ECG recorder, motion detectors, snore detector and accelerometers) run their independent software (Fig. 2). At this level, the adaptability is limited to the initial configuration (e.g. camera sensitivity, ECG input range).

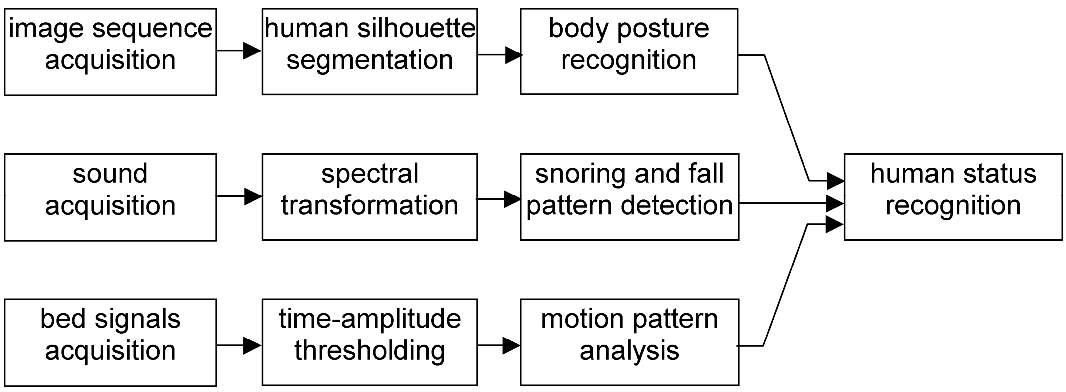

Fig. 2 Block diagram of the residential behavior tracking system [12].

The embedded ECG waveform processing includes the temporal localization of heart beats and discrimination of basic beat types. Single-lead electrocardiogram is sufficient to provide reliable temporal markers and usually also the information about the origin for each heart beat. The ECG is acquired with the sampling frequency of 500 sps and 12 bits resolution. The beats detection is performed in real time with the use of signal filtering and mathematical transformations favoring the features common for the QRS complex accordingly to a modified Pan-Tompkins algorithm [13]. Next, an adaptive threshold is applied to determine the rough position of each QRS section. The precise localization of the R wave peak is further refined to 1 ms with the use of five points-based parabola fitting [14]. A simplified classification procedure [15] distinguishes normal sinus beats (S) from arrhythmic beats (V, others, artifacts) and is organized in two stages:

– first, the rhythm stability is calculated by beat-to-beat comparison of two features: the difference of signal sections isolated in the ±100 ms vicinity of consecutive R wave peak and the difference of RR-interval,
– next, if both values fall below respective 10% thresholds, the beat origin attribute is copied from the precedent beat.

Large differences in beat shapes or RR intervals indicate the chance occurrence of extra beats that need to be excluded from HRV analysis. For verification of these beats, discriminative geometrical features are calculated and contribute to the final decision about the beat origin attribute [16].

Quantitative evaluation of the human body motion is based on the absolute value of difference between each 25^{th} video frame (i.e. in a 1 sec. time interval). For each differential frame, the value of brightness was averaged for all pixels. The motion index is then defined as percentage contribution from outlying pixels, and reveals both the value and frequency of the subject movements (fig. 4). Continuous 24-hours recording of body motion was also found useful in quantitative evaluation of behavior [17]. The body posture is also identified from the video frames. It starts with segmentation of the human silhouette from the surrounding environment background. The histograms of vertical and horizontal projections of segmented image are used for extraction of features specific to particular body postures. A more detailed report of daily limbs activity may be derived from an extra model-based step referred to matching the prepared body model to the person silhouette [18].

Acceleration data were collected from 3D sensors placed on the upper and lower limbs of the tested subject at 100 sps. This modality is complementary to the video recording since it provides not only motion quantity but also precise kinematics parameters corresponded to the pattern of motion present in definite movement [19].

The snoring phenomenon can be completely described in a frequency range of 12 kHz. Similarly to speech, snoring is produced in the vocal tract, therefore existing techniques for speech analysis may be successfully applied to identify and evaluate snoring sounds. With use of the Short-Time Fourier Transform the sound is transformed to the frequency domain in order to determine the frequency and energy distribution in local sections. The main components lie in the low frequency range, at about 130Hz. The pathological signal presents weak formants, while the normal signal has more periodicity in low frequencies, and introduces stronger formants. Calculated vectors of characteristics of the abnormal sound were quantitatively compared with normal sound, which allowed drawing conclusions from available data. The most important parameters were the fundamental frequency, moments M0-M2 and formants. The pathological importance of snoring has been related to its intensity (dB), maximal and mean intensity, number of breathing per minute of sleep, snoring frequency and formants structure [17].

Main part of data integrating software is the device identification and negotiation protocol. It should support the temporary suspension of connection leasing, the non-availability of the final data recipient and the break of transmission in the leased transmission channel. Accordingly to the protocol, the cooperation between two systems is initiated and terminated automatically depending on the measured conditions and accordingly to the specified rules. For regular solutions, TCP/IP-embedded data control mechanisms are reliable enough for maintaining the continuity of diagnostic data transmission. In the proposed prototype, additional data buffering was designed to support the acquisition when the transfer is suspended for the reason of switching from the short- to long-range data transmission and vice-versa and possible temporal absence of data carrier. Consequently, the data integrity is preserved in case of radio carrier discontinuity or unpredictable time and result of negotiations between DTSs. Besides the long- and short-range wireless links, used out- and within the reach of residential wireless connection respectively, a circular memory buffer is considered as third data recipient and works continuously in parallel as the data backup [12].

A typical behavioral pattern is represented by an attributed probabilistic graph with indexed and labeled nodes [20-24]. Node indexes correspond to different body positions {standing, sitting, lying, walking}, while node labels represent types of activities which are possible in these positions. Graph edges represent successive changes of the positions. Each node has a random label being a set of labels together with their probabilities (Fig. 3a). The random labels reflect the different probabilities of various activities resulting from taken body positions. To each label a set of attributes corresponding to the foreseen duration of activities and to biomedical measurements specifying the person's state is assigned.

The recognition of alternate behavior is performed on the semantic description of the subject's status in the context of subject's habits. It needs a definition of distance measure-ment performed in the domain of behavior descriptors [25, 26]. Our results [27] show, that recognition of unusual pattern for possible alerting is performed sufficiently only with metrics compensating for temporal shift between patterns. Best performance (sensitivity 96.5% and specificity 97%) was achieved for suspicious status recognition with use of dynamic time-warping algorithm [28, 29]. This performance was found sufficient for implementation in an automatically alerting multimodal surveillance system for elderly or disabled.

Qualification of the behavior is made by the system automatically with respect to two factors: presumptions and heuristics [30]. First mode involves human-designed definitions of ’usual’ and ’unusual’ actions based on the description of subject’s habits. The latter mode involves artificial intelligence (AI) to record, analyze and statistically process the everyday subject’s behavior and detect whether and how the recorded pattern differs from the typical performance. The qualification of the behavior aims at issue an output token describing the subject’s action as belonging to one of the following categories: {normal, suspicious, dangerous, critical}. This qualification is performed with consideration of various aspects of similarity between behavioral patterns:

– by the sequence pattern (subject is doing/undergoing an extra activity not matching to any ’usual’ pattern),
– by the sequence time (subject is doing/undergoing a typical activity in unusual time),

The subject’s premises are attributed with various functionalities (Fig. 3b), and therefore the behavior, is considered as ’usual’ or ’unusual’ with regard to the subject’s positioning.

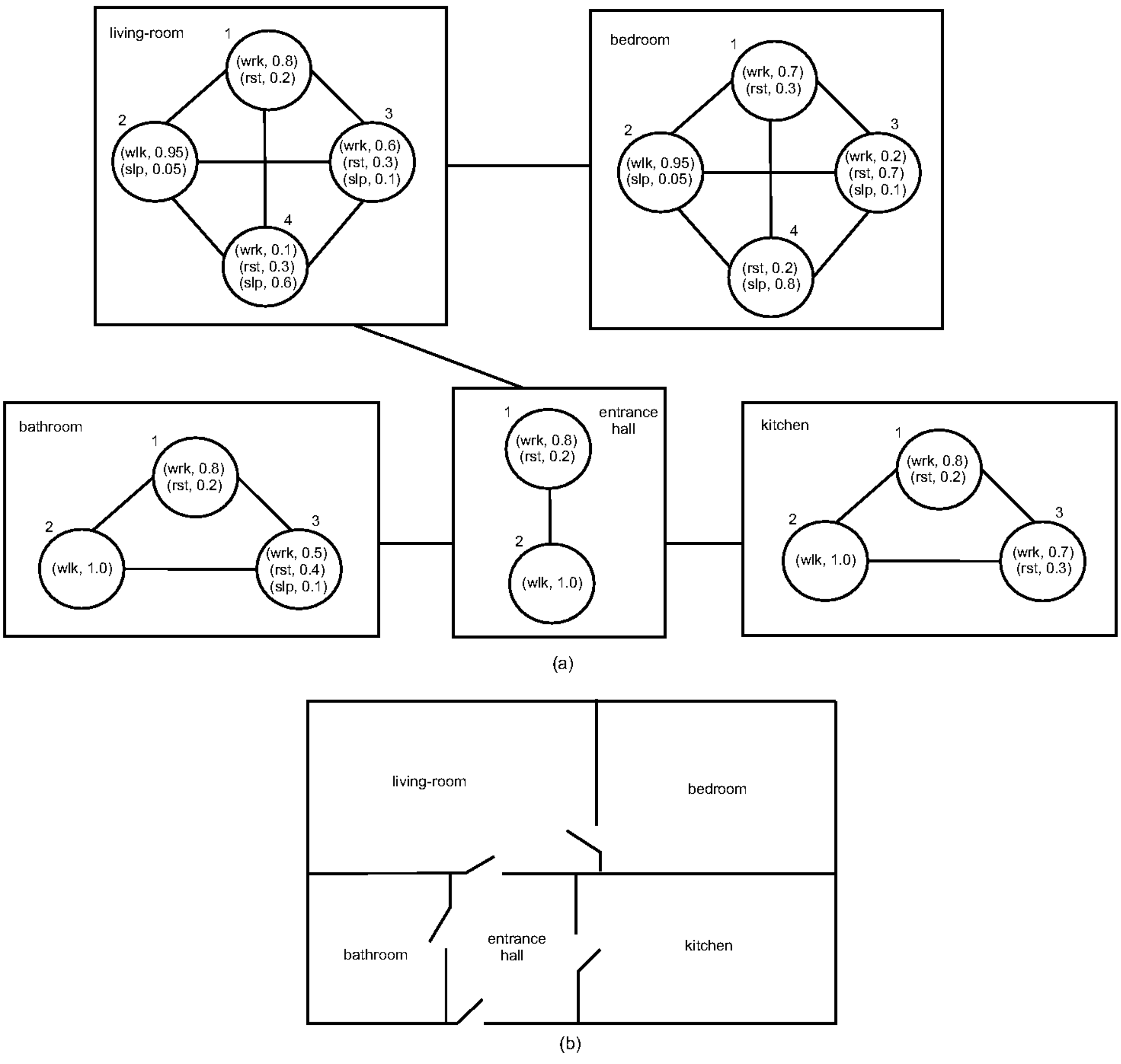

Fig. 3 a) A state-space graph of typical behavioral patterns, b) a layout of the considered apartment [24].

3. SELECTED RESULTS

3.1. TESTING CONDITIONS

The premise of the monitored subject was arranged in the laboratory as a two-piece apartment. A bedroom and a dining room provided the subject facilities for resting and working. The subject's premises are attributed with various functionalities, and therefore the behavior, is considered as 'usual' or 'unusual' with regard to the subject's action. The behavioral patterns were collected by the sensors continuously, while the subject performed a set of scheduled actions as: lying, getting up, sitting, walking, working. Each session lasts for ca. 20 minutes and aim to simulate an excerpt of everyday life. The system was expected to recognize the subject status and with respect to its temporal changes to classify the behavioral pattern into one of four possible clusters: {normal, suspicious, dangerous, critical}. The test was performed on three volunteers performing the actions accordingly to 17 schedules differing by state order and duration.

The tests of prototype cooperation between the wearable and home care systems were focused on two aspects:

– The technical correctness of data carrier switching between the default (wireless) and the alternative (wired) channel, with particular attention to the data buffering in the wearable system,
– The savings on the payment for the telecommunication service provider and the usage of the wearable system battery determining its autonomic operation time.

3.2. RESULTS

Since the volunteers strictly observed the physical exercise schedule, this can be a reference for evaluation of the subject's status as recognized by the monitoring system. Based on this reference the estimation of sensitivity was made separately for individual cardiac- and motion-based methods for subject's status recognition (Table 4).

Table 1. Estimation of sensitivity [%] of individual methods for subject's status recognition.

subject status	volunteer 1		volunteer 2		joint methods average subject
detection method	cardiac	motion	cardiac	motion	
sleeping	80	70	82	67	94,0
resting	84	71	87	67	95,5
working in house	59	86	62	83	93,9
walking in house	67	69	66	71	90,0
working out door	54	77	55	75	89,1
walking out door	61	93	59	91	96,8

It is noteworthy that {working} and {walking} has different performance, depending on the method used for motion estimation. In general, {walking} is more reliably recognized in outdoor subjects with use of accelerometers, whereas {working} recognition performs better indoor, when a video-based motion estimation is used.

The results of carrier switching delay are displayed in Table 2.

Table 2. Delay time between the packets using the standard and alternative data carriers.

switching direction	success rate [%]	average delay time [s]	standard deviation delay time [s]
wireless to wired	93	6.35	1.05
wired to wireless	71	17.3	8.10

Despite the simplified cooperation mode, the success rate representing the percentage of successful switching between the carriers is far from 100%. The most common reasons for inefficient switching were the errors in conditions detection and the average quality of both (GPRS and Bluetooth) wireless digital links.

The results of the economical aspects tests are displayed in table 3.

Table 3. Economical benefits of conditional use of the standard and alternative data carriers.

communication mode ratio	autonomy time [hours]	autonomy time gain [%]	communication payment [PLN]	communication payment savings [%]
in house 100% of time	24.7	51,5	0	100
in house 80% of time	23	41.1	19	80
in house 60% of time	21.3	30,7	38	60
in house 40% of time	19.6	20.2	57	40
out house 100% of time (no cooperation)	16.3	0	95	0

4. DISCUSSION

4.1. EVALUATION OF THE DISTRIBUTED INFRASTRUCTURE

The presented design of the infrastructure combines the personal and residential parts, conditionally cooperating in surveillance of the subject. Our design considers the system behavior in any connectivity condition, even if data transmission is broken for a long period of time. Data continuity was granted thanks to the use of large circular buffer, temporarily turning the telemedical monitor into an independent recorder in dependence on the link quality.

A relatively long response time (6.35 or 17.3 seconds, see tab. 2) resulted from the buffering of messages in the personal system until the reception of every data packet is con-firmed by the server. On the other hand, data buffering designed for the primary purpose of preventing data loss during the carrier switching is also functional in case of longer (up to 25 min) carrier absence. In conditions of our experiment the subject lost the long-range carrier at the entrance to the building, but needed another 55-75 seconds until he or she reached a WiFi-enabled premise.

4.2. EVALUATION OF THE INTERPRETATION APPROACH

The consequence of state representations using graphs, was a straightforward definition of other possible states and transients between them. This justified a quantitative measure of differences between the recorded behavioral pattern and the reference as a graph distance. The automatic classification of recorded patterns as ’usual’ or ’unusual’ and alerting are also based on this measure. The representation of the apartment topology by means of graphs, although rather conventional, was very useful to represent the room-specific range of expected actions. Recordings of scheduled actions revealed two sources of inaccuracy for behavioral patterns clustering task: automatic recognition of the status, and pursuit for the pattern similarity in presence of possible time delay. The overall high performance lies in the contextual and conditional interpretation of measured parameters from multimodal acquisition, The advantage of our approach is the unprecedented integration of multimodal data describing the subject and his environment in behavioral patterns. In the application for assisted living, the system flexibility and high degree of personalization are highly desirable. Patterns typical for the common human actions are easily separable, however, regardless the acquisition and state description accuracy, the behavior is not directly represented by behavioral patterns. This justifies the use of error probability attribute in the digital behavior representation.

Despite of a broad representation, the available patient information may be too sparse to detect some dangerous episodes. In case the system systematically misses certain types of episodes, monitoring of other complementary parameters may be included in the integrated state description. For each new subject or in presence of false alerts, the manual review and evaluation of behavioral patterns are desirable and the appropriate threshold values are to be tuned individually. Additional tuning is necessary for specifying of the balance between the status domain and time domain of behavioral patterns. Further tests in the prototype application are planned to reveal weak points of the behavioral patterns-based approach and to verify the usability in home condition.

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