# Data integration in multimodal home care surveillance and communication system

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**Abstract** This paper presents 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

Assisted living applications are commonly understood as technical environment for disabled or elderly people providing the care in the user-specific range. A considerable drawback is the equipment cost implied by the assumption of use of very reliable close-to-clinical devices in patient's home. Our proposal is based on the integration of data provided by several surveillance devices of relatively low reliability in order to provide raw diagnosis and control of the focus of detailed examinations. Additionally, the assisted living applications are not required to provide precise diagnostic information, usually the desired output is the alert message, which role is to put a feedback to the patient's behavior or medication, trigger a specialized diagnostic procedure or notify the medical staff. The role of assisted living applications is usually reported as twofold:

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- automatic detection of health risk factors in the human organism,
- providing of an alternative way of interaction between the human and his environment.

In our approach, we assume that a common idea of these tasks is the acquisition and automatic interpretation of selected vital parameters. The particular interest is the mutually correlative information gathered with use of independent recording techniques based on various physical backgrounds. The present paper describes a concept of data integration in a multimodal system for assisted living. As far as possible the system design is based on consumer-grade equipment (computers and cameras) or simplified recorders for selected biosignals. The measurement is performed with use of method-specific software and all results are presented in a common diagnostic state-space. Considering the uniqueness of certain data or redundancy of the others, the representation of the patient's state is completed or refined. Closely related subject, also concerned in this paper, is the use of selected vital signs as an alternative way of human-computer interaction. The literature survey led us to a conclusion that any brain activity or eye movement signals are interpreted unconditionally. Consequently, the laboratory results are promising, but applications in subjects' homes usually end with ambiguity of commands interpretation. Therefore, as an efficient remedy, we propose the contextual interpretation of the human commands on the background of his or her activity, topological position and status. We assume a common approach to the physiological data measurements and processing for status and command detection. The unified description of subject's status provides a reasonable tolerance of the recognition system for unintended gesture or motion similar to the command. The interpretation of status or behavioral patterns being a status sequence, is the last stage of our project, not covered in this paper.

### 2 Materials and methods

Four various sources of behavioral signals are considered in the system: two surfacerecorded vital signs, video sequences and acceleration patterns. This setup allows the use of general-purpose consumer-grade devices as main sensors of the subject's behavior. The translation of the acquired data (signal or image) to the semantic description of the subject status is performed by the dedicated software, which may be individually tuned accordingly to the patient's or environmental conditions. Depending on detected condition, selected vital signs are considered for communication of the patient with his environment. The bibliographic study show, that brain and eye motion signals are particularly useful for such application. In the proposed system, we also used EEG and EOG signals, however their interpretation is made automatically in context of the subject's status. The subject's status is described by the probability attributes in a given time point. Time-domain variability of the status is often referred to as 'behavioral pattern'. Our approach assumes the extension of this notion to both status-descriptive and intention-descriptive parameters. Such

extension unifies the output of measurement methods-dedicated procedures and facilitates the integration of syntactic description of the subject.

## 2.1 Electrical activity of the heart

The response of the human cardiovascular systems to variations of physical load and psychical conditions is very fast and thus reflects changes in subject's behavior. Main parameter used for the assessment of extracardiac influence is the heart rate variability controlled by the autonomous nervous system. Continuous monitoring the value of the cardiac rhythm is an appropriate background for the support of human activity assessment. The measurement of time-domain variability of the sinus node activation requires acquisition of a single-lead electrocardiogram, heart beat detection and exclusion of all beats other than sinoatrial (Fig. 1). These steps are usually directly followed by the statistics, interpolation of missing intervals is performed for frequency-domain analysis. Three patient's states are distinguished by

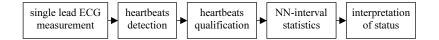


Fig. 1 Block diagram of heart rate variability signal processing

the analysis of the human heart rate:

- sleeping corresponding to low heart rate value and variability
- resting represented by low or decreasing heart rate value and high short-time variability,
- loaded or anxious represented by high or increasing heart rate value and high short-time variability.

The heartbeats are detected in the electrocardiogram with use of signal filters based on QRS-frequency, acceleration and moving window integration [4]. The custombuilt beat detector was proved for compliance with IEC60601 requirements [2] when tested on MIT-BIH Arrhythmia Database [9]. The shape-based discriminator eliminated all but sinus-originated beats. The missing RR intervals were interpolated by a successive procedure minimizing their short-term variability, accordingly to the guidelines in [12]. Finally, time-domain heart rate variability (HRV) parameters were calculated following the formulas given by Malik [7] and confirmed by other researchers [11]. Two standard quantitative HRV parameters were selected as representative:

- the square root of the mean squared differences of successive NN intervals (RMSSD), for measurements of short-time variability,
- the standard deviation of the average NN interval calculated over five minutes periods (SDANN), for measurements of long-time variability,

The HRV-based estimation of the subject's status involves a considerable delay, thus requires support from other methods in detection of sudden status changes.

# 2.2 Mechanical activity of the body

The most visible and easily obtainable markers responded to daily activity in humans are movements signals of their bodies. Many previous studies proved the utility of continuous round-the-clock registration of body arrangements and motion in behavior quantitative evaluation [3], [5], [6], [10]. In context of the proposed multimodal home care surveillance it is essential to incorporate straightforward, cheap and non-limiting patient movements sensors. Therefore to acquire desirable mechanical activity of the body, we decided to use in our project both video recordings as well as acceleration and angular velocity patterns. Setting-up such kind of different equipment allows to obtain sufficiently accurate and complete conclusions about state of the object which is supervised under conditions of daily living.

General approach consists in state recognition which is possible to extract by means of motion quantification of whole human body or its selected segments, especially upper and lower limbs. In this research we determined four main types of condition and physical activity accordingly to the level of motion quantity and variability:

- sleeping and resting when whole body motion quantity and variability in dependence of time keep on low level,
- working correspond to increasing or moderate amount and time variability of the upper limbs motion mainly,
- walking reflected in high quantity and time periodicity of both upper and lower limbs motion.

In calculation of two mentioned parameters of the exact human status (quantity and variability) from the video registrations we need to carry out preliminary processing of the obtained data. Fig. 2 presents principal stages of our approach. First step concerns segmentation of the human silhouette from the surrounding environment background. Then both vertical and horizontal projections histograms of segmented subjects are performed for the purpose of preparation and extraction of the features corresponded to particular body postures. Within the specified postures owing to the numerical criteria of motion amount, the object state is estimated. If necessary more detailed report of daily limbs physical activity, block diagram from Fig. 2 can be extended with an extra model-based step referred to matching the prepared body model to the person silhouette. That kind of approach enables to determine principal parts of the body and to give the information about their movements. In context of



Fig. 2 Block diagram of status recognition process from the video sequence recording

this particular activity semantic description, accelerometers and gyroscopes could be also very useful. Sensors placed on the upper and lower limbs of the tested subject provide not only motion quantity but also precise kinematics parameters corresponded to the pattern of motion present in definite movement (sloping, crouching, sitting down and standing up from the chair, reaching some subject, etc.).

# 2.3 Electrical activity of the brain as status determinant

The EEG signal is a sum of oscillations with characteristic frequency and Gaussian noise, thus the simplest way to describe the EEG signal is to present frequency and amplitude of component brain waves. Most of the cerebral signal observed in the scalp EEG falls in the frequency range of 1-40 Hz interval with amplitude which does not exceed 100  $\mu$ V (about 100 times less in comparison with ECG signal).

Traditionally, brain waves are named by the following letters of Greek alphabet in order of their discovery. Each wave is closely associated with the activity condition of the person subjected to an examination. Brain waves are given as follow:

Alpha (α) is the oscillations in the frequency range from 8 Hz to 13 Hz, with amplitude from 20 to 100 μV. Alpha waves originate mainly from the occipital lobe during total and wakeful relaxation with closed eyes. Alpha waves are reduced with open eyes, mental activation, or drowsiness and sleep. They are thought to represent the activity of the visual cortex in an idle state. Occipital alpha waves during periods of closed eyes are the strongest EEG brain signals.

There is a variant of alpha wave in the same frequency range, called mu ( $\mu$ ), which can be found over the motor cortex (central scalp) and is reduced with movement, or the intention of movement.

- Beta (β) is the oscillation in the frequency range from 13 Hz to about 45 Hz, with amplitude up to 20 μV. It can be detected usually on both sides of brain hemispheres in symmetrical distribution and is most evident frontally. Beta waves are associated with active, information processing, busy or anxious thinking and active concentration. Beta activity is generally attenuated during active movements. It is the dominant rhythm in patients who have their eyes open or who are alert or anxious.
- Theta ( $\theta$ ) is the oscillation in the frequency range from 4 Hz to 7 Hz, with amplitude up to 30  $\mu$ V. Theta occurs normally in young children. It may be recorded

during drowsiness or sleeping in older children and adults and it can also be seen during meditation, trance, hypnosis, dream and creative states. The occurrence of this wave in other cases is pathological.

- Delta ( $\delta$ ) is the oscillation in the frequency range up to 4 Hz and amplitude from 75 to 200  $\mu$ V. It is the highest in amplitude and the slowest wave. It occurs typically in adults in slow wave sleep. It is also seen normally in babies. In pathological situation delta wave may occur focally with subcortical lesions and in cases of metabolic encephalopathy hydrocephalus.
- Gamma ( $\gamma$ ) is the oscillation in the frequency range approximately between 35-100 Hz. Gamma rhythms are thought to connect together different populations of neurons into a network for the purpose of carrying out a certain cognitive or motor function from all parts of the brain. Having high gamma wave activity is associated with high levels of intelligence, high amounts of self-control, great memory and an increased perception of reality. However, there is no agreement on the theory.

Summing up, slow waves occur with idle, calm brain activity and fast wave occur during intensive brain activity connected with information processing.

# 2.4 Subject's motion assessment and emergency detection in context of the localization

Monitoring activities of daily living of elderly and disabled people, understanding their behavior, providing life support and alarm situations detection must be undertaken with reference to their presence localization at home. It involves division of the supervised living area to smaller regions and matching with them the most common type, intensity and time duration of the human activity. Any significant deviation from the usual behavior could be the base of alerting.

In order to detect automatically anxious or dangerous situation, specific spatial or temporal assumptions and criteria has to be set up. Transitions between different body postures regarded as a physiologically essential function and a prerequisite for gait could be also a sign of emergency. Posture change is then recognized and verified whether its occurrence, localization and duration is typical or uncommon.

In multimodal home care surveillance each of functionality requires its specific zone. Therefore presence of the subject is detected inside the following main zones:

- command zone place from which the subject is able to send commands to his or her environment (operating the computer, audio or video equipment, etc.),
- sleeping zone region where favorite sleep-related measurements devices are added to assess and control the human sleep (bed pressure detectors, ECG and EEG sensors, accelerometers placed on the lower limbs, detector and calculator of snoring, etc.),
- health zone special zone which is provided with dedicated health status measurements equipment (simple tactile ECG sensors, feet pressure detectors, etc.).

#### 2.5 Voluntary activity of the brain as command representation

Regions of the cerebral cortex involved in the planning, control, and execution of voluntary motor functions are specified as motor cortex. This areas are typically divided into three regions which have different functional roles: primary motor cortex (M1), pre-motor area (PMA), supplementary motor area (SMA). The primary motor cortex has a somatotopic representation, which means that particular groups of muscles of different body parts correspond to motor cortex areas in an arrangement. This somatotopic representation is called a motor *homunculus*. The arm and hand motor area (lying between the leg and face area) is the largest, and occupies the part of precentral. The lateral area of the primary motor cortex is arranged from the top to the bottom in areas that correspond to the shoulder, elbow, wrist, fingers, thumb, eyelids, lips and jaw. Interior parts of the motor area correspond with the legs. All of these areas are not proportional to their size in the body. The lips, face parts (especially the tongue) and hands occupy particularly large areas as the body parts which they represent perform most complicated movements. Damage, amputation or paralysis, can shift motor areas to adopt new parts of the body.

The somatotopic organization gives possibility of decoding the movement intention of different parts of the body. The movement intention are associated with different spatiotemporal patterns of increase or attenuation of neuron amplitude oscillation and it may provide additional degrees-of-freedom for command representation and control in the noninvasive methods, as electroencephalography (EEG), mainly support the multi-state BCI. The somatotopic organization allows also to reduce the number of electrodes in EEG to those which lie over motor cortex and provides better parameters for classification, hence the electrode setup time might be reduced to minimum which is very important in brain-computer interfaces.

However, there are few problems, which have limited the reliability and produced high rate of errors. They have to be considered when constructing the alternative way of interaction between the human and his environment based on EEG signal.

Firstly, the motor imaginary of movement where the subjects imagine the movement of only one limb of the body or for example tongue can be difficult task. It is important to imagine the limb movement properly which is essential for achieving purely mental control without involvement of muscle activity. Fatigue is a common problem during data collection which requires a relatively long time and repetitive motor tasks. Contamination of EMG artifacts from facial muscles may possibly cause serious problems in BCI development. Additionally, the task of the primary motor cortex is to connect the brain to the lower motor neurons via the spinal cord in order to tell them which particular muscles need to contract. In fact, the same muscle are often represented over quite large regions of the brain's surface, and there is an overlap in the representation of different regions of the body. The activity of a single neuron could cause contraction of more than one muscle, which suggests that primer motor cortex may not simply code the degree of contraction of individual muscles.

#### 2.6 Voluntary eye movements as command representation

In proposed system we used three different methods for tracking eye movements. Each method differently characterizes obtained signal. The *electrooculogram* represents electric potential, the *infrared oculography* measures intensity of reflected infrared light and *video-based eye-tracking* records sequence of images of the eye. These three methods are widely described below.

**Electrooculogram (EOG).** The eye behaves as a single electrical dipole, the cornea of the eye is electrically positive relative to the retina, therefore this dipole is oriented form the retina to the cornea. During the eye movements the dipole also changes its position and rotating adequately, thanks to these signals measurements of the eye movements are possible.

Figure 3 presents the measure of the horizontal eye movements. Two electrodes are placed outside of the left and right eye. If the eye is at rest, the electrodes have effectively this same potential and no voltage is recorded. The movement (rotation) of the eye causes change of the potential of the electrodes. For example, if eye rotates to the right, the right electrode is relatively positive to the second (left) electrode. The opposite move gives opposite effect, as illustrated in Fig. 3. Up to rotation of ca. 30 degrees the difference of the measured potential on the electrodes can be considered as proportional to the angle rotate, but beyond this limit the linearity becomes progressively worse. In this method spatial resolution can reach about 1 degree and maximum measured eye rotation can reach 70 degrees. The EOG has

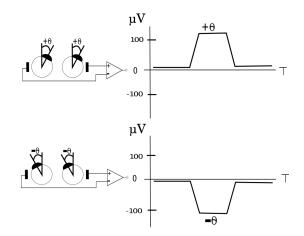
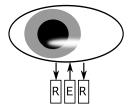


Fig. 3 Signal corresponding to the angle of eye rotation

advantages and disadvantages. The main disadvantage is that corneoretinal potential is not fixed and changes as a result of act of light, fatigue, and other qualities. These are reasons of frequent calibration. Signal is measured with respect to a head. This enforces stabilization of the head, or there is a need to use some other devices Data integration in multimodal home care system

to tracking of the head movements. The measured signal is sensitive to muscle artifacts. As advantages we should classify: easy to use, even for children and patient confined to bed, the recordings may be made in total darkness and with closed eyes.

**Infrared oculography.** In this eye tracking method, eye is illuminated by infrared light which is reflected by the sclera (Fig. 4). A pair of sensors (phototransistor) registers reflected light and quantity of difference between sensors make possible to measure eye movements. The light source and sensors can be placed on special glasses.



**Fig. 4** Infrared light illuminated by an emitter (E) is received by phototransistor (R)

The *infrared oculography* has less noise than EOG, but is more sensitive on changes of external light tension. The main disadvantage of this method is that it only works well for about 30 degree of eye deflection from the center. The advantages include ability to measure eye movements in darkness. Spatial resolution is about 0.1 degree. Setup is quick but the calibration is necessary. Like in EOG the measured signal is respected to the head, so another devices is needed to measure head movements if we want to have relatively free movements.

**Video-based eye-tracking.** This is the third method we used to track the eye movements. This method is base on an infrared source, which illuminates the eye and a camera for capturing an image of the eye. The result of such illumination is that the pupil is well visible and with big contrast to the rest of the eye. Beside this reflection occurs on the boundaries of the cornea. The cornea reflection center and the pupil center make a vector which is used for calculation degree of eye movements.

Usage of infrared light for illumination, makes that this method become useless for outdoors activities. During the daytime can occur too many artifacts. The main advantage is the possibility of usage of this method in remote and head-mounted systems. As presented in figure 5 each method of eye movements measurement has different features. These features allow to select the adequate method dependent on environmental needs.

In the proposed system, eye movements is obtained by multimodal method which choice is adequate to environmental needs. Idea of multimodal input for the system is illustrated in Fig. 7. Each method characterizes different output signal, therefore requires a specific preprocessor which yields previously defined tokens. These tokens are commands to execute for the command system (see Fig. 6 and Fig. 7).

Methods:	EOG	Infrared Oculography	Video based with infrared illumination	
Spatial resolution:	1°	0.1°	1°	
Temporal resolution:	500 Hz	500 Hz	25 60 Hz	
Ability to record horizontal, vertical movements:	$h = v = \pm 70^{\circ}$	$h = \pm 30^{\circ}$ $v = \pm 20^{\circ}$	$h = v = \pm 40^{\circ}$	
Subject contact:	electrodes	glasses	head mounted or none if remote	
Disadvantages:	<ul> <li>need preparing a skin for electrodes placement,</li> <li>frequently calibration needed,</li> <li>another device to measure head movements,</li> <li>sensitive to muscle artifacts</li> </ul>	<ul> <li>need calibration,</li> <li>record small eye deflection,</li> <li>sensitive on change of external light tension,</li> <li>another device to measure head movements</li> </ul>	<ul> <li>small temporal resolution,</li> <li>useless in outdoors activities during daytime,</li> <li>need another device to measure head movements (if head mounted),</li> <li>subject must stay within a relatively confined area of operation (if remote)</li> </ul>	
Advantages:	<ul> <li>+ easy to use, also for children and patient confined to bed,</li> <li>+ recordings may be made in total darkness,</li> <li>+ and with closed eyelids</li> </ul>	<ul> <li>+ fast setup,</li> <li>+ recordings may be made in darkness,</li> <li>+ high spatial resolution,</li> </ul>	<ul> <li>+ fast setup,</li> <li>+ do not need calibration,</li> <li>+ do not need another</li> <li>device to measure head</li> <li>movements (if remote),</li> <li>+ no contact with subject</li> <li>(if remote)</li> </ul>	

Fig. 5 Comparison of features of three eyetracking methods

Left     L       Right     R       Up     U       Fig. 6 Five tokens (commands) refer to eyes move-     Down	Command	Abbreviation
Fig. 6 Five tokens (com-     Up     U       mands) refer to eves move-     Down     D	Left	L
Fig. 6 Five tokens (com-     Down     D       mands) refer to eves move-     D	Right	R
mands) refer to eves move-	Up	U
mands) refer to eyes move-	Down	D
ments.	Error	E

# **3** Results

Preliminary studies on detection of the subject's status and intention based on separate recording techniques led us to distinguishing of several subject-specific behavioral patterns (Fig. 8). Although the subject's status is determined with limited reliability (Table 1), thanks to the stability of everyday measurement conditions we are able to detect abnormality of subject behavior.

#### Data integration in multimodal home care system

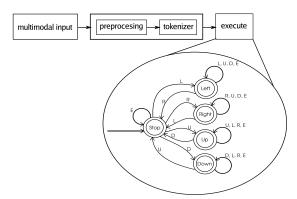


Fig. 7 Schematic diagram of selected eye movements interpretation

Table 1 Estimation of sensitivity [%] of individual methods and multimodal status recognition

recording modality vs. subject status	sleeping	walking	resting	working
Electrical activity of the heart	80	60	85	55
Mechanical activity of the body	70	90	70	75
Electrical activity of the brain	90	70	85	70
Multimodal status recognition	99.4	98.8	99.3	96.7

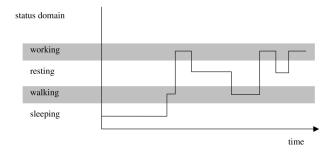


Fig. 8 Example of behavioral pattern recorded in the morning

# **4** Discussion

The multimodal system for diagnostic and control aspects of assisted living has been sketched with consideration of the measurement method selection, their reliability, usability in home condition and costs. The novelty of our approach is twofold:

- contextual and conditional interpretation of measured parameters from multimodal acquisition,
- common status and command description at measurement and processing stages.

Expected reliability of the proposed system is still not sufficient to comply with requirements for medical-grade equipment. However in assisted living application, the main objective is to provide general information or alerts rather than precise medical data. Further tests in the prototype application are necessary to reveal weak points of this approach and to verify the usability in home condition.

Acknowledgements Scientific work supported by the Polish State Committee for Scientific Research resources in years 2009-2012 as a research project No. N N518 426736.

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