A Graph Representation of the Subject's Time-State Space

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Abstract Surveillance systems are currently the most developed branch of assisted living applications providing the disabled or elderly people with unprecedented security in their independent life. This paper presents a design of a telemedical surveillance system, where graph theory is used to describe subjects' states. Patient's states expressed by sets of medically-derived parameters and his or her daily activity (a behavioral pattern) are represented by attributed probabilistic graphs with indexed and labeled nodes. This representation provides high flexibility in a state and transient description as well as a reliable measure of behavior divergence, which is a basis for automatic alerting. The system is designed for the subject's apartment and supports a localization-dependent definition of his or her usual and unusual behavior. The apartment topology is also represented in the form of a graph determining subject's pathways and states. This approach has been found very flexible in all aspects of personalization, appropriate to work with the behavioral presumption set or with the auto-adaptive artificial intelligence recognition engine. Also the patient's state, thanks to the semantic description may be easily extended or refined if necessary by adding new, complementary data capture methods.

1 Introduction

Assisted living applications benefit from the wide range of biomedical measurements being derivatives of clinical diagnostic systems. The pursuit for simplicity of usage and public availability of the home care equipment often decreases the reli-

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ability of each single measurement. As a promising remedy to maintain the overall system performance in home surveillance and alerting, multimodal measurement approaches are developed worldwide [1], [3], [4], [7]. They principle benefits from several measurements performed simultaneously with the use of different methodologies, results of which are integrated on the level of a universal semantic description of the patient's status [6], [20].

Regardless of the method used, the patient's status is determined by a sorted list of symbols representing his or her conditions, attributed by the numeric value of occurrence probability. At this stage, biomedical measurements are completed by environmental variables of two kinds:

- stimuli, influencing the subject's behavior (i.e. room lighting),
- results, being consequences of subject's actions (i.e. subject's coordinates).

It is worth a remark that such a measurement infrastructure supports not only passive capturing of the subject's status, but also active interaction and stimulation aimed at subject's assessment and detection of events. Including temporal variability in the multimodal surveillance of status allow us to define the behavioral pattern as a sequence of predefined status vectors appearing in a given order and complying with specified temporal restrictions. Putting aside possible delay and inaccuracy of values of some status components, the subject's behavior may be captured and analyzed in real time in order to detect abnormalities and to warn about possible health danger. Such preventive analysis is highly welcome in general surveillance of elderly people living on their own, as well as in specific situations as car driving or similar.

A multimodal surveillance system providing a semantic description of basic subject's health parameters (e.g. heart rate), subject's motion and sounds is currently under development in Biocybernetic Lab, AGH-University of Science and Technology. Its principal purpose is the recognition of abnormalities in behavioral patterns and classification of events into one of four categories implying further actions. The recognition of alternate behavior is performed on the semantic description of the subject's status in the context of subject's habits. This step is in main focus throughout this paper.

Chapter 2 presents principles of the surveillance system and specifies the subject's state and behavior observation, chapter 3 reveals a graph-based representation of the patient's state and defines a distance measure between the 'usual' and 'unusual' behavior. Chapter 4 includes discussion and final remarks.

2 Principles of the surveillance system

Automatic semantic summarization of human activity and detection of unusual inactivity are useful goals for video-based systems operating in a supportive home environment. Learned models of a spatial context are used in conjunction with a tracker to achieve these goals. The surveillance is oriented to detect 'unusual inactivity' an example of which is fall detection [12], [15]. Falls are a major health hazard for the elderly and a major obstacle to independent living. The estimated incidence of falls for both institutionalized and independent persons aged over 75 is at least 30 percent per year [16].

Four various sources of behavioral signals are considered in the system: two surface-recorded vital signs, video sequences and acceleration patterns. This setup allows for 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's status is performed by the dedicated software, which may be individually tuned accordingly to the patient's or environmental conditions.

2.1 State and behavior observation

Health records usually provide several organ-specific descriptors and principal global parameters describing the whole organism in aspects representing it as organ's environment influencing its functionality. For describing a subject state, we use a parameter-domain representation, in which the subject S is described by the set of diagnostic parameters $S_p = \{p_1 \cdots p_N\}$, considered as the projection of his physiological state on the modality-dependent N-dimensional state space $\mathbf{S}^N$. The projection is limited due to restrictions on the count N of values available for measurement and inaccurate due to measurement errors ε_N and additive interferences ρ_N [19]. In the proposed system, the state observation complies to the following requisites:

- the multimodal acquisition has to provide a reliable description of subject's behavior,
- the system infrastructure has to be feasible in home-care conditions and preferably to use only a customer-grade equipment.

The most visible and easily obtainable markers representing daily activity in humans are movements signals of their bodies [13]. Many previous studies proved the utility of continuous round-the-clock registration of body arrangements and motion in behavior quantitative evaluation [9], [11]. To acquire the mechanical activity of the body, the proposed system is equipped with video [8], acceleration and angular velocity sensors. Additionally, the human activity is represented well by the response of the human cardiovascular system to variations of physical burdens and psychical conditions. The main parameter used for the assessment of extracardiac influence is the *heart rate variability* (HRV) 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 [10]. 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. Accordingly to [22] these steps are usually directly followed by the statistics, interpolation of missing intervals is performed for frequency-domain analysis.

The subject's behavior is usually referenced to as changes of the state with time. The distinction of the typical human behavior is thus based on the temporal synchronization of the parameters' sequences. The sequence of multimodal state descriptions is known as the *behavioral pattern* (fig.1). Since the time is a distinctive factor of behavioral patterns, first question to be answered while designing the system is the state sampling frequency. The resulting value is a compromise between two contradictory requirements:

- technical and methodological feasibility (e.g. video system throughput [8], necessary averaging of HRV parameters [22]),
- expected temporal resolution of the system defined by the duration of the shortest events.

In the proposed system the value is set to 1 minute, however this should be verified by the prototype test. Patterns typical for the common human actions are easily

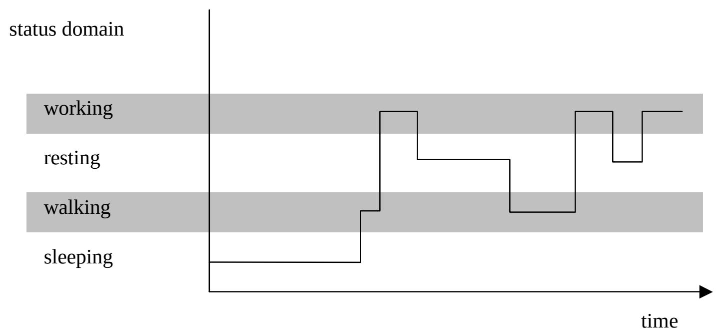

Fig. 1 Example of a behavioral pattern recorded in the morning

separable, however, regardless the acquisition and state description accuracy, the behavior is not directly represented by behavioral patterns. This justifies the attribute of probability p_b used in the behavior representation in the system. The behavioral patterns represented in the system belong to a finite list L_p (see. tab. 1).

2.2 Qualification of the behavior

Qualification of the behavior is made by the system automatically with respect to two factors: presumptions and heuristics. 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

Table 1 Examples of behavioral patterns and their acquisition modes

acquisition mode	parameter representation	state aspect	behavioral examples
single-lead electrocardiogram	heart rate variability	workload	{working, resting, sleeping}
video recording	image analysis	posture detection	{standing, sitting, lying, walking}
accelerometric recording	signal analysis	motion classification	{resting, working, walking}

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),
- by the response to the stimulus (subject is not performing the action expected as a response to the stimulus).

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 positioning. The example of the behavior permitted in given rooms defined in the presumptions-based behavior qualification is presented in Table 2.

Table 2 Presumptions on the allowed subject's activities in particular rooms

room type / behavior type	living room	bedroom	kitchen	bathroom	entrance hall
working	+	-	+	+	+
resting	+	+	+	-	-
lying	+ $\leq$60 min	+	-	-	-
sitting	+	+	+ $\leq$10 min	+ $\leq$10 min	-
walking	+	+ $\leq$1 min	+	+ $\leq$1 min	+

As usually in case of artificial intelligence-based systems [21], the proposed system has two operation modes:

- a learning phase, in which the main task is the acquisition of behavioral patterns typical to each specific subject and the analysis of generalized results by a supervising person - on this stage the abnormalities severity and necessary actions are also defined.

- a working (or testing) phase, in which the system is expected to detect and classify specified events, and consequently to trigger a desired action.

Although formally separated, these operation modes may partially overlap: the data acquired during the testing phase may be used for refinement of system responses and to define other factors of possible danger, which have not been previously considered.

3 A graph representation of the subject's behavior

As graphs provide an easy way to depict complex structures visually, they are one of the most frequently used data structures in computer science, engineering, designing, business analysis and so on [14]. To represent objects with a number of different elements related in various ways hierarchical graphs are often used [2], [5], [18].

3.1 Definition of a subject's state graph

A typical behavioral pattern is represented by an attributed probabilistic graph with indexed and labeled nodes. 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. 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 node labeling of the proposed graph is a modification of the way of labeling random IE graphs used for distorted patterns analysis [17].

Definition 3.1 An attributed probabilistic graph, called a ***state graph***, is a five-tuple $G = (V, E, \Sigma, \varphi, \alpha)$**,** where:

1. V is a finite, nonempty set of nodes with indices ascribed in an unambiguous way,
2. $E \subseteq 2^V$ is a set of edges such that $\forall\, e \in E: |e| = 2$,
3. Σ is a finite, nonempty set of node labels,
4. $\varphi: V \rightarrow 2^{\Sigma\times[0,1]}$ is a node labeling function, where each random node label $\varphi(v)$ is a set of pairs of the form (σ, p), $\sigma \in \Sigma$, $p \in [0,1]$ is a probability of labeling a node v with σ, such that the sum of the second elements of these pairs is equal to 1,
5. $\alpha: \Sigma \rightarrow 2^A$, where A is a set of node attributes, is a node attributing function, which assigns finite subsets of A to node labels of Σ.

A state graph representing a typical behavioral pattern for a given person located in a living-room is shown in fig. 2. This graph is composed of four nodes, where the node number 1 represents standing position, the node number 2 - walking position, while the nodes 3 and 4 represent sitting and lying positions, respectively. The elements of the set of node labels $\{wrk, wlk, slp, rst\}$ denote the following activities: working, walking, sleeping and resting, respectively. Probabilities of these activities are different for each node. Also the range of values for attributes (like the heart rate, limb acceleration etc.) assigned to labels denoting various activities can be different for each node. One of the attributes assigned to the label *slp* is t_s denoting the foreseen duration of the sleep. It is assumed that the period of this activity in the living-room should be shorter than 60 minutes.

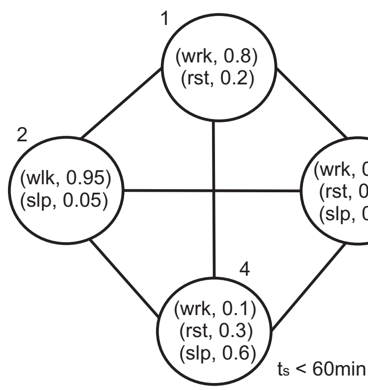

Fig. 2 A state graph of a typical behavioral pattern

3.2 A graph representation of subject's habits

As the behavioral pattern strongly depends on the room the person is located in, the status of the patient who is surveyed by the home care equipment will be represented by a hierarchical graph, where hierarchical nodes correspond to rooms of the apartment, while edges connecting them represent the accessibility relation between rooms. The nodes are labeled by names reflecting the functionality of rooms. In each hierarchical node a state graph describing a behavioral pattern typical for the corresponding type of room is nested.

Let $\mathtt{G}$ be a family of state graphs describing typical behavioral patterns.

Definition 3.2 A hierarchical graph, called a ***state-space graph***, is a five-tuple $H = (N, E, \Gamma, \phi, \eta)$, where:

1. N is a finite, nonempty set of hierarchical nodes,

2. $E \subseteq 2^V$ is a set of edges such that $\forall\, e \in E{:}\ |e| = 2$,
3. Γ is a finite, nonempty set of hierarchical node labels,
4. $\phi{:}\ N \rightarrow \Gamma$ is a hierarchical node labeling function,
5. $\eta{:}\ N \rightarrow \boldsymbol{G}$, is a nesting function, which assigns a state graph to each hierarchical node.

An example of a state-space graph obtained as a result of a learning phase, in which typical behavioral patterns reflecting subject's habits are determined, is shown in fig. 3a. Different state graphs are nested in hierarchical nodes representing rooms of an apartment presented in fig. 3b. Coming out of one room and entering the other according to an edge connecting hierarchical nodes representing these rooms can be treated as coming from the node number 2 (which represents walking position) of the state graph nested in one hierarchical node to the node number 2 of the state graph nested in the second hierarchical node.

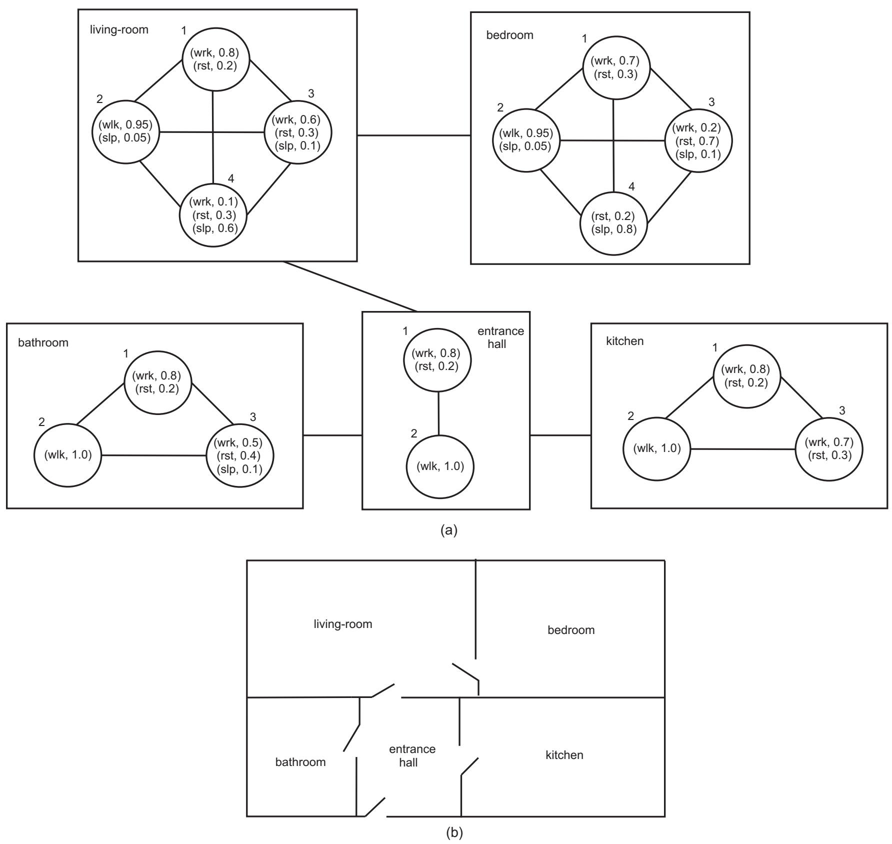

Fig. 3 a) A state-space graph of typical behavioral patterns, b) a layout of the considered apartment

3.3 Quantifying of behavior differences

The proposed representation of behavioral patterns allows us to specify the behavior divergence as the distance between two state graphs. The distance is computed between a state graph representing the typical behavior of the subject in a given room and a state graph corresponding to the present subject's behavior in the same room, which is obtained at the working phase of the system. On the basis of this distance the subject's state is classified.

It should be noted that the distance is computed only between two isomorphic state graphs. As state graphs used presently are complete ones, the isomorphism in this case means that both graphs have the same number of nodes with the same indices, i.e., representing the same body positions. If a state graph representing a present behavioral pattern has more nodes than the state graph of a typical behavior, the alert is triggered as it means that an unexpected body position has been found.

Definition 3.3 Let v_k be a node with the index k of a state graph G.

Let $P_k = \{(\sigma_k^1, p(\sigma_k^1)), \ldots, (\sigma_k^r, p(\sigma_k^r))\}$, where σ_k^j, $j = 1, \ldots, r$, is a j-th label of the node v_k and $p(\sigma_k^j)$ is a probability of the label σ_k^j, be a probability distribution of labels assigned to v_k.

Let v_i, v_l be two nodes with r labels with probability distributions P_i, P_l, respectively.

The **distance** between v_i and v_l is defined as: $\delta(v_i, v_l) = \sum_{m=1}^{r} |p(\sigma_i^m) - p(\sigma_l^m)|$.

Definition 3.4 Let G_1 and G_2 be two isomorphic state graphs with n nodes.

The **distance between G_1 and G_2** is defined as $\Delta(G_1, G_2) = \sum_{i=1}^{n} \delta(v_i^1, v_i^2)$, where v_i^1 and v_i^2 denote nodes of G_1 and G_2, respectively.

Let us consider a state graph G_2 representing the present subject's behavior in the bathroom (fig. 4a). The distance between this graph and the state graph G_1 representing the typical behavior in a bathroom (fig. 3a) is computed as $\delta(v_1^1, v_1^2) + \delta(v_2^1, v_2^2) + \delta(v_3^1, v_3^2) = 0.4 + 0 + 0 = 0.4$. The distance between a state graph G_3 (fig. 4b) and G_1 is computed as $\delta(v_1^1, v_1^2) + \delta(v_2^1, v_2^2) + \delta(v_3^1, v_3^2) = 0 + 0 + 1 = 1$. The first result indicates that the state of the surveyed person can be suspicious as he/she rests more frequently than usually. The second result is great enough to classify the state as dangerous, because the subject does not perform their normal working activity at all.

Classification of subject's behavior as {normal, suspicious, dangerous, critical} is based on comparison of the current behavior divergence expressed by the graph distance (see def. 3.4) and the appropriate threshold value. Even in the presumptions-based system these values cannot be set arbitrarily without the experimental verification of the tolerance margins, wide enough to cover a range of 'usual' states. The thereshold values depend on several factors:

- the subject's action repetitiveness,
- state measurement methodology and accuracy,

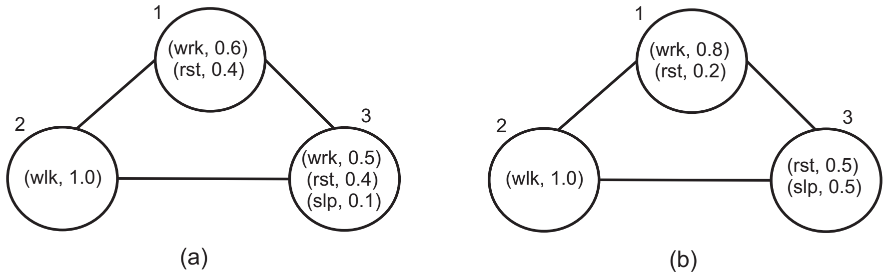

Fig. 4 Two state graphs representing different behavioral patterns

- subject's localization (in some rooms unexpected states are more dangerous than in the others),
- the current state (some states are more precisely defined than the others).

In the AI-based surveillance system, the states selected as 'usual' during the supervised learning phase are statistically processed in order to calculate threshold values providing best sensitivity and specificity of the danger recognition. These statistics provide subject-specific threshold values $T_S(m,l,s)$ in the three-dimensional context of the measurement, localization and state.

4 Discussion

The application of the behavioral pattern analysis methodology to recognition potentially dangerous events in pursued subject was presented and designed. Three aspects of novelty are presented in this paper:

- the representation of the subject's state as an attributed probabilistic graph,
- the use of behavioral patterns considering the temporal aspect of state changes,
- the interpretation of the behavioral patterns in the context of subject's localization which considers various functionalities of rooms in subject's apartment.

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.

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.

Although the measurement of specific vital signs is not precise, the integration of data in a multimodal system provides a reliable stepwise alerting. The alerting may then be used as a trigger of a health-oriented message, on-demand medication, a nurse visit or medical intervention.

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.

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