A hybrid Knowledge-Based Methodology for Multivariate Simulation in Home Health Telecare

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Abstract

This paper deals with monitoring the health status of a patient at home so as to detect critical evolutions over a scale of several days or weeks. A multivariate simulation is used as a way to overcome the lack of experimental data required for studying this decision-making issue. The simulation process needs to be driven in a rigorous and robust way. Due to that, and to deal with heterogeneity and complexity, we make use of an hybrid and refinement methodology. It involves the fusion of several types of models and knowledge, as well as the implementation of a cascade structure for the simulation process.

1 Introduction

Home health telecare systems are built upon a global medical information system for monitoring elderly people living on their own. Most of the current works dealing with home health telecare are focused on the architecture issue, dedicated to specific pathologies, or concern basic alarms related to the person's situation at home [7]. Basic alarms are raised by "smart" sensors or low layers of a "local intelligence unit" when a problem occurs at a short temporal scale: either one parameter overpasses a critical value (nocturia, pollakisuria, fall, hypertensive crisis, etc.), or a critical scenario involving the value of possibly more than one parameter is recognized (asthma crisis, etc.). Our focus is on the broadcasting of high level alarms about the person's health status, which correspond to the detection of slow changes in the behavior – along several days or weeks – that are not easily spotted by a daily visit from caregivers. The aim is then to support the caregivers by providing some previously unknown information about unusual trends in the person's behavior. These changes are potentially observed through the variation of complementary parameters representative of the health status, and monitored through a provision of sensors of different types (activity, environment, and physiology) installed and networked in the home.

Dealing with this decision-making issue, and considering the lack of experimental data, we propose to set up a simulation process. The aim is to generate multivariate time-series relevant for the study of the person's behavior. The simulation process is designed to preserve the problem's complexity and requires as input commonsense and academic knowledge, as well as knowledge extracted from a set of experimental data. The methodology is based on cycles of refinement in order to better match the requirements of the decision's purpose.

2 Why a simulation process?

The study of any decision-making process requires realistic and accurate data collection. In relation to experimentation, setting up a simulation process enables researchers to have a full and tightly controlled universe of data sets. The advantages are at least five fold: (1) producing large sets of data to experiment with decision-making algorithms, (2) generating data representative of many situations and many peoples' profiles, (3) building a process that is credible and easily understandable by any actor of the system, in contrast with an analytic modeling approach, (4) providing a better *a posteriori* knowledge of the parameters observed at home and the trends of their joint variations, and (5) testing the efficiency and the robustness of detection algorithms by varying the simulation parameters.

Even though simulation has many strengths, it is not without drawbacks. According to Shannon [9], the usefulness of a simulation process depends on: (1) the quality of the model; (2) the appropriateness and quality of the data; and (3) the accurate specification of the simulation conditions to generate data consistent with the purpose of the study, that means neither oversimplifying the model, nor carrying too much details. However, Chwif [2] highlights a lack of methodologies to lead a modeler to obtain a simpler model, and, more generally, Kelton [4] underlines that simulation faces general methodological problems. In [6], Ören presents a simulation taxonomy which leads to the definition of almost up to 100 types of simulation. Then, extracting general guidelines becomes almost impossible.

However, there is a critical step required in any simulation process: the validation and the verification of the model and their behavior, which aim at checking respectively whether: (1) the simulation process operates the way the analyst intended, and (2) it behaves the way the real system does or will. In [8], Sargent exclusively discusses validation and verification of simulation models, and particularly how they relate to the model development process.

In our context of research, the simulation process includes several original features related to the use of an incremental and hybrid approach. The methodology is incremental to allow the process refinement at two levels: (1) within the scope of the problem solving scheme, and (2) at the stage of the simulation model building and validation considering a given purpose and context. An hybrid approach is required: (1) to deal with heterogeneous data, (2) to support the generation of multidimensional and correlated data sets, and (3) to integrate different kinds of knowledge in the process: commonsense and academic knowledge, as well as new knowledge extracted from experimental data sets.

3 Methodology for simulation

3.1 Simulation as part of a problem solving scheme

Setting up a simulation process makes sense only in its context and purpose of use, so that a simulation process should be considered as part of a problem solving scheme. This aims at narrowing and specifying the space of information and knowledge to consider by answering questions like: what are the relevant observations to set up? or which level of detail to consider? There is a compromise to be found between the necessity to save the complexity of phenomena in a simulation process, and the restriction to a level of detail that meets the decision's purpose, so that the generated time-series are appropriate to the decision making.

Considering that the detection of slow changes in a person's behaviour at home is a "high level" issue, the sequences of data used for the decision making may not require a high degree of detail and accuracy while remaining realistic. The aim is not to interpret precisely the problem that occurred, but to set up the context of occurrence of the changes. It is the joint variation of the parameters monitored that is more crucial. However, a difficulty lies in the lack of *a priori* knowledge about these joint variations. That requires a reliance on the diversity of informational sources, which are *a priori* knowledge – that is commonsense and academic knowledge – and experimental data sets. Some new useful knowledge – so called "extracted knowledge" – may be extracted from the experimental data.

On its own side, the simulation process is a cycle of refinement to better match the requirements of the problem entity [8]. It includes sequentially: (1) the conceptual model building according to the analysis of the general purpose and context of the problem; (2) the implementation of this model in a computerized model; and (3) experimentation to generate large sets of data. The critical points of verification and validation are relevant at all these steps, so that they are conducted as part of the simulation development process [8].

3.2 A hybrid simulation scheme

Fusion is commonly used to deal with complexity and heterogeneity. In setting up the simulation process, we considered it essential to integrate several kinds of knowledge at each stage of its conception and validation, that is: (1) <u>commonsense knowledge</u>, (2) <u>academic knowledge</u>, and (3) <u>knowledge extracted from experimental data sets</u>. Commonsense knowledge is exclusively qualitative, whereas academic and extracted knowledge may be either qualitative or quantitative. Qualitative knowledge is interesting at two levels: (1) it gives an idea of fundamental concepts underlying the simulation model, and (2) commonsense knowledge from experts may be used for the validation of both the conceptual model and the data produced by the simulation when facing a lack of quantitative knowledge and / or experimental data. Quantitative knowledge allows validation and / or quantification of the concepts in order to get a model ready for implementation. It may be extracted from one part of the experimental data set (modeling data set). The other part is used for the operational validation (validation data set).

The kinds of knowledge involved at the different stages of the simulation process determine the techniques of modeling and validation [8]: (1) <u>rationalism and logic deductions</u> integrate commonsense knowledge and assume that everyone knows whether the underlying assumptions are true; (2) <u>empiricism</u> involves academic knowledge and then requires every assumptions to be empirically validated; (3) <u>mathematical analysis and statistical methods</u> are used to test theories and assumptions underlying the conceptual model using experimental data set, and produce new so called extracted knowledge; and (4) face validity involves asking people knowledgeable about the system whether the model looks reasonable, calling on their commonsense knowledge. Concerning the operational validation – that is the validation of the output's of the simulation model – the major attribute affecting the selection of a relevant technique is whether the system is observable. If data about the real system are available, appropriate techniques consist of comparing the model and system input-output behaviors, for instance by the means of graphical displays or using statistical tests and procedures. Otherwise, the data sets produced by the model are validated subjectively by experts, or by comparisons to the results of other models.

4 The context of home health telecare

In the context of detecting bad trends in health status, the purpose of the simulation is, first, to generate sequences of data representative of usual conditions of life. Later, the simulation of the disruption of these sequences will allow us to test the efficiency and robustness of decision algorithms.

4.1 Observable parameters

In defining the observable parameters, a compromise needs to be found between: (1) being easily observable and non invasive; and (2) gaining a full appreciation of the person's condition, sensitive to any change in the health status. Our observables' selection for a first step of simulation is based on the following assessments: (1) a deterioration of a person's health status usually entails behavioral disorders; and (2) the heart rate is an important and easily observable physiological measure representative of both the activity and the health status [5]. Thus, we decided to consider the following four parameters: (1) the person's moves, (2) their postures, (3) the activity level, and (4) the mean heart rate. All these parameters can be defined from a provision of sensors. (1) The moves are recorded through infrared motion sensors; (2) the postures using a set of accelerometers; (3) the activity levels are measured by a portable accelerometer worn on the chest and estimated through the body acceleration along the anterior-posterior axis; and (4) the mean heart rate is computed from the data recorded by an ECG portable recorder.

4.2 Simulation inputs: data and knowledge

In our context, records of data from sensors installed in a person's home are not available. However, we have got data corresponding to the monitoring during two non-consecutive periods of 24 hours of twelve young, normotensive, and healthy subjects in their everyday life, male or female, between 20 and 30 years old. Data recorded include: (1) the date and time; (2) the annotation of activity types (every 15 minutes), ranked in 14 increasing levels: sleeping, lying down, sitting still, sitting and speaking, sitting and working, eating, standing, standing and working, ridding bicycle, walking slowly, walking quickly, running, climbing stairs, and going down stairs; (3) a kind of activity level, measured on an arbitrary scale, and corresponding to the norm of the acceleration along the anterior-posterior axis averaged every minute; and (4) the mean heart rate (every minute), corresponding to the average of data recorded by an ECG portable device. This experimental set of data is restricted so that it is relevant in the context of home health telecare, that means we select data corresponding to activity of intensity from low to moderate.

Useful commonsense knowledge concerns the activities of daily living (ADL) of a person at home: (1) the distribution of activities within a day, (2) the expected moves and postures during the different kinds of activities, and (3) the mean activity level according to the activity types.

Academic knowledge of interest (taken from [5]) are related to some features of the mean heart rate and its variability in relation to activity types. The mean heart rate is generally computed from ECG records by an average every 30 seconds to 1 minute. Monod and Pottier [5] note the influence of the posture on the mean heart rate: (a) when sitting, the mean heart rate is 10% higher than when lying down, and (b) when standing, it is from 20 to 30% higher than when lying down. The effect of a low activity on the mean heart rate is also described, as follows: (1) quasi-linear increase of the heart rate with the activity level (a saturation effect is observed for the values corresponding to high activity levels), (2) rapid stabilization of the values, and (3) need for 1 to 3 minutes to recover. Moreover, mean heart rate values are characterized by a large variability.

5 Conceptual model building and validation

5.1 Principle of model building

The conceptual model building is guided by a priori knowledge about the dependence between parameters in order to preserve the problem's complexity, that is especially the joint variations of the parameters. The conceptual model is then defined using a cascade structure with four sub-models, and run in four steps

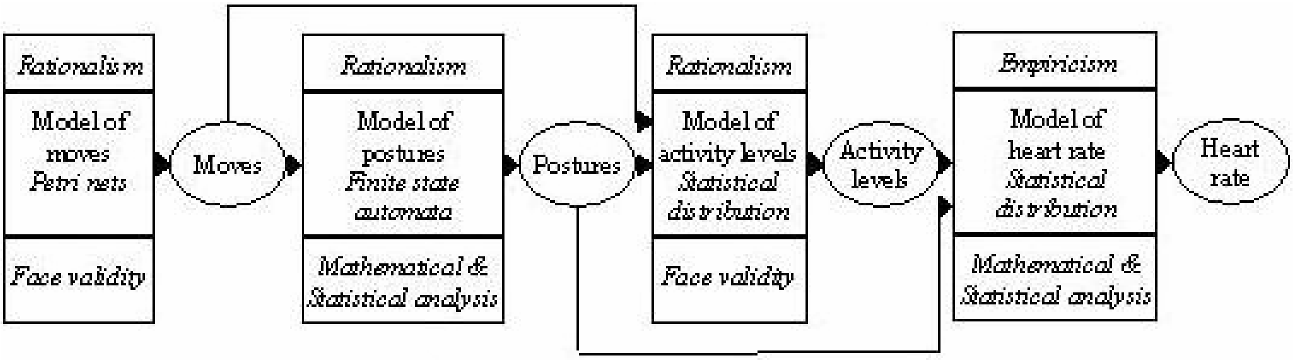

Figure 1. A cascade structure for simulation
The figure shows in ⬭ the simulated parameters, and in ▭ the sub models used for the simulation, detailing from top to bottom: (1) the technique used for modeling, (2) the model built, and (3) the technique of validation

(figure 1) to successively generate time-series corresponding to: (1) the moves of the subject in a given period of time, (2) their successive postures, (3) the sequences of the activity levels, and (4) the values of the mean heart rate.

5.2 Moves

The model defined for the generation of the moves is based on rationalism and logic deductions about the activities of daily living. The validation is performed with experts using face validity because no experimental data are available. This model has been built and implemented by Virone [10]. It is made up of a set of Petri nets representing the expected moves for a person according to the moment of the day, one day being divided into seven periods. The house is supposed to have six rooms on the same floor: (1) kitchen, (2) living room, (3) bedroom, (4) bathroom, (5) toilets, and (6) corridor.

5.3 Postures

As in the previous case, the model defined for the generation of the postures is based on commonsense knowledge about the characteristics of a person's postures in their activities of daily living. The lack of experimental data requires to perform face validation with knowledgeable people. The model is based on finite state automata with three states – the possible postures, that is: (1) standing, (2) sitting, and (3) lying down. One assumption is that the "lying down" and "standing" postures are only reachable through a "sitting" posture. The transition probabilities are defined intuitively according to the room occupied and the moment of the day (one of the seven moments defined for the model of moves), just as the parameters of the gaussian distribution used to randomly determined each transition time.

5.4 Activity levels

The model is based on the intuitive expectation of: (a) an average increase of the values with the types of movement observed – that is, in this order, movements when lying down, sitting, standing, and walking (subset of movements when standing); and (b) a distribution of the values about a mean. The model validation is performed using statistical analysis on experimental data, confirming the commonsense knowledge previously described. Thus, the activity levels are randomly generated at any time according to a distribution characteristic of the type of movement observed at the same time. These distributions appeared to match a mix of: (1) a normal distribution at low levels, and (2) an exponential distribution at higher levels. That may be interpreted as the concentration of activity levels about a mean value considering a given type of movements, with possible occasionally higher values.

5.5 Heart rate

The model defined for the generation of mean heart rate values is based on academic knowledge that especially shows: (a) an inter-subject variability in heart rate values, and (b) a dominant sensitivity of this parameter to the posture and activity level. Part of the subject's specificity in their heart rate variations lies in the features of their resting values, so that we consider in the simulation process: (1) the generation of a time-series for the resting heart rate, and (2) the introduction of some aleas on these values according to the posture and activity level at the same time. The model validation is performed using statistical analysis on experimental values. This sequentially includes study of: (1) the characteristics of variation of the resting heart rate for any subject, (2) the temporal correlation between activity level and heart rate, (3) the relation between the aleas from the resting heart rate and the activity level considering each possible posture, and (4) the distribution of mean heart rate values according to a given posture and activity level.

1) Characterizing the resting values

Considering a physiological parameter such as the mean heart rate, the resting variations very nearly follow a circadian rhythm (period of 24 hours). We decided to analyze roughly the circadian rhythm of every subject using the cosinor technique [1,3], in which collected over 24 hours are represented by the best sinusoidal function using the "least squares" calculation. The analysis showed average values about: (1) 70 bpm for the average level around which the oscillation occurs, (2) 6 bpm for the extent of rhythmic change, and (3) 16h for the time of the maximum value.

2) Aleas on the heart rate from the resting values

Considering the need for time to recover after any activity, the temporal correlation between the activity level and heart rate is analyzed to determine the time interval preceding a measure of heart rate during which the activity level has an influence on the measured heart rate. An analysis of intercorrelation between these two parameters shows a peak when the two time-series are in phase, indicating that the temporal relation can be described as (1), where HR(t) represents the value of heart rate at time t, and PST(t) and ACT(t) the ones of respectively the posture and activity level at the same time:

$$\mathrm{HR}(t) = f(\mathrm{PST}(t), \mathrm{ACT}(t), \mathrm{ACT}(t\text{-}1), \mathrm{ACT}(t\text{-}2), \ldots). \quad (1)$$

Moreover, the best correlation is obtained when activity levels are averaged over the two minutes preceding heart rate determination, so that, at last, the equation describing the temporal relation is as (2).

$$\mathrm{HR}(t) = f(\mathrm{PST}(t), \mathrm{mean}(\mathrm{ACT}(t), \mathrm{ACT}(t\text{-}1))). \quad (2)$$

Thereafter, the relation (2) is detailed, for each posture independently, using a statistical and mathematical analysis on experimental data. Given that the experimental data are recorded from several people, the mean heart rate values are normalized for each subject by removing the resting variations. To face the effect of saturation in the values of heart rate with high activity levels, we decided to study the relation between the aleas on heart rate and the logarithm of the mean activity level over the two minutes preceding any measure of heart rate. The results, presented on figure 2, show a quasi-linear relation between these two parameters. We must note that there are only few data available for moderate to high activity levels. A linear regression over average values gives an estimate of the parameters linking activity level and heart rate. The slope and ordinate values of the linear fit increase with the effort required by the posture. The variability of heart rate values can also roughly be described as a linear function of the mean activity levels, whatever the posture. Considering now a given posture and activity level, a study shows the aleas on the heart rate values are about distributed along a normal curve.

Finally, the mean heart rate values are calculated by adding: (a) the circadian features of heart rate variations for the "simulated" subject; and (b) the values of aleas, which are randomly generated from a normal distribution whose mean and standard deviation are determined from the linear features of the relation (3), according to the postures and activity levels observed. A sample of the sequences of data produced by the model of simulation is shown on figure 3.

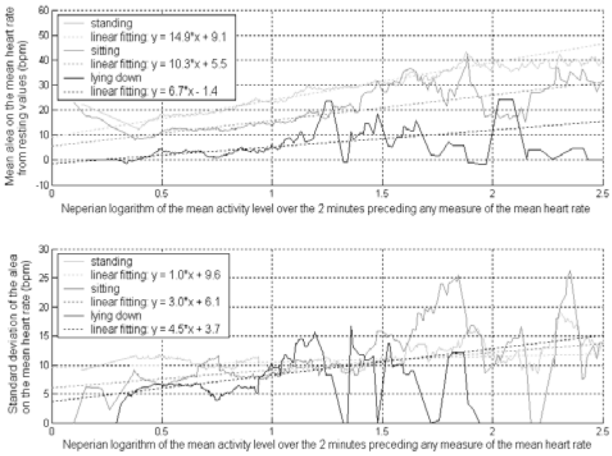

Figure 2. Mean (at the top) and standard deviation (at the bottom) of aleas on the mean heart rate according to the mean values of activity level over the two minutes preceding any measure of the mean heart rate

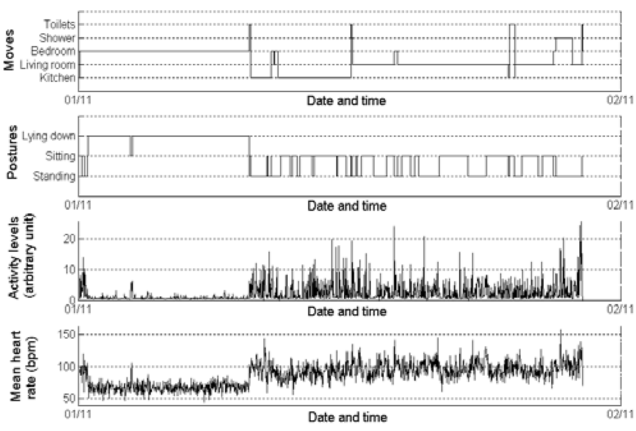

Figure 3. Sequences extracted from the simulation data set

6 Experimental and operational validation

Once implemented using Matlab, we carry out the experimentation of the simulation model, and the validation of its outputs – the operational validation – by comparison with time-series observed on a real system. Concerning moves and postures of a person at home, we do not have any experimental records, so that the validation of the corresponding times-series is performed by face validity, with knowledgeable people. In the case of the two remaining parameters (activity levels and heart rate), we have put aside for operational validation a data set quite close to our experimental conditions. Then, in order to get experimental time-series that are suited to the context of simulation, so that they are relevant for comparison with the simulated ones, we restrict and rearrange this experimental data set. The selection of the sequences of pairs (activity levels, heart rate alea) which are relevant to the sequences of moves and postures produced by the simulation is based on the subjects' annotations about their actitivity and the time of the records. Once a pair is selected, the next pair in the experimental time-series is preferably selected, if relevant. Finally, the values of heart rate are calculated by adding the circadian features of the "simulated" subject. A part of the validation data set obtained in that way is shown in figure 4.

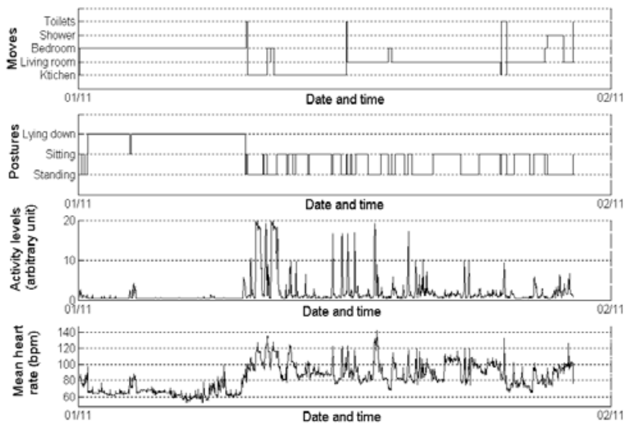

Figure 4. Sequences extracted from the validation data set

The assessment of the quality of the simulation results for the activity levels and mean heart rate values is based on the comparison between the simulation and validation data sets (figures 3 and 4). Before any objective approach using statistical tests and procedures, a subjective judgement on the overall aspect of the signals shows a higher variability in the simulated values than in the validation ones. However, the distributions of activity levels in both cases of simulation and validation look similar, due to the way in which these values were modeled. That means that features other than statistical characteristics of activity levels may have been integrated in the model to get a more realistic aspect for the simulated sequences.

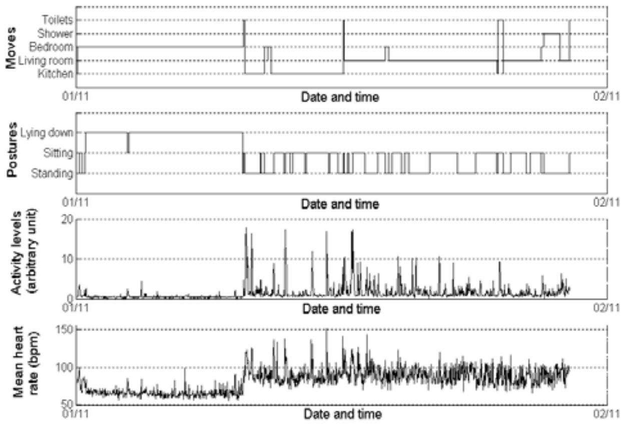

Figure 5. Sequences extracted from the pseudo-validation data set obtained with an individual and random selection of pairs (activity level, heart rate)

An intuitive idea is the need for information about the temporal arrangement of these sequences. This is confirmed by the observation of a validation data set obtained without any temporal constraint, that means without the preferably selection of pairs that follow one another in time: the aspect of these signals is much closer to that of the simulated data (figure 5).

7 Simulation refinement: introducing time constraints

The next cycle in building and experimenting the simulation process consists of introducing additional time constraints for the generation of the values of activity level and mean heart rate. The temporal componenent is crucial considering the purpose of detecting critical evolutions of some parameters over time. That results in a temporal reorganization of the values generated from distributions over each period of time when the same type of activity is observed, in order that single perturbations are grouped together, reducing high frequency variability while keeping the low frequency features of the full time-series. This temporal rearrangement is based on the general principle of physical continuity, which means, in our context, that the absolute difference between successive values of both activity level and heart rate is most often quite small in a short interval of time. The validation of this intuitive assumption is performed by an analysis of experimental time-series. This study particularly shows that the mean absolute difference between two successive measurements increases linearly as the values observed increase. That results in the definition of a tolerance interval for a single value according to the preceding one in sampling time, as described by (4), where *val*(t) represents the value observed at time t, and a and b are respectively the slope and ordinate of the linear function characterizing the tolerance interval width. The values a and b are specific to each parameter.

$$| val(t) - val(t-1) | \leq a * val(t-1) + b. \quad (3)$$

The activity levels are reorganized along the time of every activity performed (same type of movement observed), and the heart rate values are reorganized during periods where the person is maintaining the same posture, and the activity levels remain close. The temporal reorganization of activity levels is performed before generating values for the mean heart rate, in order to preserve the sequential mode of simulation underlying the cascade structure.

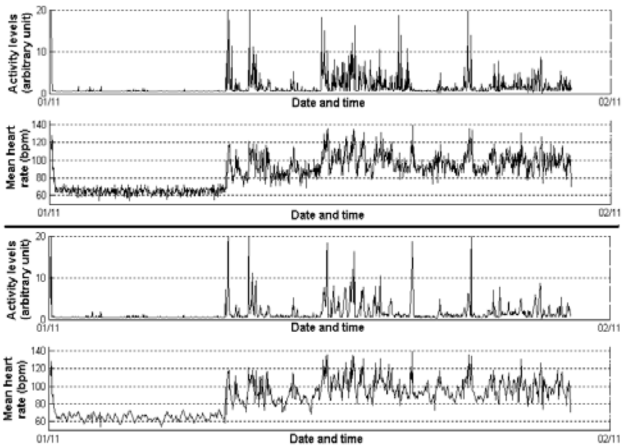

Figure 6. Sequences produced by the simulation process. The two first graphs represent the times-series without any temporal reorganization, unlike the two last ones.

The time-series produced using the updated simulation model (figure 6) are validated by comparison with, on one hand, the previous sequences of data obtained by the simulation process, and, on the other hand, the real sequences of data available. We can note that the temporal reorganization effectively results in less high-frequency variability, while keeping the general shape of signals. Therefore, the time-series look much closer to the real sequences (figure 4). Computing some correlation coefficients between the activity levels and the heart rate values indicates the newly obtained time-series better match the ones produced by the real system: the correlation coefficient is on average increased by about 0.05 to 0.15 points after temporarily reorganizing the sequences of values, putting it very close to the mean value of about 0.6 obtained with real sequences.

The main advantage of the algorithm suggested is that the initial statistical properties are preserved. The drawbacks include that this algorithm maybe somewhat restrictive, since it requires that the gap between two successive values rarely exceeds a given tolerance value. However, several thresholds, such as the tolerance intervals, may be adjusted so that the results of the simulation process match the requirements in terms of variability reduction.

8 Discussion, conclusion and perspectives

This paragraph is built around three major points: (1) the validity of the experimental data set, (2) the simulation model building, and (3) the results of its experimentation.

The experimental data used for the simulation process may not be completely satisfactory since they have been recorded from a restricted class of people (young, normotensive, and healthy people, between 20 and 30 years old), which does not fit the one targeted by home health telecare projects (elderly people). Moreover, the information about the activities performed by the subjects are given by subjective annotations written down by the subjects themselves, so that it may be difficult for instance to discriminate activities like “walking quickly” and “walking slowly” in the same manner for every subject. Finally, the data following activities of high intensity (even if the closest ones have been removed) might be somewhat inaccurate because of the time needed to recover. All these reasons may bias the model of simulation.

Other remarks can be made on the model building itself, especially concerning the simulation of heart rate values. Activities and postures have been considered as the main factor influencing the heart rate values. That is probably true in general, but many other factors may have an influence as well, such as many external factors (outside temperature, use of medicines, stress, external events such as phone ringing, etc.) or the organism productivity (vegetative activity, etc.). The methods for estimating the circadian rhythms and normalizing the heart rate values are also far from perfection given the underlying inaccuracies and assumptions.

In spite of the imprecision described above, the results produced by the model are not inappropriate from the point of view of the simulation’s purpose. Indeed, the sequences of simulated data are expected to be used for the study of mean- to long-term critical trends in a person’s behaviour, that is a “high level” analysis. Before any other simulation refinement, we then need to go on defining and experimenting the decision making system in order to more accurately determine the level of details required within the time series. Then we will better know how to adjust the parameters of the simulation process, and eventually, whether or not another cycle of refinement is required so that the simulation generates more appropriate data sequences. The steps of validation with experts need to be conducted in the same time.

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