Single-Occupancy Simulator for Ambient Intelligent Environment

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Abstract

In this paper, the simulation of an occupant's behaviour in a single-occupant ambient intelligent environment is addressed. The algorithm of the simulator is designed flexible enough to accept different environmental profiles including the number of areas and the connections between them along with different occupant's profiles including expected daily occupancy pattern of him/her and the uncertainty of his/her behaviour to follow this occupancy pattern. The generated occupancy signal by the simulator represents the occupancy of areas by assuming a signal level for the occupancy of each area in a single-occupant environment with the resolution of one minute in a whole day activity of the occupant in the environment. The validity of the simulator will be verified by tuning the simulator's parameters to occupancy data collected by sensory agents from a real equivalent environment. By applying the generated data from this simulator to the data mining techniques, the ability of different techniques will be investigated.

Keywords: Single-Occupant, Ambient Intelligent, Sensory Agent, Occupancy Signal, Simulation.

1 Introduction

Modeling the human behaviour is very challenging due to the complexity of this behaviour in terms of psychology [1]. However, the simplification of the human behaviour to a particular activity can reduce the modeling challenges. For instance, it should be easier to model how an occupant occupies the areas of his/her living environment rather than modeling all of his/her daily activities.

As a part of our ongoing research with the subject of Predictive Ambient Intelligent Environment [2], to choose and adapt suitable data mining prediction techniques, it is required to monitor the occupancy of a single-occupant environment with different designs and different occupant's behaviour. To achieve this, a number of sensory agents are employed to collect the required occupancy data from a single-occupant environment. Each employed sensory agent consists of a Passive Infrared (PIR) sensor and a ZigBee wireless module interfaced with a simple microcontroller [3]. Collected data is then applied to different data mining (prediction) techniques in order to adapt a suitable technique for prediction [4].

Taking into account the diversity of environmental designs as well as occupants' behaviour, to choose and adapt a suitable data mining technique, it is essential to do experiments considering different environmental profiles as well as different occupant profiles. To reduce the number of experiments and the number of resources required for these experiments, it is aimed to create a simulator that can generate the data required for our experiments. To evaluate the occupancy signal generated by this simulator, the results from a number of real experiments will be used to tune the parameters of the model. The overall architecture of our ambient intelligent environment is shown in Figure 1.

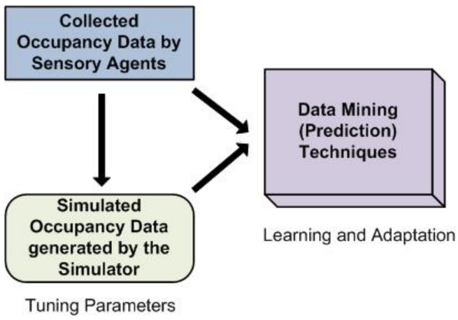


Figure 1- Predictive Ambient Intelligent Environment (Overall Architecture).

The applied methodology for creating the above mentioned simulator for the occupancy modeling in a single-occupant environment is basically a statistical model. This model simulates the occupant's pattern of occupancy by considering the occupant's expected pattern of occupancy. To model the occupancy signal, both movements in the environment between different areas and the time spent in each area are considered [5].

The simulator's interface gives enough flexibility to generate the occupancy signal for any environment by the choice of the number of areas as well as the connections among them. It is also very flexible in terms of accepting different profiles of an occupant including the occupant's expected pattern of occupancy and the uncertainty in his/her behaviour to follow the expected pattern.

In this paper, section 2 covers the modelling scenario for the occupancy signal in a single-occupant environment. The simulation algorithm is explained in Section 3 followed by user interface of the simulator in Section 4. Experimental results are provided in section 5, and relevant concluding remarks are discussed in the final section.

2 Modeling Scenario

In a single-occupant environment consisting of several areas, the occupancy signal is basically a number of movements between different areas (transition) as well as the time spent by the occupant in each area (duration). This signal can be generated by assuming different levels for each area in the environment.

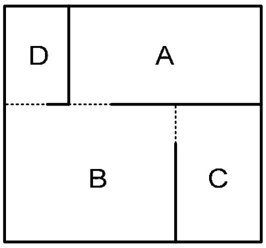


Figure 2 – A proposed single-occupant environment with four areas.

For example, the occupancy signal of a proposed 4-area environment shown in Figure 2 contains four different levels (Figure 3) [2].

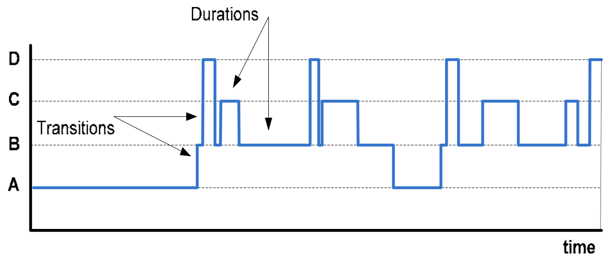


Figure 3 – The occupancy signal.

To model the occupancy signal, both parts of the signal, namely transition and duration parts should be modeled properly. Therefore, an occupancy signal generator is created based on the model explained below:

2.1 Modeling the transition part

The transition between different levels of a single-occupant occupancy signal (which is the representation of movement through the areas in the environment) is dependant on the profile of the environment including the number of areas and the design of the environment [6]. For instance, in Figure 2 as a single-occupant environment, a transition between areas A and B is possible but there is not a possible transition between areas A and C, or A and D.

In order to model these transition possibilities a state diagram shown in Figure 4 is proposed. In this diagram, each area of the environment is represented by a state and transition possibilities are shown as the directional links between the states. The weights on the links are the probability of the transitions between states where for states with only one transition possibility the weight is 1 (e.g. states A, C, and D) and for states with more than one transition possibility the weights are the probability of that transition (e.g. state B). In the states with more than one transition possibility, the sum of transition probabilities should be 1 (e.g. for state B: $p1 + p2 + p3 = 1$).

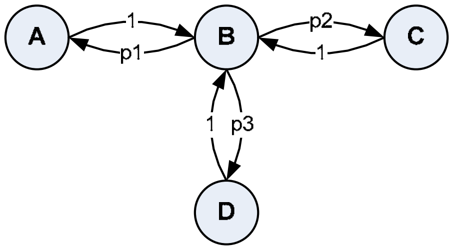


Figure 4 - Transitions state diagram.

To model this state diagram, it is proposed to apply a uniform distribution for any state of the diagram with more than one transition possibilities [7].

	A	*B*	*C*	*D*
A	x	1	0	0
B	p1	x	p2	p3
C	0	1	x	0
D	0	1	0	x

Figure 5 - Transitions probability matrix.

For instance, state B of the diagram shown in Figure 4 in which the probabilities of transitions from this state to other states are shown in Figure 5 can be modelled by generating random numbers [8] as depicted in Figure 6. For example, a random number R_i with the condition $p_1 \times 100 \le R_i < (p_1 + p_2) \times 100$ represents the transition from state B to state C.

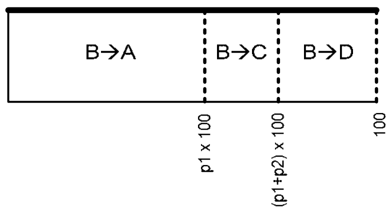


Figure 6 - Transitions modelling method.

The transition between different areas of a single-occupant environment is also dependant on the profile of the occupant [5]. If we assume that there is a daily pattern of occupancy in the proposed environment, then the impact of this pattern should be considered in the modelling of the occupancy signal. As an example, in the daily occupancy pattern of the occupancy signal shown in Figure 7, the probability of the transition from state B to other states in different points of the pattern is different. In state B, the first, third, sixth, and ninth transitions are to state D but the second, fourth, seventh, and eighth transitions are to state C and a transition from B to A occurs as the fifth transition of state B in the daily pattern.

Therefore, the probabilities p1, p2, and p3 should be changed based on where in the pattern they are. In other words, three transitions probability matrices are needed to model the transitions in the occupancy signal of the pattern shown in Figure 7.

A pattern detector [9] is used to choose among the transitions probability matrices by finding out where in the pattern the occupancy signal is.

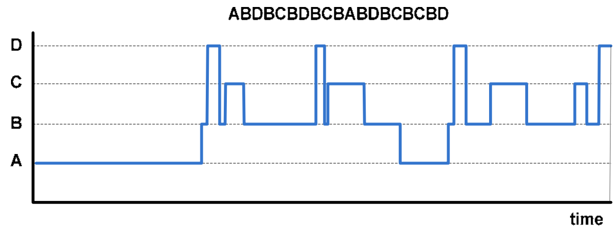


Figure 7 - Daily occupancy pattern in the proposed single-occupant environment.

The expected occupancy pattern in the simulator can be set manually. The best way to find out this expected pattern of occupancy is to monitor the actual equivalent environment by sensory agents for couple of days.

2.1 Modeling the duration part

The duration in each state is defined as the time spent by the occupant in each area of the proposed environment. For instance, in the daily occupancy signal of the Figure 7, the occupant spends 7 hours in the area A (e.g. Bedroom) in the beginning of a new daily activity and 10 minutes in the area B (e.g. Lounge) after he/she left the area A (e.g. Bedroom). Figure 8 is an illustration of the durations in a state diagram without any transitions.

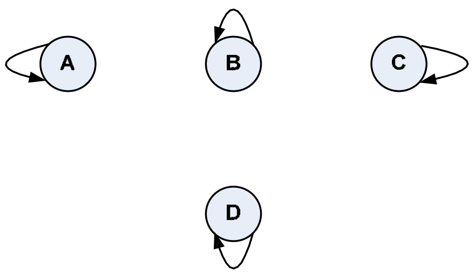


Figure 8 - Durations in a state diagram with no transitions.

Apparently, the occupant spends different times in each area (duration in that area). This is obvious from the daily occupancy signal that the occupant spends more time in area A (e.g. Bedroom) than area D (e.g. Bathroom).

To model the durations in the occupancy signal, it is proposed to apply a normal distribution for the time spent in each area of the proposed environment [7]. For instance, a normal distribution of the duration in area A at the beginning of the daily activity with the mean of 7 is depicted in Figure 9. The mean values are the values of the time spent by the occupant in his/her expected occupancy pattern.

Different normal distributions are proposed for different areas of the proposed environment. Furthermore, it is necessary to consider the pattern of occupancy for applying normal distribution to model each area. For example, the normal distribution of the duration in which the occupant stays in the area B (e.g. Watching TV in the Lounge) should be completely different to that where the occupant only is passing through the area B (e.g. Passing Lounge to Kitchen or Bathroom).

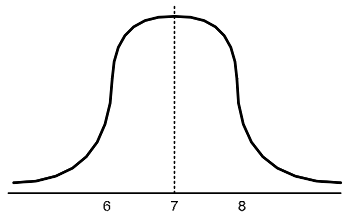


Figure 9 - A normal distribution for the duration in area A.

By generating random numbers based on the normal distributions, it becomes possible to model the duration part of the single-occupant occupancy signal. Equation 1 is used to generate a random number based on a normal distribution [7].

$$y_i = \mu + \sqrt{\sigma^2}\,\left(\sum_{i=1}^{12} R_i - 6\right) \qquad (1)$$

In equation (1), μ is the mean of the normal distribution, σ^2 is the variance of the normal distribution and R_i is a random number.

3 Simulation Algorithm

By considering the following criteria, an algorithm is designed and implemented to simulate the behaviour of an occupant in a single-occupant environment. The code of this algorithm as a signal generator for daily activity is flexible enough to accept different environmental profiles as well as variety of occupant's profiles of behaviour.

- Each daily occupancy signal can affect the occupancy signal on next day. For instance, a next day activity cannot start in bedroom (A) if the previous day activity is not finished in lounge (B) or bedroom (A),
- Daily observed occupancy pattern can become longer than an expected occupancy pattern,
- The design of the environment is represented by transitions possibility matrix as well as probably the type of each area (bedroom, kitchen, lounge, bathroom …),
- The occupant's behaviour profile is represented by his/her expected occupancy pattern, his/her transitions probability matrices, his/her expected duration matrices in each area, as well as his/her unexpected duration,
- The first area met on the first day of activity simulation would be the first area of the expected occupancy pattern in the occupant's profile,

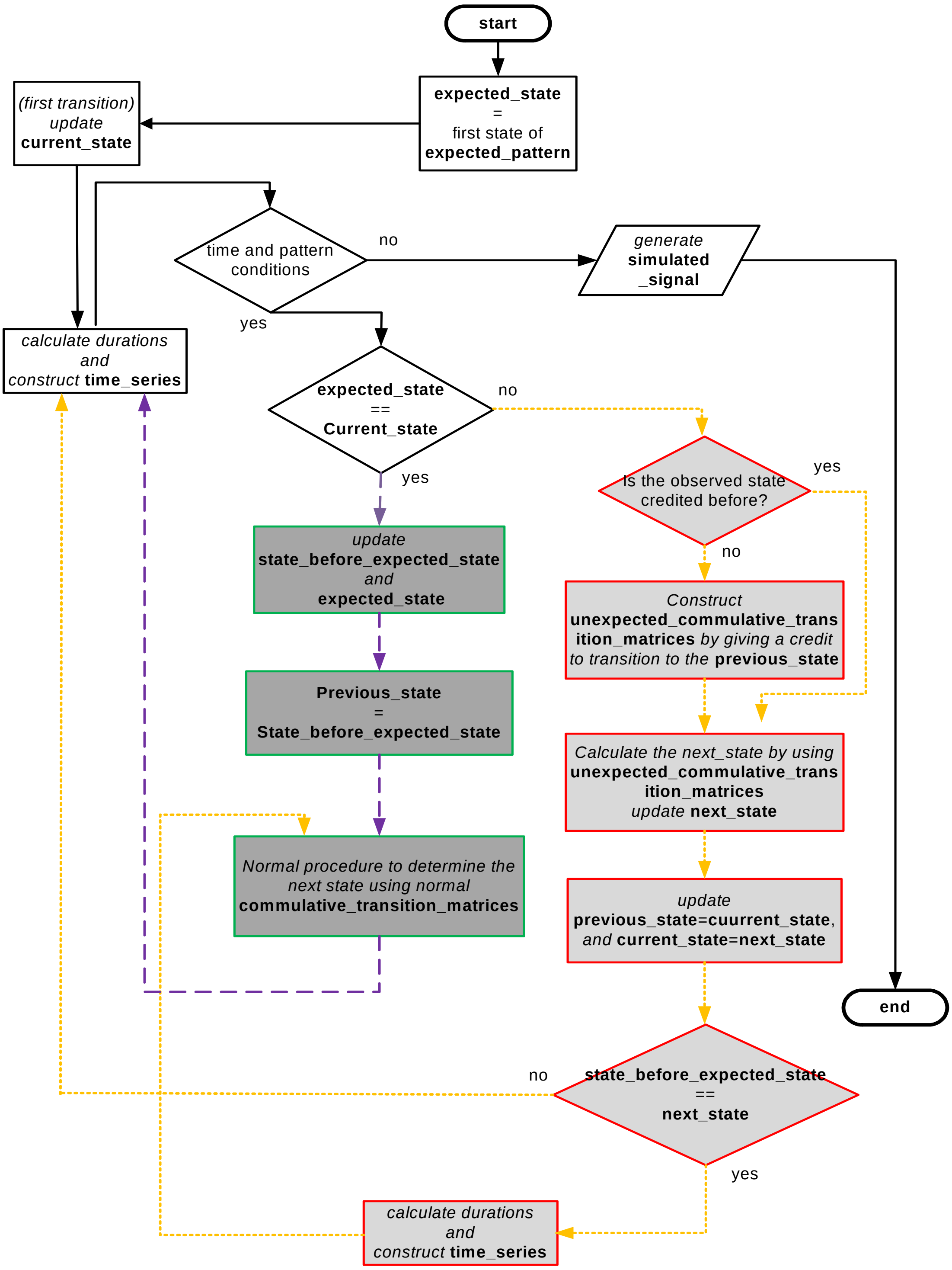


Figure 10- Simulation algorithm.

- In the case of unexpected transition, it is proposed that a return to the previous state be the most probable action happening next. A return procedure should lead to expected state,
- It is possible for the occupant to find another way to follow the pattern instead of returning to previous passed states.

In this algorithm, depicted in Figure 10, there are some parameters that should be assigned at the beginning of simulation including environmental parameters (e.g. design and number of areas) and behavioural profile of the occupant (e.g. expected pattern of occupancy, mean durations for the expected pattern of occupancy, uncertainty in the expected pattern of occupancy, and the mean duration for unexpected transitions).

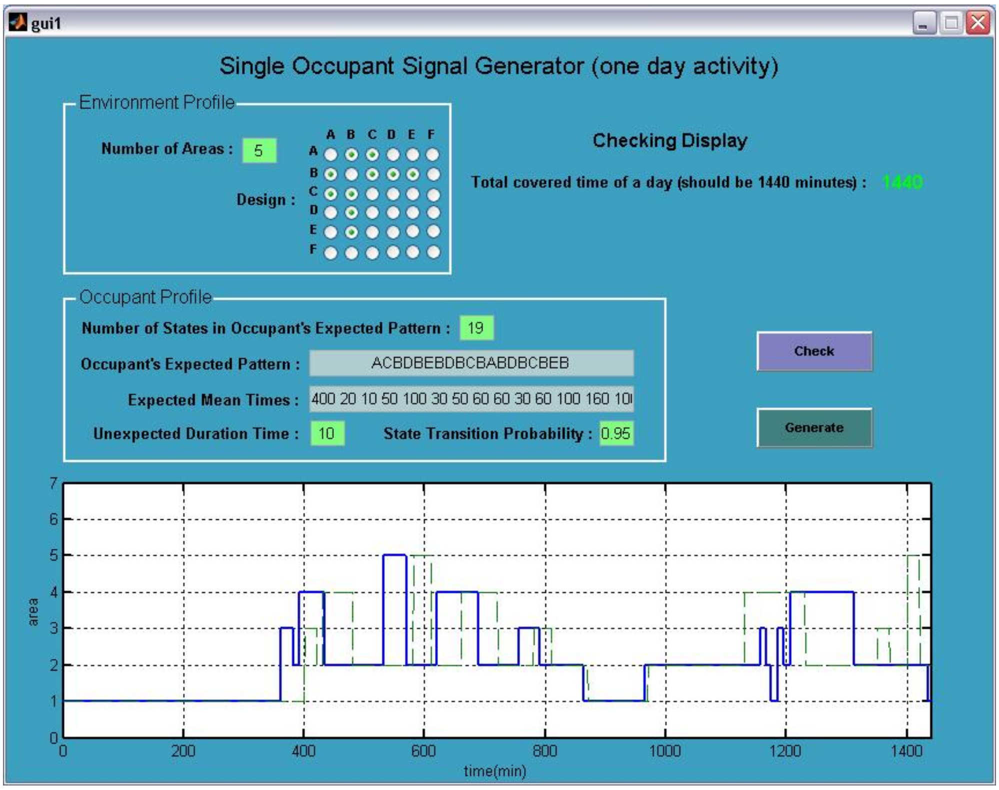


Figure 11- A snapshot of the simulator's user interface.

The algorithm starts from the first state of the expected pattern (Solid lines, White boxes). If the expected state is met by the algorithm as it might not met due to the uncertainty of the behaviour, then a normal procedure determines the next state of the pattern and the duration of the current state will be calculated based on the mean and variance defined for the normal distribution of the duration in the state which is met (Dashed lines, Dark grey boxes). On the other hand, if the state met is an unexpected state, then responsibility will be given to unexpected part of the algorithm to generate unexpected duration for the state met (Dotted lines, Light grey boxes).

If unexpected states are met continuously, then the algorithm keeps on in unexpected section until an expected state is met and the responsibility is given to the expected section in the algorithm. The algorithm ends if the time and pattern conditions (either the expected pattern is recognized or time goes beyond 1440 minutes i.e. a day) are not satisfied anymore. Finally an occupancy signal will be constructed from the states and durations generated by the algorithm.

4 Simulator's User Interface

Using the behaviour modelling algorithm explained above, an occupancy signal generator is implemented. This application generates an occupancy signal based on different designs of the environment as well as different behaviours of occupants. A snapshot of the occupancy signal generator is shown in Figure 11.

The signal generator implemented in this section can generate a simulated occupancy data for prediction if the expected pattern of behaviour, expected mean durations, and uncertainty in the pattern is assigned accurately. This is feasible if the simulated data is validated by the real data collected from the simulated environment.

5 Experimental Results

In order to tune the parameters of the simulator including expected occupancy pattern with its mean times, the uncertainty of the occupant's profile, and the mean unexpected duration time, a flat of single occupancy was monitored for couple of weeks.

The flat is located in Nottingham and occupied by an elderly lady. It has five areas with the design shown in Figure 12. Five sensory agents were deployed in the flat to cover the whole environment.

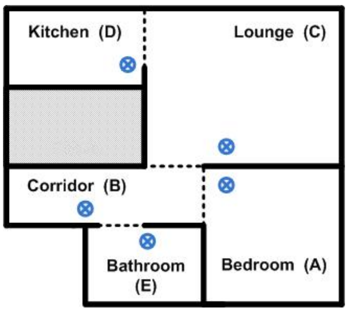
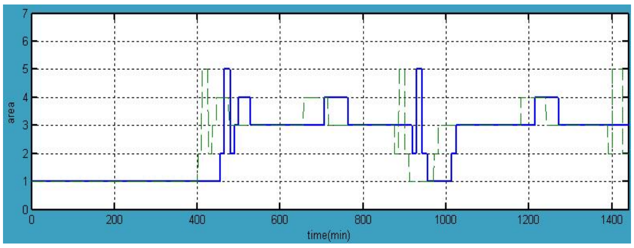


Figure 12- An elderly living flat equipped with five sensory agents.

After 10 days, the expected occupancy pattern of the elderly occupant in her flat was extracted from the collected raw data. The expected occupancy pattern is a sequence of labels *“ABEBCDCDCBEBABCDCBEB”* representing the occupancy of the areas shown in Figure 12. Comparing the expected occupancy pattern of the elderly lady with her observed occupancy signal, the uncertainty of her profile is set to 10%, and the mean of the unexpected duration is set to 5 minutes.

To illustrate the effect of uncertainty in the behaviour of the elderly occupant to her occupancy signal, the occupancy signal generator is set to a 5-area environment with a design shown in Figure 12. The first occupancy signal depicted in Figure 13-a shows the elderly occupant’s behaviour without uncertainty. The second occupancy signal in this Figure 13-b shows the occupancy signal of elderly lady with 10% uncertainty in her behaviour, and the final occupancy signal in Figure 13-c is elderly occupant’s occupancy signal with 25% uncertainty in her behaviour in a simulated environment equivalent to the experimented flat.



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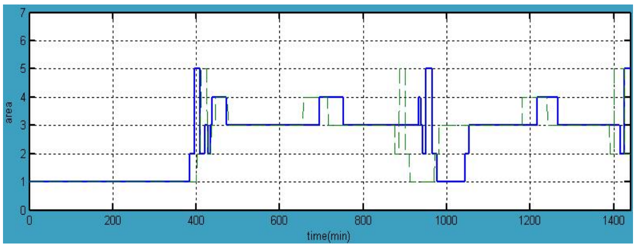

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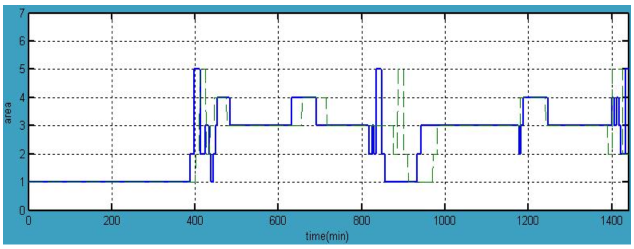

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Figure 13- Occupancy signal simulation for a 5-area environment with three different uncertainties in the behaviour of the occupant.

It is apparent from the occupancy signal that the number of unexpected transitions increases by increasing the uncertainty in the behaviour of the occupant. In other words, it is more likely that an occupant with higher uncertainty will not follow his/her expected pattern of occupancy.

6 Conclusion

In this paper a scenario based on a statistical model for modelling the occupancy signal in a single-occupant environment was proposed. According to the scenario, an algorithm was designed and a flexible occupancy signal generator was implemented. It was shown that how the uncertainty in the behaviour of the occupant can affect his/her movements and respectively the occupancy signal in the environment. To tune the parameters of the simulator, it was suggested to monitor the movements of the experimented occupant for some days by employing sensory agents in the equivalent single-occupant environment to extract his/her expected pattern of occupancy as well as the uncertainty in his/her pattern of behaviour. By tuning these parameters, the occupancy simulator can become very helpful for generating required occupancy data for the purpose of choosing and adapting data mining (prediction) techniques suitable for a predictive ambient intelligent environment. Hence, the number of experiments as well as the number of required resources can be reduced remarkably.

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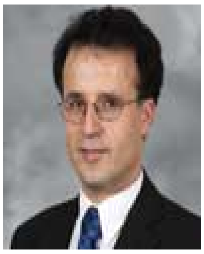

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