
RFID-based solution for galleries and museums visit modelling using Markov model, BBN's and MAP decisions

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Abstract: RFID technologies are becoming increasingly popular and widely used in many applications. Tags can be used for environment and habit monitoring, healthcare applications, home automation and pedestrian or vehicle traffic control. This paper describes the method of building a robust N-state Markov model that describes visitor's behaviour in a gallery room. The built model can be used in planning of exhibitions, in modelling of visitor's preferences, and/or in generation of predictions related with exhibition lasting, expected sales and pricing. Presented system performance improvements are realised through Bayesian belief network (BBN) and maximum a posterior probability (MAP) decision approximation algorithm.

Keywords: algorithm describing visitor's behaviour; Markov model of visitors; RFID based applications; visitors tracking; Bayesian network; MAP decision making.

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1 Introduction

RFID technology (radio frequency identification) costs are reducing nowadays and there are many ideas how to make the localisation using such a cheap technology. Price of \$0.15 (Barcode Inc, prices) per passive UHF RFID tag is the effective way of monitoring and controlling human environment. Other localisation technologies like Bluetooth, WLAN or ultra-wideband (UWB) are not cost effective like RFID (Subramanian et al., 2008). There are three types of RFID tags (Finkenzeller, 2003):

- Passive – have no power supply. They are designed to absorb power from incoming signal in order to power CMOS and transmit data to reader. It means that antenna needs to be designed both to receive and transmit data.
- Active – have own power supply. Power supply is used to transmit data back to the reader. Powering a tag means higher signal power that is transmitted.
- Semi-active – have own power supply which is used only to power microchips and data storage, but not to transmit data. The transmission power is similar to passive tags.

There are advantages and disadvantages of each tag type. Most important factors for a tag implementation are its price and range (Subramanian et al., 2008). Passive tags are cheaper and they have lower read range than active RFID tags. Proposed system includes visitors wearing badges integrating passive RFID tags. Once visitors enter the museum/gallery, they are captured on the entrance of the show rooms and by the exhibit. Their trajectories are recorded by the RFID capturing system, during the visiting time. For the system validation purposes we have simulated visitors' trajectories results. Tags used in our experiments on passive RFID performances have reading-range of five meters and price of \$0.19 per each tag (Intermec Inc., tag prices).

In this paper we combine RFID technology used for visitors tracking and an adequate Markov state model to estimate visitor behaviour by probabilities of moving through different locations inside museum or gallery. Visitor behaviour is complex function of environment, destination, distance, route, etc., so its estimation depends on large number of parameters and factors (Antonini, 1997; Pentland and Liu, 1999) not easy to estimate. Once estimated, question is how reliable they are.

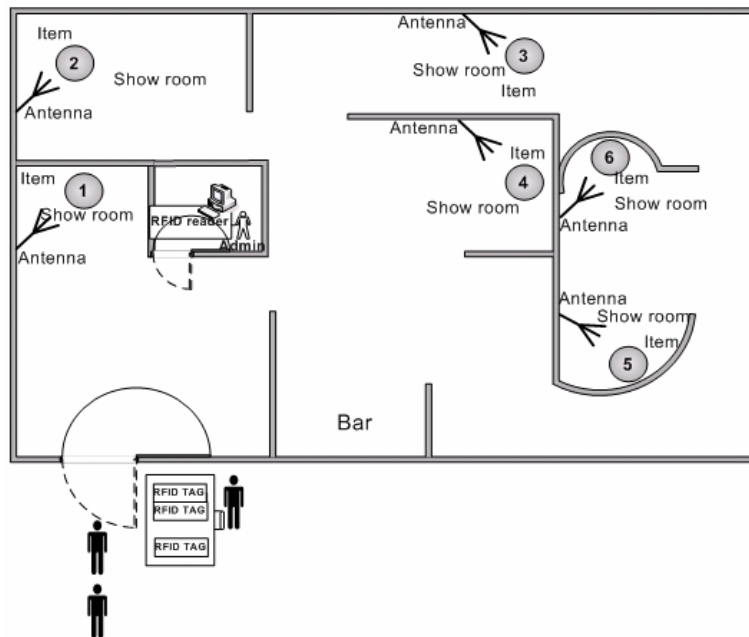
With a large number of measurements, estimated probability distributions for Markov model can be considered reliable enough to be used in realistic situations. In cases with low tag information inflow to the system (small number of visitors in the gallery), we

propose improvement of reliability estimation by including experts opinions and gallery look using Bayesian belief network (BNN) (Zukerman and Albrecht, 2001) and its decision algorithm.

Considering the exhibition costs model (Fopp, 2004), there is little chance to use standard economics model costs used in industry, because increase of gallery or museum income will only result in increase of costs and diminishing returns being applied. The proposed model in this paper can help gallery or museum managers to build up the new planning model and reducing costs based on estimated visitors interests.

This paper is structured as follows: in Section 2, we describe the proposed system that we use in our analysis. In Section 3 the model of visitor's behaviour is considered by using Markov state model. The second part of Section 3, describes algorithm used to estimate visitor's behaviour in gallery based on RFID measurements. Section 4 is dedicated to simulation of three typical scenarios including their analysis. System performance analysis in cases of the small RFID data set is described and addressed in Section 5. Section 6 provides example of the Exhibition planning. In the Section 7 we give some concluding remarks.

Figure 1 The proposed system based on RFID visitors tracking



2 The proposed system

Let consider a gallery with a number of show rooms. Tickets designed as badges, which visitors wear, integrate passive RFID tags. Each person enters the gallery will get a badge. Each gallery show room is equipped with an antenna used for RFID reading and logging tag responds. It is supposed that antennas are mounted on ceiling and the entrance in the show room, to avoid situations where person body blocks tag readings but

also to log all persons entered the show room. When person with tag enters the show room, RFID logs that TAG_ID. Figure 1 illustrates an example of gallery with six show rooms.

Using RFID technology it can be detected, whether visitor is only passing by an exhibit or visiting and stay at it, and how long. It can be easy realised by counting the number of RFID tag responds in each show room, and storing that information to the database. It is supposed that RFID system has enough antennas to cover all gallery exhibits, without signal interference with each other. Lack of the interference allows us to strictly define which Show Room visitor entered. Once setup is done, the minimal time of visit must be defined. It depends on type of observed exhibit, so it is defined accordingly. For example, it is reasonable to consider that visiting each exhibit cannot last less than five seconds. Events shorter than five seconds should be considered as passing by, according to (Antonini, 1997), with 10% of variation (5% of slow walkers and 5% of fast walkers). If RFID system captures tag for ≥ 5 seconds (on single port in time i.e. tag signal reading from one location), that case should be considered as a visit. If visit lasts much longer than five seconds, it means that exhibit is more interesting for the visitors. Assuming large number of visitors, probability of visiting each gallery exhibit can be calculated from corresponding Markov model. The adequate Markov Model can be defined for special cases including groups (guided tours) or individual visits. The case will reflect to the algorithm for calculation of the probabilities.

Prediction and modelling of the visitor behaviour represent important information for the museum or the gallery managers. They can see which exhibits visitors prefer, and which they found less interesting. In order to maximise visits to gallery exhibition organisation should be modified according to visitor's preferences.

Information from RFID logs and statistics derived from the logs are used in generation of probability model, exhibition visitor model, predictions of visiting, etc. In this paper we propose Markov model for modelling visitor's behaviour, built from RFID logs.

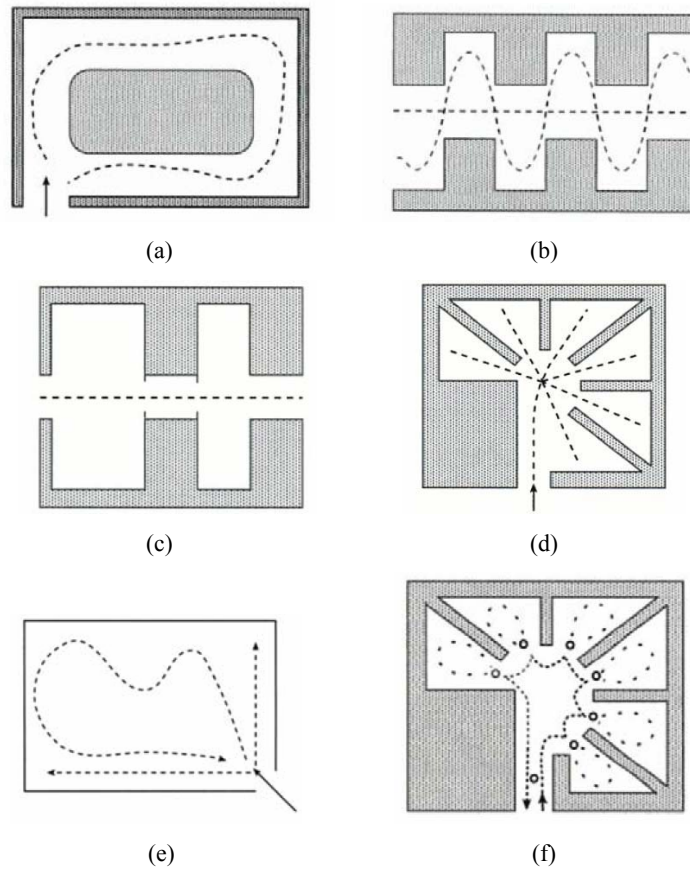
A priori information on gallery architectural design is important factor for visits maximisation. (Hooper-Greenhill, 1999) has proved that the openness of the gallery look is important factor for better results in the terms of visits maximisation. According to the purpose of the gallery thematic and curator/manager ideas are several ways for gallery organisation.

Figure 2 depicts design patterns considered by (Hooper-Greenhill, 1999).

- a arterial design circulation main path is continuous and there are no options for visitors to skip exhibits; path is straight
- b comb circulation refers to circulation pattern where main circulation and optional one allow visitors to stop or by-pass gallery exhibits
- c chain model is specific for presenting self-contained units and varied path between rooms
- d star or fan design pattern presents visitor all of the exhibits from the single point. High visibility factor inside gallery increases exhibits visits
- e block design is important for visitors to choose the route by themselves
- f using information points before the entrance to the room allow users to enter rooms they like.

Each of the proposed patterns is used for the emphasis on exhibition details and emphasis on the exhibition thematic.

Figure 2 Proposed gallery and museum designs (a) arterial designs (b) comb pattern (c) chain pattern (d) star of fan pattern (e) block pattern (f) information points



3 Markov model of visitors' behaviour

Markov model in which a current state depends only on the previous state is

$$\begin{aligned}
 p(S_n/S_{n-1}, S_{n-2}, \dots) &= p(S_n = S_n/S_{n-1} = S_{n-1}); \\
 S_n \in S &= \{S_1, S_2, \dots, S_M\}
 \end{aligned} \tag{1}$$

which represents well known first-order Markov process or chain (Meyn and Tweedie, 2005).

In addition, if transition probabilities do not depend on the time n , thus

$$P\{S_n = S_n/S_{n-1} = S_{n-1}\} = P\{S_2 = S_2/S_1 = S_1\}, \forall S_n \in X$$

Markov chain is time invariant or time-homogenous. If $P(S_n)$ do not depend on the instant n too, the corresponding Markov chain is stationary i.e., $P(S_n)$ is stationary distribution.

Homogenous Markov chain can be completely defined by its initial state and its transition probability matrix $P = [p_{ij}]$; $i, j \in \{1, 2, \dots, K\}$, where

$$p_{ij} = P(S_n = S_j / S_{n-1} = S_i); 1 \leq i, j \leq K \tag{2}$$

with $p_{ij} \geq 0 \quad \forall i, j$ and $\sum_{j=1}^K p_{ij} = 1, \forall i$.

With an initial distribution P_0 , distribution at instant n for homogenous chain is

$$P_n = P_0 P^n \tag{3}$$

where

$$P_{ij,n} = p(S_n = s_j / P_0 = s_i)$$

Probabilities

$$p_n(s_j) = \lim_{n \rightarrow \infty} p_{i,j}^{(n)} \tag{4}$$

where $p_{i,j}^{(n)}$, (i, j) th element of matrix P^n , represent stationary probability of state s_j .

Stationary state distribution P_s for homogenous Markov chain is defined by

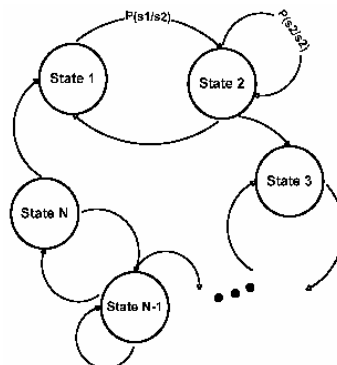
$$P_s = P_s P \tag{5}$$

hence P_s is uniquely defined with a transition matrix P .

Based on relationship (4) it is possible to calculate probability of states by only measurement transitional probabilities in the model, which we use in modelling of visitors as it is explained in Section 4.

Markov model is widely applied in engineering, in operational research and in time series analysis. We use it to model transitions between different gallery exhibits. Figure 3 displays N-state Markov model diagram with transition probabilities between states.

Figure 3 N-state Markov model



Here, states represent gallery or museum show rooms, and transitions represent visitor movements among show rooms. Computation of state probabilities is described as follows.

3.1 Estimation of probabilities

Markov model includes probabilities of visiting exhibits, and transition probabilities which describe visitor movements between exhibits. With a large number of visitors, estimation of probabilities would be more reliable, thus more adequate to real situation. Based on the model and the difference between the estimated model and real situation, it is possible to explain possible special events and define groups for people with similar goals (guided tours).

Main factors that influence a group to form, or help in human crowd modelling are (Musse and Thanmann, 1997) include list of goals, list of interests, human emotional status, human relations with other groups and human domination values.

Group visits are treated differently than individual visits. It means that each group member is guided by group leader and group member opinion is imposed by others, so each group member should get lower factor when calculating probabilities than individuals, whose trajectory is made only by at his/her will.

3.2 The algorithm

Based on data gathered by RFID system it is possible to calculate probabilities necessary for building the model. After we get probability of transitions, we build up Markov model by defining P in (2) and compute stationary probabilities P_s . Elements of transition probability matrix P then follows from

$$p_{ij} = \frac{n_{ij}}{N} \quad (6)$$

p_{ij} probability of visiting exhibit j after exhibit i

n_{ij} number of visits moving from exhibit i to exhibit j

N total number of visits

Algorithm

-
- 1 Set initial values of measure variables to 0
 - 2 Set RFID system antenna on entrance to record tags that enter gallery
 - 3 Set RFID system to read and log all tags in the show rooms
 - 4 Record transitions and time spent on visiting each gallery exhibit and add it to measured variables
 - 5 Compute transition probabilities from RFID system logs, using (5)
-

Full pseudo code of the algorithm can be found in the Appendix A. Many factors influence the behaviour of visitors during the visit to gallery, and they contribute to adequateness of the estimated model in real happening. Human behaviour social factors, including human groupings according to the similar goals or similar emotional state, very

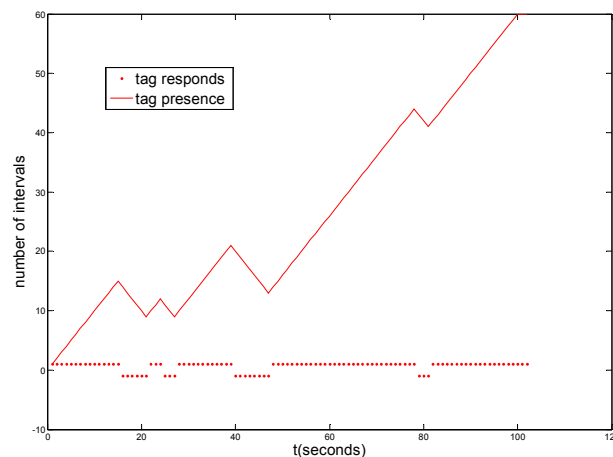
often are guided tours. In order to improve the model, groups should be detected and the modifications correctly implemented into the algorithm to reduce possible deviation (Antonini, 1997).

Algorithm for detecting of groups is defined in Appendix B. Note that detecting of groups can be integrated by clustering algorithms (e.g., k-means algorithm) (Basu et al., 2008).

Crowded areas should be also treated differently, because crowded rooms cause problems in visitor movement and in antenna shadowing. In that case capturing will be disturbed. Possible way for minimising the problem is based on the detection of crowd situation and defining how many group members are making crowd (depending on show room size) and increasing the detection intend accordingly.

We tested performances of the tag in real scenario. Figure 4 shows results of monitoring the considered show room during 102-second time frame. When the room is visited RFID system counts 'ones' otherwise it counts '-ones'. Full line represents integral of successive bits – when visiting, growth explains tag presence, and fall explains tag absence.

Figure 4 Example of RFID system trace on gallery exhibit 1, single antenna readings (see online version for colours)

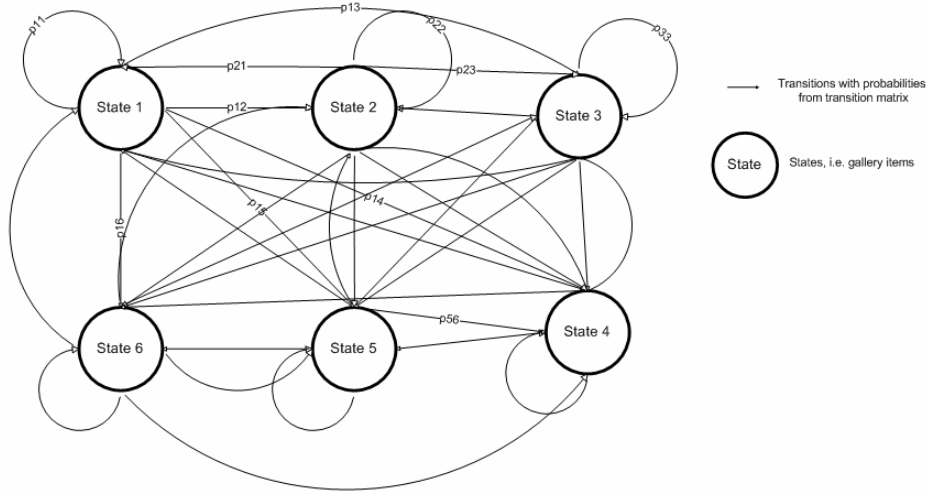


4 Simulation results

Let us consider an example of gallery with six show rooms. Algorithm output is used to generate models of the gallery that include different scenarios and their parameters. For simulation purposes we use random simulation generated results. Let us consider three typical scenarios:

- 1 general model
- 2 group model
- 3 model of individuals.

Figure 5 Markov state model for six-room gallery



4.1 Scenario 1, general model

Assume N visitors enter the gallery. Visitors move from exhibit to exhibit according to her/his preferences. Based on the recorded moving trajectories we can estimate elements of the transition matrix in the following way: Let m people have moved from exhibit i to exhibit j . Then the estimate of p_{ij} is m/N_i , where N_i represents a number of people entered the room i . Thus we can create Markov model depicted on Figure 5.

$$P = \begin{bmatrix} 0.1 & 0.6 & 0.05 & 0.1 & 0.1 & 0.05 \\ 0.2 & 0.05 & 0.3 & 0.08 & 0.07 & 0.3 \\ 0.03 & 0.07 & 0.1 & 0.6 & 0.15 & 0.05 \\ 0.01 & 0.02 & 0.03 & 0.21 & 0.67 & 0.06 \\ 0.02 & 0.03 & 0.01 & 0.76 & 0.17 & 0.01 \\ 0.02 & 0.15 & 0.03 & 0.7 & 0.01 & 0.09 \end{bmatrix} \quad (7)$$

Let us consider transition matrix (7). According to (2), sum of the each row in the transition matrix must be 1.

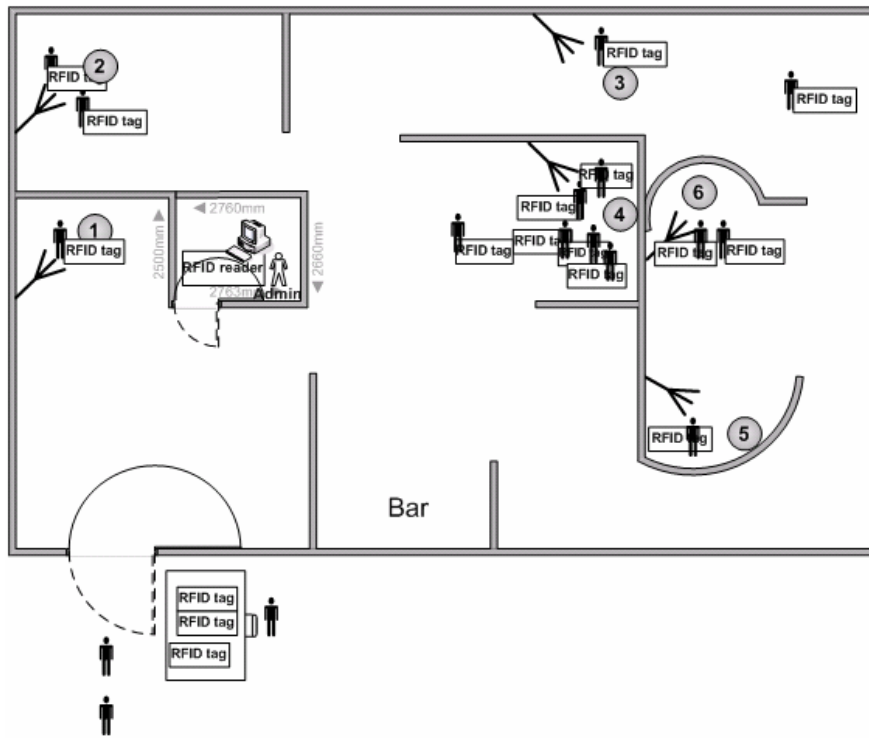
Assuming homogeneous Markov chain, probabilities of visiting each state (exhibit) correspond to stationary probabilities. From (5) and (7) we compute stationary probabilities by solving six linear equations:

$$P(s) = \begin{bmatrix} 0.0633 \\ 0.1533 \\ 0.0867 \\ 0.4083 \\ 0.195 \\ 0.0933 \end{bmatrix} \quad (8)$$

A large probability means more visiting. Provided result (8) suggests that almost 41% visits is related with exhibit 4, which is the exhibit with highest probability of visiting.

Figure 6. illustrates a typical visitors position in scenario 1.

Figure 6 Scenario 1, gallery occupation with most interests on exhibit 4



4.2 Scenario 2, group model

If there is a guided tour, visiting gallery show rooms 1, 2, 3, 5, an example of transition matrix is

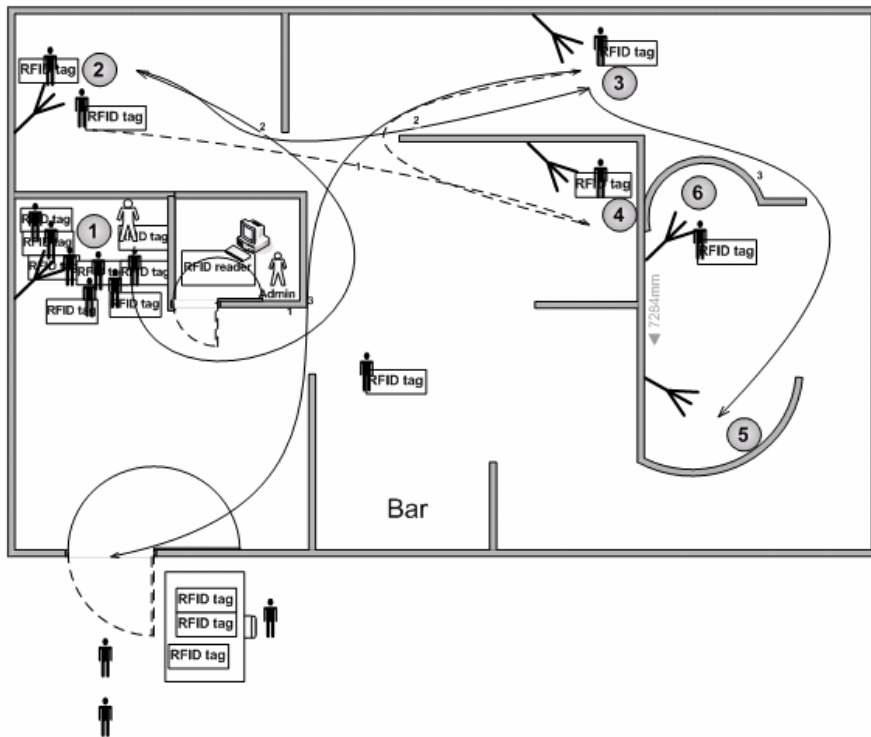
$$P = \begin{bmatrix} 0 & 0.85 & 0.05 & 0.03 & 0.02 & 0.05 \\ 0.02 & 0 & 0.88 & 0.01 & 0.07 & 0.02 \\ 0.04 & 0.04 & 0.02 & 0 & 0.86 & 0.04 \\ 0.95 & 0.01 & 0.01 & 0.01 & 0 & 0.02 \\ 0.9 & 0.02 & 0.02 & 0.01 & 0.03 & 0.02 \\ 0 & 0.01 & 0.01 & 0.98 & 0 & 0 \end{bmatrix} \quad (9)$$

Probabilities of visiting each exhibit follow in the same way as in computing (8):

$$P(s) = \begin{bmatrix} 0.3183 \\ 0.155 \\ 0.165 \\ 0.1733 \\ 0.1633 \\ 0.025 \end{bmatrix} \quad (10)$$

Figure 7 illustrates a guided tour scenario, during the period when a group is mainly gathered on galley exhibit 1. It is possible for some persons roaming between objects to meet the group and system could recognise individuals as a group members. Tracking group members at the same time, through the whole presentation, can contribute to better estimation of a number of group members and a number of individuals.

Figure 7 Scenario 2, example with guided tour visiting show rooms 1, 2, 3 and 5



4.3 Scenario 3, model of individuals

It is reasonable to expect different model when we observe situation when there are individuals among the different types of visitors. To model individuals we define transition matrix where transition probabilities are mainly uniform. For example the transition matrix is:

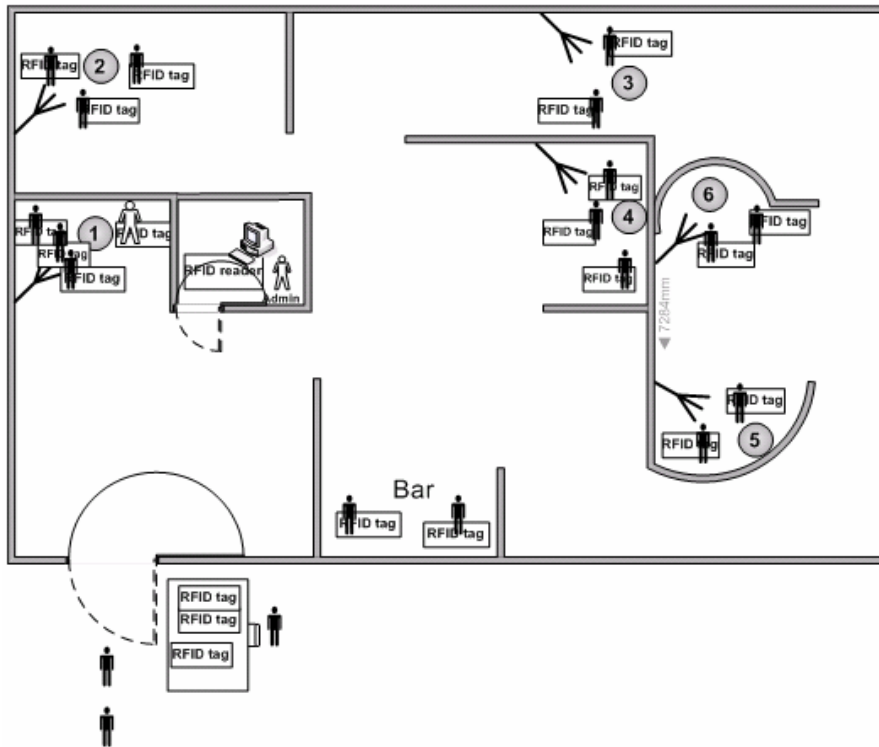
$$P = \begin{bmatrix} 0.16 & 0.16 & 0.14 & 0.13 & 0.18 & 0.23 \\ 0.14 & 0.2 & 0.16 & 0.18 & 0.15 & 0.17 \\ 0.12 & 0.22 & 0.16 & 0.17 & 0.12 & 0.21 \\ 0.17 & 0.15 & 0.15 & 0.2 & 0.2 & 0.13 \\ 0.19 & 0.2 & 0.15 & 0.17 & 0.16 & 0.13 \\ 0.2 & 0.18 & 0.12 & 0.25 & 0.12 & 0.13 \end{bmatrix} \quad (11)$$

Probability of visiting each exhibit follows from (5)

$$P(s) = \begin{bmatrix} 0.1633 \\ 0.185 \\ 0.1467 \\ 0.1833 \\ 0.155 \\ 0.1667 \end{bmatrix} \quad (12)$$

Figure 8 illustrates scenario when visitors are only individuals.

Figure 8 Scenario 3, example with individual visit in a gallery



5 BBN modelling and MAP decision application

Due to a low reliability of estimates computed from measurements obtained from RFID system in a relatively short period, this section introduces using of BBN and maximum a-posterior probability (MAP) decision making process in order to increase the confidence of the results (Howard, 1970; Rozic, 2003). Based on *a priori* information about visits, BBN is derived which combines the experts' information with RFID measurements to make MAP decisions. These results are used to improve estimation of future visits and correction of the previous results.

BBN model has been found as a successful tool for describing complex decision processes across variety of fields in analysis, simulation, prediction and diagnosis (Pourret et al., 2008). The Belief Network consists of the nodes and relations between them. Relations are described with a series of conditional probabilities. Application of the BBN's is particularly useful in scenarios when 'information pool' is not big enough for reliable estimation, thus making a base for reasoning under uncertainty.

Our approach is to use BBN in the gallery or museum design to improve modelling of each gallery/museum exhibit visits. Decision is made according to the pre-defined rules and opinions of scenario important actors including curator, artist, educator or collector. Their opinion is supervised by museum/gallery manager preferences in decision making system. Manager chooses gallery design parameters and outside information important for managing the museum/gallery setup. When all information is included, BBN calculates the most probably visit scenario. Those results are combined with RFID measured scenario to obtain decision scenario. Decision making process includes utility function – U , which describes utility of each combination in museum/gallery design, expected scenario and real random scenario. Utility function is created in accordance with expert opinion and design parameters (Samis, 2001; Kuhnert, et al., 2009). Decision node differs from the probability node, and it is designed as the utility for decision making. Decision node values are explained as an importance (priority) of the showroom exhibits realisation. Negative values are interpreted as a non-important exhibit in next decision making and can be excused in future modelling as a negative expectation of the observed model.

For definition of the BBN we used NeticaTM software package with eight discrete probability nodes, utility MAP decisions function and decision node.

Decision is made through MAP decision making. Each element of decision making is already defined in BBN and its probabilities have its own variance. Variance of expected scenario depends on expert's variance (expert reliability) and manager's variance. Variance of RFID measurements is high at beginning due to small number of collected data, but during the time, when a lot of tag reads is collected and get close to the reality, variance become lower, and expected scenario has become as close as possible to the real scenario. In this case decision distribution become close to measured scenario. Initially, experts and managers are considered as a reference because of low reliability RFID collected data.

Scenario described on the Figure 9 uses indifferent manager decision on outcome information and mixed design pattern. Expected scenario distribution is calculated and real random scenario does not exactly match the expectation. To maximise visitor satisfaction, it is necessary to adopt our expectation model to the Real Scenario. From the Figure 9 we can see that real random scenario most visited room is Room4, so

reorganisation step is required and oriented on the Room4 exhibit. Decision expected scenario is built in that way.

Figure 9 BBN created from the experts and manager opinions and requests on architectural design (see online version for colours)

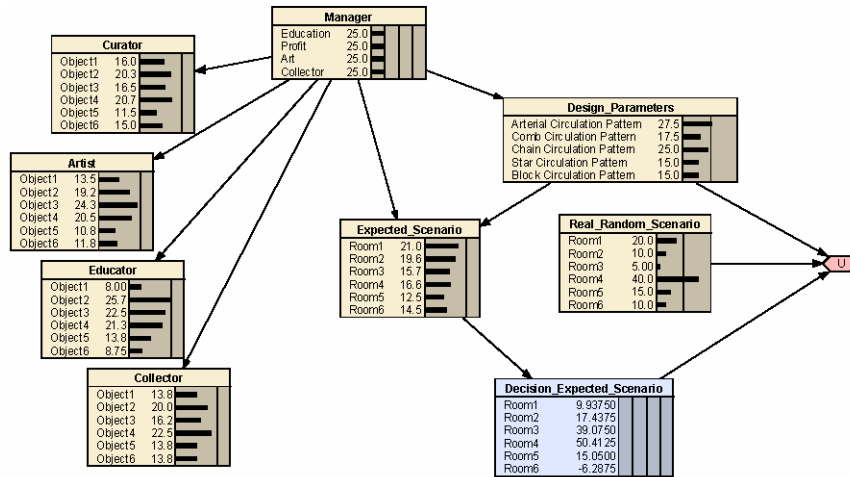
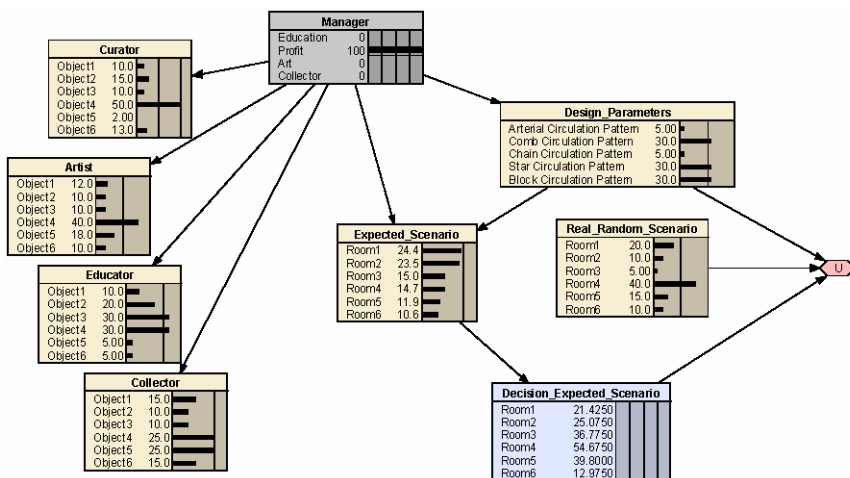


Figure 10 BBN reorganisation for profit maximisation objective (see online version for colours)



On the Figure 10 manager profit maximisation proposal influences gallery with patterns of comb, star or block design where visitors are able to see all exhibits from a few of points inside building. Manager information of profit maximisation is propagated to the all experts and their suggestions are created accordingly. Profit maximisation, in this case maximum iteration of the number of visitors in the gallery, is achieved through the highest visibility gallery structure (Choi, 1999; Kaynar, 2000).

We estimate the number of visits \hat{x} , using MAP estimation based on:

$$\hat{x} = \frac{\sum_{i=1}^N \frac{x_i}{\sigma_j^2}}{\sum_{i=1}^N \frac{1}{\sigma_j^2}} = \frac{\frac{x_1}{\sigma_1^2} + \frac{x_2}{\sigma_2^2} + \dots + \frac{x_N}{\sigma_N^2}}{\frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2} + \dots + \frac{1}{\sigma_N^2}}$$

where $x_i, i = 1, 2, 3, \dots, N - 1$ represents manager and experts estimated number of visits and σ_i the corresponding standard deviation, respectively. The x_N represents estimation of number of visits obtained from RFID reader and σ_N is its standard deviation. In the observed example BBN provides a number of visitors x_A , calculated from $x_i, i = 1, 2, 3, \dots, N - 1$, with variance σ_A . In that case let us take $x_B = x_N$, and $\sigma_B = \sigma_N$, where $x_B = p_s, N$ and p_s is the stationary probability calculated from Markov model for the observed room. Value N represents a total number of visitors, entered the gallery. Hence, we take that

$$\hat{x} = \frac{x_A}{\sigma_1^2} + \frac{x_B}{\sigma_2^2} / \frac{1}{\sigma_A^2} + \frac{1}{\sigma_B^2}$$

and

$$\sigma_{\hat{x}} = \frac{\sigma_A^2 \sigma_B^2}{\sigma_A^2 + \sigma_B^2}$$

Assuming x_B is Normal distributed random variable with deviation σ_{x_B} , standard deviation of estimate x_B follows from (Blumer, 1979):

$$\sigma_{x_B} = \frac{\sigma_x}{\sqrt{M}}$$

where

$$\sigma_{x_B} = \sqrt{\frac{\sum_{i=2}^M s_i}{M - 1}}$$

Value s_i represents the predicted number of visitors calculated from $s_i = p_i(s) M, p_i(s)$, where $p_i(s)$ is the stationary probability which defines probability of visiting the room, and M is the number of data processing steps.

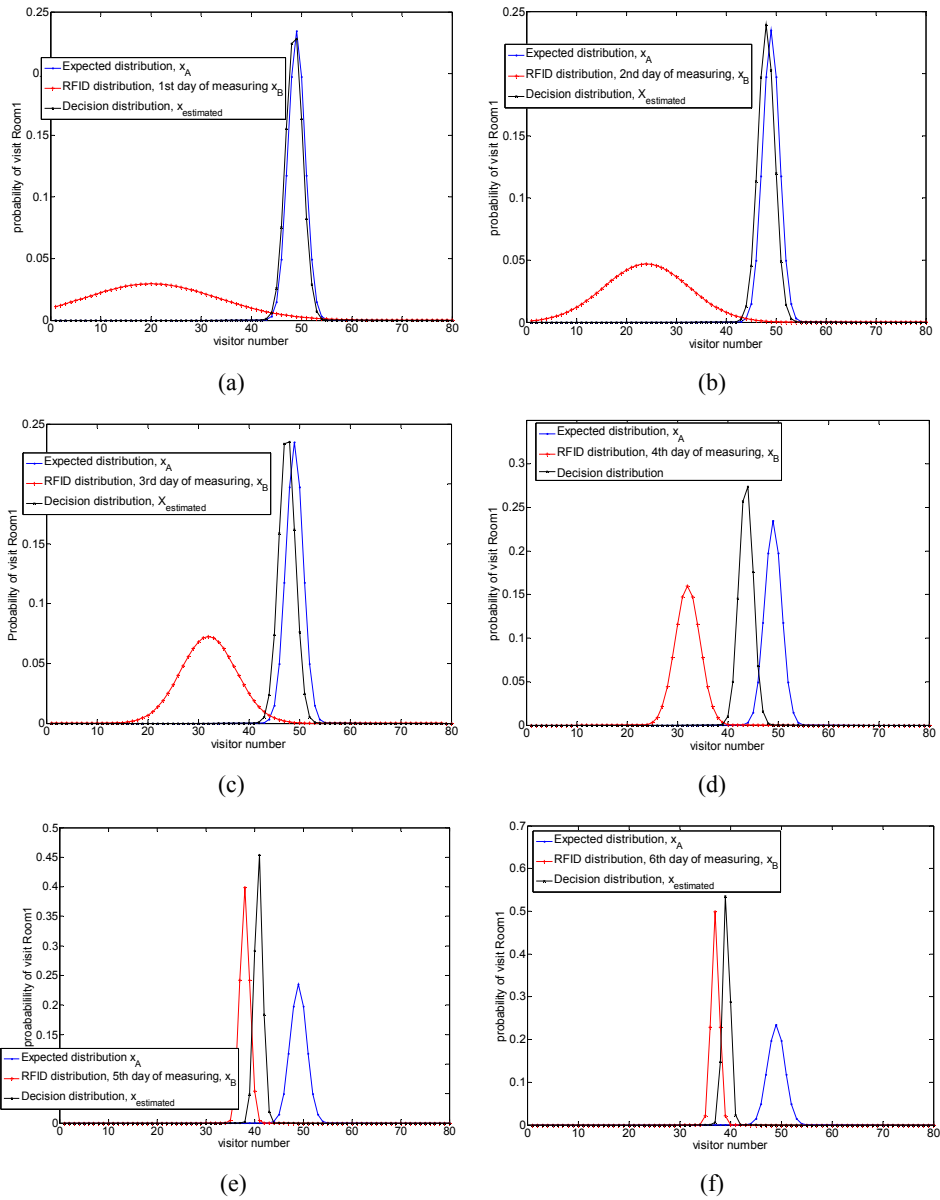
Example on Figure 11 depicts probability distributions for scenario when data processing frame is a daily process. It shows distributions for x_A, x_B and \hat{x} for every day of monitoring using information from previously defined BBN. Mean value \hat{x} is considered as an estimate, with its variance which depend on the experts scenario variance and variance of the RFID measured data assuming stationary distribution.

Finally, when RFID data collection is large enough, the estimated model is close to the model derived from the observations, i.e., RFID data parsing collections and stationary probabilities, because of low RFID data collection deviation.

Figure 11 depicts MAP decision estimation, implemented in the BBN network. On the figures (a)–(f) we see convergence of distribution to the RFID collected data model as the amount of collected data on visits increase. Final estimation is still, but only a little

influenced by the expert and manager expectations. It means that their opinion is still valuable but not as much as RFID based model.

Figure 11 MAP decision estimation based on means and variances of the RFID collected data and expected scenario (a) system convergence after 1st day of measurement (b) system convergence after 2nd day of measurement (c) system convergence after 3rd day of measurement (d) system convergence after 4th day of measurement (e) system convergence after 5th day of measurement (f) system convergence after 6th day of measurement (see online version for colours)

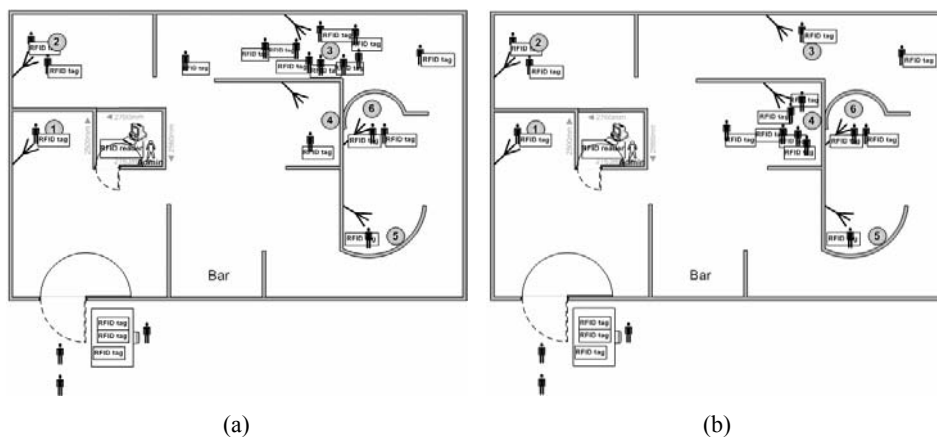


Notes: Figures (a)–(f) show model behaviour convergence to the RFID collected data model as data inflow grows.

6 Exhibition planning example

Gallery or museum manager can use results from the previous analysis for gallery/museum rearrangement. If the considered gallery/museum exhibit realises high rate of visits and was located in a small show room, it could be transferred to a larger and perhaps more reachable show room (for example closer to the entrance). Example of museum rearrangement is depicted on the Figure 12.

Figure 12 Example of the gallery exhibits rearrangement (a) visits are concentrated on show room 3 (relatively small show room) (b) after gallery rearrangement, exhibit from show room 3 is transferred to the more reachable show room 4



Notes: Figures (a) and (b) shows rearrangement of gallery exhibits using RFID measurements and Bayes model.

Arrangement of the gallery exhibits in the previous day is based on measurements of the $i - 1$ day and the results of the Bayes model. As it is shown on the Figure 12(a), gallery exhibit k is assigned to show room 3 based on decision strategy. Using i th day measurements, Bayes model and strategy decision, gallery item k is transferred to the show room 4 [Figure 12(b)].

7 Conclusions

In this paper we propose visitors behaviour modelling based on the integration of RFID technologies, Markov chain model and BBN. Developed model output can help managers in museums or galleries to make better visits estimation in the case specific exhibition organisation. Usage of the proposed model is a feasible basis for the estimation of visitor preferences, exhibition duration planning, pricing policy, etc.

In the scenario with a low RFID data collection, Markov chain model based estimation is improved by including the additional information about experience and confidence of Experts, Managers and reliability of RFID collected data. Improved estimation is obtained using the additional information in BBN.

Simulation results justify proposed scheme.

RFID system is a cost effective way of building the model described in this paper. Implementation of the proposed algorithm is simple and effective for estimation of the model parameters.

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Appendix A

Algorithm for calculation of Markov model probabilities

```

TimeSpentOnEachExhibit.Size = Antenna.Count;
For(i = 0 to TimeSpentOnEachExhibit.Size)
TimeSpentOnEachExhibit[i] = 0; //initial values

Antenna[0].Read(); //antenna at entrance start reading all tags
If(!ListOfTags.Contain(TAG_IN_GALLERY))
ListOfTags.Add(TAG_IN_GALLERY);

For(i = 0 to antenna.Count)
Antenna[i].Read(); // antenna read TAG_ID and time spent in antenna area for each TAG_ID

For(i = 0 to ListOfTags.Count){
For(j = 1 to Antenna.Count){ //first one, indexed by 0, is used on entrance to add tag on
ListOfTags
Transition[i].Values = ListOfTags[i].NextAntennaId; //get Antenna_ID of transition
If(Antenna[j].History contains ListOfTags[i] )
TimeSpentOnEachExhibit[j].Value += Antenna[j].SpentTime;
}}

For(i = 0 to ListOfTags.Count){
For(j = 1 to Antenna.Count){
If(Transition[i].Values == Antenna[j].ID)
Antenna[j].Transitions.Add(Transition[i].Values) // remember transitions of tags
}}

TimeSpentOnAllExhibits = 0;
For(i = 0 to Antenna.Count){
TimeSpentOnAllExhibits += Antenna[i].SpentTime;
TransitionProbability[i] = Antenna[i].Transitions.Count / ListOfTags.Count // calculate
transition probabilities
}

For(i=0 to TimeSpentOnEachExhibit.Size)
ProbabilityOfVisitingEachExhibit [i] = TimeSpentOnEachExhibit[i].Value /
TimeSpentOnAllExhibits;

```

Appendix B

Algorithm for detecting groups

```
For (i = 0 to Antenna.Count){  
  For (j = 0 to Antenna.Count){  
    If(Antenna[i].TagList contains at_least_pair_of_tags at same_time in Antenna[j].TagList)  
      GroupOfPeople[i].Size = RegistratedGroups.NumberOfMembers;  
  }  
}
```
