

RFID-based Visitors Modeling for Galleries using Markov Model

P. Solic *, N. Rozic * and S. Marinovic **

* University of Split, Split, Croatia

** Profectus Company, Split, Croatia

psolic@fesb.hr, rozic@fesb.hr, smarinovic@fesb.hr

Abstract— RFID are becoming increasingly popular and are 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 behavior in a gallery room. The built model can be used in planning of exhibitions, in modeling of visitor's preferences, and/or in generation of predictions related to exhibition lasting, expected sales and pricing.

Index Terms—Algorithm describing visitor's behavior, Markov model of visitors, RFID based applications, Visitors tracking.

I. INTRODUCTION

RFID technology (Radio frequency identification) costs are decreasing and there are a lot of ideas how to make localization using such a cheap technology. Price of 0.15 \$ [1] per passive UHF RFID tag is the reason these tags are used for to monitor and control human environment. Other technologies for localization such as Bluetooth, WLAN or UWB (Ultra-wideband) are not cost effective like RFID [2].

There are 3 types of RFID tags [3]:

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

There are many advantages and disadvantages of each tag type. Most important factor for a tag implementation is price, and range [2]. Passive tags are lower range and cheaper than active tags but more expensive. Tags used in experiments are passive with range of 5 meters and price of 0.19\$ each [4].

In this paper we describe visitors behavior which is complex function of environment, destination, distance, route, etc. , so its estimation depend on large number of parameters and factors [5] which are not easy to estimate. Once estimated, question is how accurate they are.

Using RFID technology and an adequate model such as Markov state model, it is possible to make an estimation of visitor behavior and define probabilities of moving through different locations inside museum or gallery. After building such a model, comparison between accurate Markov model and estimated one can be made. With a large number of measurements, estimated probability distributions for Markov model can be considered reliable enough to be used in realistic situations.

According to [6], there is little chance to use standard economics model costs used in industries, because increase of gallery or museum income will only result in increase of costs and diminishing returns being applied. The proposed model helps gallery or museum managers to build up the new model of planning and reducing costs based on visitors interests.

This paper is structured as follows: in Section II, we describe the proposed system that we use in our analysis. In Section III the model of visitor's behavior is considered by using Markov state model. In the second part of Section III, described algorithm is used to estimate visitor's behavior in gallery based on RFID measurements. Section IV is dedicated to simulation of three typical scenarios and their analysis. Section V gives some concluding remarks.

II. THE PROPOSED SYSTEM

Let us consider a gallery with show rooms. Tickets designed as badges which visitors wear, have passive RFID tags integrated. Each person who enters gallery will get a badge. Every single gallery is equipped with antenna reading and logging tag responds. It is supposed that antennas are mounted on ceiling to avoid situations where person body blocks tag readings. When a person with a tag enters show room, antenna log that TAG_ID. Figure 1 illustrates an example of gallery with 6 show rooms.

Using RFID technology it can be detected whether the visitor is only passing by an item or visiting and staying at it, and how long. It can be easily done by counting tag responses. This is performed by antenna which monitors the show room and stores the information in database. It is supposed that antennas cover all gallery items, without interference with each other. Once setup is done, the minimal time of visit must be defined. It depends on type of observed items, so it is defined according to that. For example, it is reasonable to consider that visiting each item can not be less than 5 seconds. Events shorter than 5

seconds should be considered as passing by, according to [5], with 10% of variation (5% of slow walkers and 5% of fast walkers). If antenna captures a tag for ≥ 5 seconds, that case should be observed as visit. If visit duration is much longer than 5 seconds, it means that item is more interesting for visitors. Assuming large number of visitors, probability of visiting each gallery item can be calculated from corresponding Markov model. In algorithm of calculating visit probabilities, special cases like groups (guided tours) or individuals can be taken into account calculating those values.

Prediction and real state modeling is important information for museum or gallery managers. They can see which items visitors like, and which they don't. In order to maximize profit, gallery should be modified according to visitor's preferences.

Information from logs and its statistics can be used in generation of probabilities model, exhibition visitor's model, predictions of visiting, etc. In this paper we propose Markov model for modeling visitor's interests that will be built from logs.

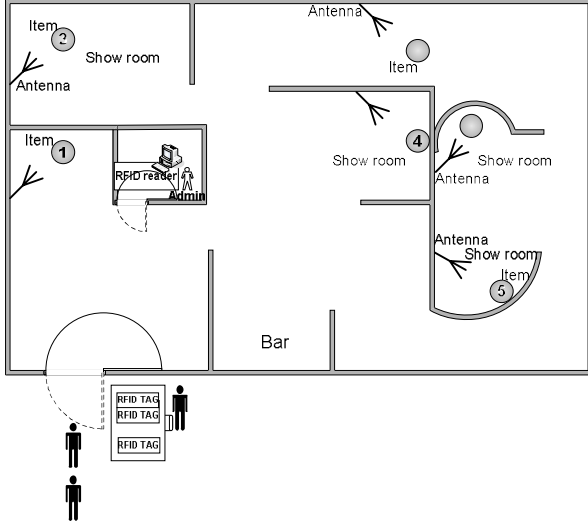


Figure 1. The proposed system based on RFID visitors tracking

III. MARKOV MODEL OF VISITORS BEHAVIOR

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

$$p(S_n / S_{n-1}, S_{n-2}, \dots) = p(S_n = s_n / S_{n-1} = s_{n-1}); \quad (1)$$

$$s_n \in S = \{s_1, s_2, \dots, s_M\}$$

represents well known first-order Markov process or chain [7].

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 $\mathbf{P} = [p_{ij}]$; $i, j \in \{1, 2, \dots, K\}$, where

$$p_{ij} = P\{S_n = s_j | S_{n-1} = s_i\}; \quad 1 \leq i, j \leq K \quad (2)$$

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

With initial distribution \mathbf{P}_0 , distribution at instant n for homogenous chain is

$$P_n = P_0 P^n \quad (3)$$

where

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

Probabilities

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

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

Stationary state distribution P_s for homogenous Markov chain is defined by

$$P_s = p_s P \quad (5)$$

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 measuring transitional probabilities in the model. We use this in modeling of visitors by Markov model as is explained in Section IV.

Let us say that Markov model is widely applied in engineering, in operations research and in time series. In this paper it will be used to describe transitions between different gallery items. Figure 2 displays N-state Markov model diagram with transition probabilities between states.

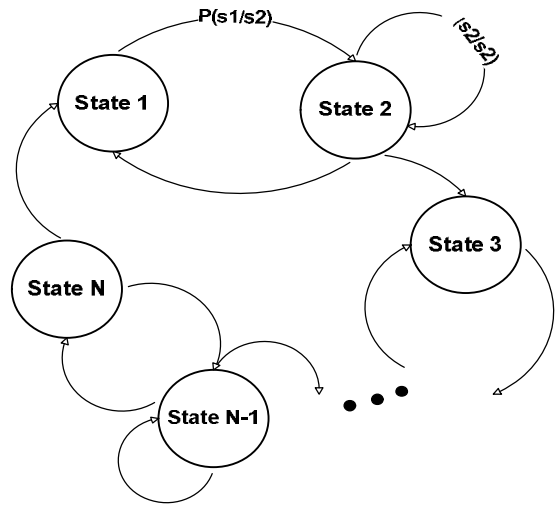


Figure 2. N-State Markov model

States are gallery or museum show rooms (items), and transitions represent visitor's movements between these objects. Calculation of state probabilities is designed below.

Estimation of probabilities

Markov model includes probabilities of visiting items, and transition probabilities which describe visitor's movements between items. With large number of visitors, estimation would be more reliable, and more adequate to real situation. Based on the model it is possible to consider: difference between estimated model and real situation, with explanation of difference (possible special events), the way to the estimated model parameters, decompose the model of visitor's behavior and define groups for people with similar goals (guided tours).

Main factors that influence group forming and help human crowd modeling are [8]: list of goals, list of interests, human emotional status, human relations with other groups and human domination values.

Groups are treated differently than individual visit. 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 themselves.

A. The Algorithm

Based on data gathered by RFID system it is possible to calculate probabilities needed for building a model. After we get probability of transitions, we build up Markov model by defining P in (2) and calculate 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 item j after item i

n_{ij} – Number of visits moving from item i to item j

N – Total number of visits

Algorithm description:

- 1.) Set initial values of measure variables to 0
- 2.) Set antenna near entrance to record tags entering gallery
- 3.) Set antennas to read and log all tags in show rooms
- 4.) Record transitions and time spent on each gallery item and add it to measure variables
- 5.) Calculate transition probabilities from antenna logs, using (5)

Full pseudo code of the algorithm can be found in Appendix of this paper.

Many factors influence behavior of visitors during the visit to gallery that contribute to adequateness of the estimated model. Human behavior social factors like human groupings according to similar goals or emotional state are special cases, however, very often are guided tours. In order to make it better these factors should be

detected and correctly implemented into algorithm to reduce possible deviation in observed model [5].

Algorithm for detecting groups is defined in Appendix of this paper. Note that detecting groups can be integrated by clustering algorithms (e.g. k-means algorithm) [9].

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

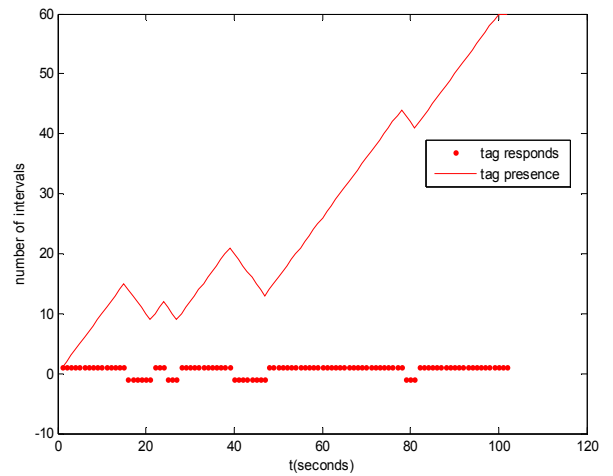


Figure 3. Example of antenna trace on gallery item 1

Figure 3 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.

IV. SIMULATION RESULTS

Let us consider an example of gallery with 6 show rooms.

Algorithm output is used to generate the model of the gallery including different scenarios and their parameters. Here we consider the following typical scenarios: i) General model, ii) Group model and iii) Model of individuals as shown in Figure 1.

A. Scenario i) General model

Let us consider transition matrix. We generate sequence of $N=500$ uniformly distributed integers and divide them according to transition probabilities in transition matrix (7).

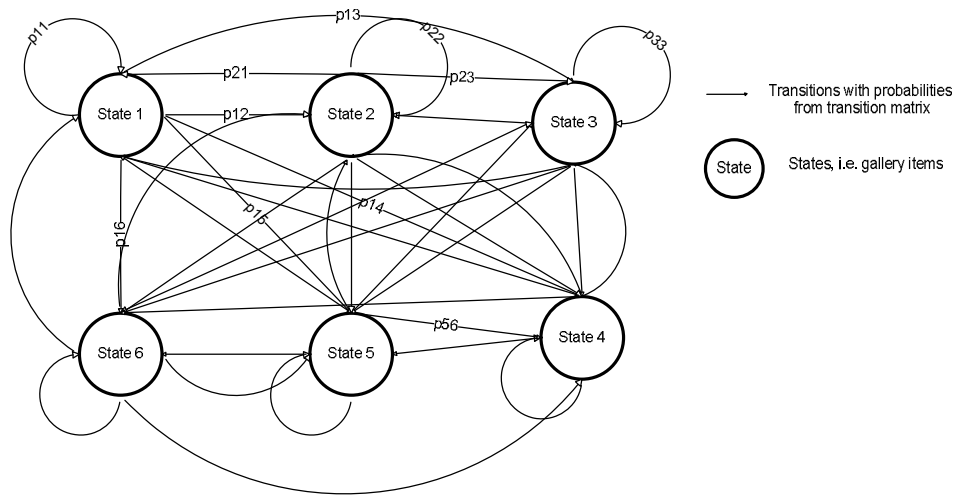


Figure 4. Markov state model for six-room gallery

$$P = \begin{bmatrix} 0,1 & 0,6 & 0,05 & 0,1 & 0,1 & 0,05 \\ 0,2 & 0,05 & 0,3 & 0,08 & 0,07 & 0,3 \\ 0,03 & 0,07 & 0,1 & 0,6 & 0,15 & 0,05 \\ 0,01 & 0,02 & 0,03 & 0,21 & 0,67 & 0,06 \\ 0,02 & 0,03 & 0,01 & 0,76 & 0,17 & 0,01 \\ 0,02 & 0,15 & 0,03 & 0,7 & 0,01 & 0,09 \end{bmatrix} \quad (7)$$

Sum of each row must be 1.

Assuming homogeneous Markov chain, probabilities of visiting each state (item) corresponds to stationary probabilities hence from (5) by solving 6 linear equations

$$P(s) = \begin{bmatrix} 0,0633 \\ 0,1533 \\ 0,0867 \\ 0,4083 \\ 0,195 \\ 0,0933 \end{bmatrix} \quad (8)$$

To simulate P i.e. almost 41% of visits are related to item 4.

A large probability means more visiting. It is interesting to note that item or state 4 has the highest probability of visiting.

Figure 5 illustrates a typical visitors position in scenario i).

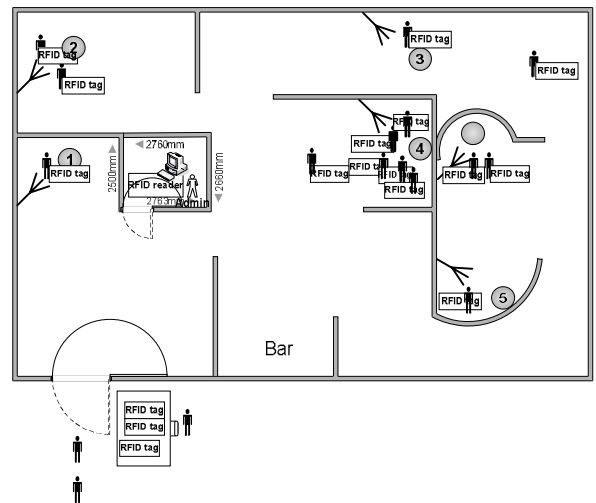


Figure 5. Scenario i) Gallery occupation with most interests on item 4

B. Scenario ii) Group model

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

$$P = \begin{bmatrix} 0 & 0,85 & 0,05 & 0,03 & 0,02 & 0,05 \\ 0,02 & 0 & 0,88 & 0,01 & 0,07 & 0,02 \\ 0,04 & 0,04 & 0,02 & 0 & 0,86 & 0,04 \\ 0,95 & 0,01 & 0,01 & 0,01 & 0 & 0,02 \\ 0,9 & 0,02 & 0,02 & 0,01 & 0,03 & 0,02 \\ 0 & 0,01 & 0,01 & 0,98 & 0 & 0 \end{bmatrix} \quad (9)$$

Probability of visiting each item:

$$P(s) = \begin{bmatrix} 0,3183 \\ 0,155 \\ 0,165 \\ 0,1733 \\ 0,1633 \\ 0,025 \end{bmatrix} \quad (10)$$

Figure 6 illustrates a guided tour scenario, during the period when a group is mainly gathered on gallery item 1. It is possible for person roaming between objects to meet group and system could recognize individual as a group member. 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.

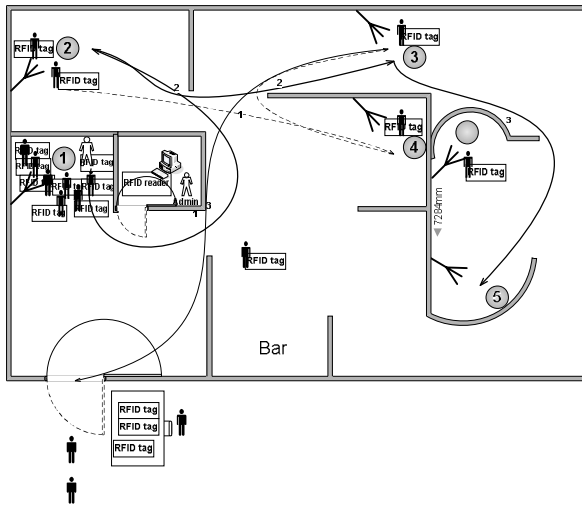


Figure 6. Scenario ii) Example with guided tour visiting show rooms 1, 2, 3 and 5

C. Scenario iii) Model of individuals

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

$$P = \begin{bmatrix} 0,16 & 0,16 & 0,14 & 0,13 & 0,18 & 0,23 \\ 0,14 & 0,2 & 0,16 & 0,18 & 0,15 & 0,17 \\ 0,12 & 0,22 & 0,16 & 0,17 & 0,12 & 0,21 \\ 0,17 & 0,15 & 0,15 & 0,2 & 0,2 & 0,13 \\ 0,19 & 0,2 & 0,15 & 0,17 & 0,16 & 0,13 \\ 0,2 & 0,18 & 0,12 & 0,25 & 0,12 & 0,13 \end{bmatrix} \quad (11)$$

Probability of visiting each item follows from (5)

$$P(s) = \begin{bmatrix} 0,1633 \\ 0,185 \\ 0,1467 \\ 0,1833 \\ 0,155 \\ 0,1667 \end{bmatrix} \quad (12)$$

Figure 7 illustrates scenario when visitors are only individuals.

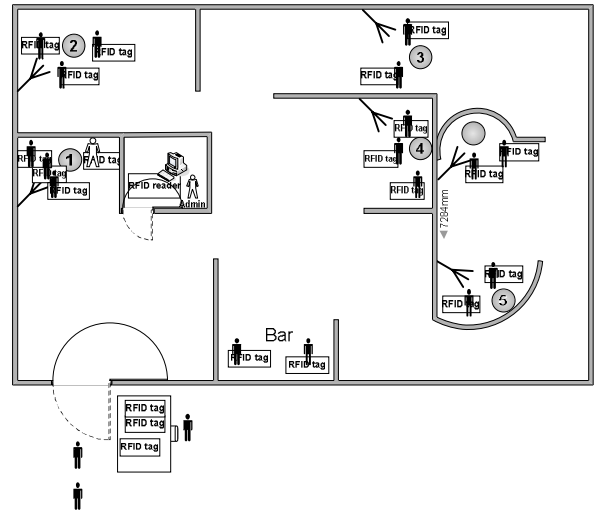


Figure 7. SCENARIO iii) Example with individual visit in a gallery

V. CONCLUSION

The proposed RFID-based model can help museums or galleries managers make better estimation of visits with purpose of making exhibitions better organized. Using Markov model is feasible basis for estimation of visitor's preferences, planning of exhibition duration, pricing policy, etc.

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

APPENDIX

A. Algorithm for calculation of Markov model probabilities:

```
TimeSpentOnEachItem.Size = Antenna.Count;
For(i=0 to TimeSpentOnEachItem.Size)
TimeSpentOnEachItem[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])

TimeSpentOnEachItem[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
}
}

TimeSpentOnAllItems=0;
For(i=0 to Antenna.Count)
{
TimeSpentOnAllItems +=
Antenna[i].SpentTime;
```

```
TransitionProbability[i] =
Antenna[i].Transitions.Count /
ListOfTags.Count
// calculate transition probabilities
}
For(i=0 to TimeSpentOnEachItem.Size)
ProbabilityOfVisitingEachItem[i] =
TimeSpentOnEachItem[i].Value /
TimeSpentOnAllItems;
```

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 =
RegisteredGroups.NumberOfMembers;
}
}
}
```

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