IntelligentAutomationAndSoftComputing,2019
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Vol.25,no.4,673–681
https://doi.org/10.31209/2018.100000035

State-Space based Linear Modeling for Human Activity Recognition in Smart Space

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ABSTRACT
Recognition of human activity is a key element for building intelligent and pervasive environments. Inhabitants interact with several objects and devices while performing any activity. Interactive objects and devices convey information that can be essential factors for activity recognition. Using embedded sensors with devices or objects, it is possible to get object-use sequencing data. This approach does not create discomfort to the user than wearable sensors and has no impact or issue in terms of user privacy than image sensors. In this paper, we propose a linear model for activity recognition based on the state-space method. The activities and sensor data are considered as states and inputs respectively for linear modeling. The relationship between the states and inputs are defined by a coefficient matrix. This model is flexible in terms of control because all the elements are represented by matrix elements. Three real datasets are used to compare the recognition accuracy of the proposed method to those of other well-known activity recognition model to validate the proposed model. The results indicate that the proposed model achieves a significantly better recognition performance than other models.

KEY WORDS: Embedded sensors, Human activity recognition, Inferring the activity, Linear model, Rule-based method, Rule learning algorithm.

1 INTRODUCTION

THE recognition of human activity is one of the major requirements for smart space. Smart space is equipped with several different types of sensors: microphones and image sensors, wearable sensors, embedded sensors with devices (or objects) to realise the state of the smart space. Among those sensors, embedded sensors are inexpensive, invisible, and can unobtrusively capture information about the environment. In smart spaces, users interact with various devices according to their needs. The activity of an inhabitant can be inferred by analysing the information of the device with which the person interacts at any given moment in time. The development of a fully automated human activity recognition system capable of classifying personal activities with a low error rate is a challenging task. Annotating behavioural roles is time-consuming and requires knowledge of a specific event. Moreover, intra-and interclass similarities make the problem amplify the challenge. Vrigkas (2015), et al. have proposed that the way that humans perform activities depends on their habits, and this makes it more difficult to identify the underlying activity. Human activity recognition methods can be categorized into stochastic and rule-based methods. Stochastic methods apply statistical models to recognize the human activity. On the other hand, rule-based methods use a set of rules to recognize the human activity.

The goal of this work is to develop an activity-recognition model that can transform low-level sensor data into meaningful high-level activity of inhabitants based on the wireless sensor network. Binary sensors are attached to devices (or objects) to get the states of the devices (or objects) interacted with by home users. The logical relationship between the sensor data, with the activity is then defined using a state-space based method. The next state of the activity can be described using the current state of the activity and information

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regarding the current state of devices (or objects). After that, the logical relation is translated into a linear model using the sum of the product (SOP) canonical form and the logic vector (ith column of an identity matrix Ik, where k is equal to logic values) which was proposed by yang, (2016) et al. The proposed state-space based linear model can be helpful to control, because all the variables are expressed by matrix elements, and the relationship between every variable is expressed by a co-efficient matrix. The performance of the proposed model is evaluated in terms of the activity recognition and a comparison is made using three fully-annotated real-world datasets created by Kasteren et al. The results of the experiment indicate that the linear model performs better than other activity recognition models. Using a state-space based linear model, the problem of activity recognition is translated into a linear algebraic equation which can be easily solved by applying conventional algebraic procedures.

The remaining part of the paper is organized as follows: Section 2 presents an overview of related works. Section 3 describes the details of the linear model of activity. Section 4 reports the experimental setup and results obtained followed by the conclusion and considering of future work in section 5.

2 RELATED WORK

ACTIVITY recognition is an important task in diverse applications such as healthcare, safety and security work, context-awareness services, etc. Researchers have proposed many methods to recognize the activity. Virgkas, et al. (2015), Yang, et al. (2016), Van Kasteren (2011), Su, et al. (2015), Jalal, et al. (2014), Ke, et al. (2013), Yatani and Troung (2012), Li, et al. (2017), Karaman, et al. (2014), Arif, et al. (2017), Lara, et al. (2012), Augustyniak, et al. (2014), Van Kasteren. et al. (2011), Tapia, et al. (2004), Fatima, et al. (2013), Palmes, et al. (2010), Wilson, et al. (2005), Cook (2012), Van Kasteren, et al. (2007), Nazerfard, et al. (2010), Cook, et al. (2013), Ordonez, et al. (2013) have proposed whichcan be classified based on the type of sensor used, method used to model the activity, how to learn modeling parameters and how to infer activity using modeling. Su, et al. (2015), Jalal, et al. (2014), Ke, et al. (2013), Yatani and Troung (2012), have proposed Microphones and video-camera-based activity recognition which are very complex to implement because it requires processing of multidimensional data and may violate issues of user's privacy. Li et al. (2017) present a novel activity recognition method based on missing data processing and multi-sensor data fusion that can be applied to identify Activities of Daily Living (ADLs).

Karaman et al. (2014) presented a hierarchical hidden Markov model for indexing activities of daily living in videos acquired from wearable cameras. Arif et al. (2017) have used wavelet transform based rotation forest classifier to recognize seventeen different types of physical activities using wearable sensors. Lara, et al. (2012) and Augustyniak, et al. (2014) have proposed method which is effective in recognising a primitive sequence of movements (walking, sitting, standing, etc.) but difficult to recognise activity (showering, grooming, preparing meals, etc.) using wearable sensors. Home users perform an activity by interacting with appliances (or objects) within nearby location at a given time. Van Kasteren. et al. (2011), Tapia, et al. (2004), Fatima, et al. (2013), Palmes, et al. (2010) have used embedded sensors. Devices or object use information retrieved from an attached or embedded sensor. Embedded sensors are inexpensive, invisible and non-intrusive, having no impact on regular life activities. Tapia et al. (2004) have presented how simple binary sensors have solid potentials for solving the activity recognition problem in the home. Binary sensors can also be applied in human-centric problems such as health and elder care. Kasteren et al. (2013) use binary sensors and motion sensors for performing activity recognitions in a house setting. However, sensor based activity recognition is challenging, due to the inherent noisy nature of the input. In this context, the temporal probabilistic reasoning and machine-learning approach are very effective. Several objects use based models that have been used to recognise activity from binary sensors such as Bayesian Networks proposed by Tapia, et al. (2004), Conditional Random Field (CRF) proposed by Nazerfard, et al. (2010), Hidden Markov Model (HMM), Hidden semi-Markov model proposed by Van Kasteren (2007). Cook, et al. (2013), employed support vector machines (SVMs) to models the activities. Machine-learning models (Naïve Bayes, Hidden Markov Model, Conditional Random Fields, Support Vector Machines, etc.) are robust in the presence of noise and are designed to handle sequential data. Ordonez, et al. (2012) have proposed a hybrid approach using HMM to model the sequential data and a machine-learning scheme to model the HMM state distributions which the increases accuracy of the classical activity recognition methods. The limitations behind stochastic approaches are: i) The representation of the model is not only inefficient but also difficult to interpret when the state space is large and ii) In the learning phase, if the model parameters are not learned well, then over-fitting may occur during the reasoning phase. Yang, et al. (2016) have presented a mathematical modeling of smart space, using a state-space method. This linear smart-space model is helpful for control because it converts the problem to solving a linear algebraic equation. Using a linear state-space based model, it is possible to recognize human activity. Better recognition accuracy proves that this linear state-space model can be used for recognition of human activity.

3 LINEAR MODEL OF ACTIVITY

ACTIVITY modeling is the central parts of any activity recognition system. Different types of sensors are used to collect data about the environment, which will be used to make the model. After getting the sensor data, then different types of features are extracted from raw sensor data. The featured data are then divided into two parts. One is used for training the model, which is treated as learning data, and the other set is used to evaluate the performance of the learned model treated as testing data. From the learning data, using different types of the related algorithms, we determined parameters for the model. The inference section was used to make inferences about the activity based on testing data using a predefined inference algorithm. Figure1 shows the block diagram of an activity recognition system using a linear model.

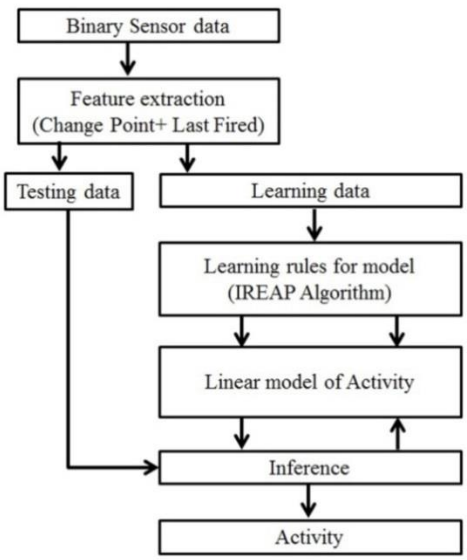


Figure1. Block diagram of an activity recognition system using a linear model.

Considering y= {y_1, y_1, y_2…….,y_n} as the set of n different activities. Inhabitants are interacting with several devices while performing many activities. Using sensors, a device/object used retrievable information. Let, x={x_1, x_2, ……….,x_m} is the set of sensors used to recognise the activity. We can define each activity using a set of functions as given below:

$$\begin{gathered} y_1(t+1) = f_1(y_1(t),\dots,y_n(t),x_1(t),\dots,x_m(t)) \\ y_2(t+1) = f_2(y_1(t),\dots,y_n(t),x_1(t),\dots,x_m(t)) \\ \vdots \\ y_n(t+1) = f_n(y_1(t),\dots,y_n(t),x_1(t),\dots,x_m(t)) \end{gathered} \quad (1)$$

where, f_i={1,2,….n} are functions which describe the activities, x_i={1,2,…m} are data used by the object and x_i={1,2,…n} are y_i={1,2,…n} are activity states.

The right-hand side of equation (1) can be expressed as the SOP in a canonical form:

$$\begin{gathered} f_1(y_1(t),\dots,y_n(t),x_1(t),\dots,x_m(t)) = (l_{1,1}\cdot p_0 + l_{1,2}\cdot p_1 + \cdots + l_{1,2^{n+m}}\cdot p_{2^{m+n-1}}) \\ f_2(y_1(t),\dots,y_n(t),x_1(t),\dots,x_m(t)) = (l_{2,1}\cdot p_0 + l_{2,2}\cdot p_1 + \cdots + l_{2,2^{n+m}}\cdot p_{2^{m+n-1}}) \\ \vdots \\ f_n(y_1(t),\dots,y_n(t),x_1(t),\dots,x_m(t)) = (l_{n,1}\cdot p_0 + l_{n,2}\cdot p_1 + \cdots + l_{n,2^{n+m}}\cdot p_{2^{m+n-1}}) \end{gathered} \quad (2)$$

The right-hand side of equation (2) can be represented by n linear equations as given below:

$$\begin{gathered} y_1 = [l_{1,1} \quad l_{1,2}\cdots \quad l_{1,2^{m+n}}]\cdot\begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_{2^{m+n-1}} \end{bmatrix} \\ y_2 = [l_{2,1} \quad l_{2,2}\cdots \quad l_{2,2^{m+n}}]\cdot\begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_{2^{m+n-1}} \end{bmatrix} \\ \vdots \\ y_n = [l_{n,1} \quad l_{n,2}\cdots \quad l_{n,2^{m+n}}]\cdot\begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_{2^{m+n-1}} \end{bmatrix} \end{gathered} \quad (3)$$

All the elements of the coefficient matrix and y_i in equation (3) are logic variables and those are represented as $l_{i,j} = \begin{bmatrix}\bar{l} \\ l\end{bmatrix}$ and $y_i = \begin{bmatrix}\bar{y} \\ y\end{bmatrix}$, with l and y∈{0,1} and are expressed as follows:

$$\begin{gathered} \begin{bmatrix}\bar{y}_1 \\ y_1\end{bmatrix} = \begin{bmatrix} \bar{l}_{1,1} & \bar{l}_{1,2}\cdots & \bar{l}_{1,2^{m+n}} \\ l_{1,1} & l_{1,2}\cdots & l_{1,2^{m+n}} \end{bmatrix}\cdot\begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_{2^{m+n-1}} \end{bmatrix} \\ \begin{bmatrix}\bar{y}_2 \\ y_2\end{bmatrix} = \begin{bmatrix} \bar{e}_{2,1} & \bar{e}_{2,2}\cdots & \bar{l}_{2,2^{m+n}} \\ e_{2,1} & e_{2,2}\cdots & l_{2,2^{m+n}} \end{bmatrix}\cdot\begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_{2^{m+n-1}} \end{bmatrix} \\ \vdots \\ \begin{bmatrix}\bar{y}_n \\ y_n\end{bmatrix} = \begin{bmatrix} \bar{l}_{n,1} & \bar{l}_{n,2}\cdots & \bar{l}_{n,2^{m+n}} \\ l_{n,1} & l_{n,2}\cdots & l_{n,2^{m+n}} \end{bmatrix}\cdot\begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_{2^{m+n-1}} \end{bmatrix} \end{gathered} \quad (4)$$

If y_1 and y_2 are two logic variables that are represented as $y_1 = \begin{bmatrix}\bar{y}_1 \\ y_1\end{bmatrix}$and, $y_2 = \begin{bmatrix}\bar{y}_2 \\ y_2\end{bmatrix}$ with y_1 and y_2∈{0,1}, then the Kronecker product (⊗) of the two logic variables is calculated in the following way:

$$y_1 \otimes y_2 = \begin{bmatrix}\bar{y}_1 \\ y_1\end{bmatrix} \otimes \begin{bmatrix}\bar{y}_2 \\ y_2\end{bmatrix} = \begin{bmatrix} \overline{y_1 y_2} \\ \overline{y_1} y_2 \\ y_1 \overline{y_2} \\ y_1 y_2 \end{bmatrix} = \begin{bmatrix} p_0 \\ p_1 \\ p_2 \\ p_3 \end{bmatrix} \quad (5)$$

Equation (5) shows that the Kronecker product between two logic variables represents all the minterms; similarly, the following can also be shown:

$$y = \begin{bmatrix}\bar{y}_1 \\ y_1\end{bmatrix} \otimes \begin{bmatrix}\bar{y}_2 \\ y_2\end{bmatrix} \cdots \otimes \begin{bmatrix}\bar{y}_m \\ y_m\end{bmatrix} \quad (6)$$

The minterm vector can be calculated by y(t)⊗x(t), where y = y_1⊗y_2⊗….. ⊗y_n and x= x_1⊗x_2⊗ ….. ⊗x_m, as follows:

$$y \otimes x = \begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_{2^{m+n-1}} \end{bmatrix} \tag{7}$$

By applying the Khatri-Rao product (*) proposed by Ljung, et al. (1982) between all the coefficient matrices, we can obtain the coefficient matrix E for equation (4). The dimensions of the coefficient matrix, Lis equal to 2^n-by-2^{m+n}, where n is the number of state and m is the number of sensor used for an object used data collections, as follows:

$$L = l_1 * l_2 * \cdots * l_m$$

$$L = [Col_1(l_1) \otimes Col_1(l_2) \otimes \cdots Col_1(l_m) \quad Col_2(l_1) \otimes Col_2(l_2) \otimes \cdots Col_2(l_m) \quad \cdots \quad Col_{2^n}(l_1) \otimes Col_{2^n}(l_2) \otimes \cdots Col_{2^n}(l_m)] \tag{8}$$

From equation (4), the usage of equations (6), (7), and (8) can be written as follows:

$$y(t+1) = L \cdot y(t) \otimes x(t) \tag{9}$$

The block diagram of the proposed linear model of activity is shown in figure 2.

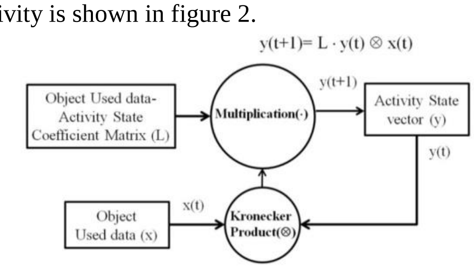


Figure 2. Block diagram of the proposed linear model of activity.

3.1 *Learning the rules for Modeling*

We have used a RIPPER (Repeated Incremental Pruning to Produce Error Reduction) algorithm for rule learning which is more competitive with respect to error rates than other well-known method and much more efficient on datasets. Chen (1995) has proposed RIPPER algorithm. This algorithm is based on IREP (Incremental Reduced Error Pruning). Nor Harizon, et al. (2012) have proposed Reduce Error Pruning and was used where it isolated some data for training and decided when to stop adding more conditions to a rule. By using the heuristic based on minimum description length as a stopping criterion. Post-processing steps followed the induction rule, revising the regulations in the estimates obtained by global pruning strategy, and it improves the accuracy. There are two major parts in the IREP algorithm: Separate and Conquer, and Pruning. At first, the initial rule set is obtained using IREP. This rule set is then optimised, and finally, rules are added to cover any remaining positive examples using IREP.

3.2 *Inferring the activity*

The best activity state is selected using algorithm 1.

```
Algorithm 1: Activity(L,y,x)
Data: Object Used data-Activity State matrix L, at a given time, List of Object used data l, List of Activity State J, Input vector x, state vector y.
Result: Activity
x, y initialization;
/*Next Activity state calculation */
for i=1 to m do
    /*m is the total no. of Object used data in list of l */
    x=x⊗lj;
end
for j=1 to n do
    /*n is the total no. of Activity State used data in list of J */
    y=y⊗Jj;
end
x=L ×y⊗x;
```

4 EXPERIMENTAL SETUP AND RESULTS

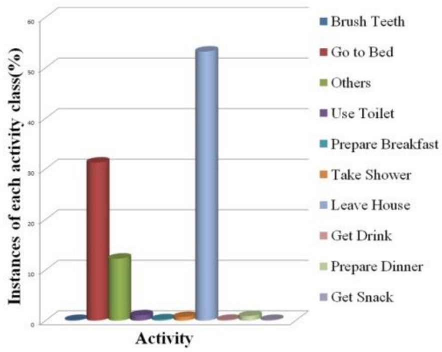
4.1 *Dataset*

WE used three fully annotated datasets created by Van Kasteren (2011). A wireless sensors network was deployed to recognise the activity of inhabitants inside the house by collecting sensor data, which represents the device/object interacting with the user. Many sensors are attached to each of the network nodes, such as reed switches to measure whether doors and cupboards are closed or open, pressure mats in bed to measure lying or sitting, mercury contacts to detect the movement of object, passive infrared (PIR) to detect motion in a specific area, and float sensors to measure the toilet being flushed. Detailed summery of the datasets are tabulated in Table 1.

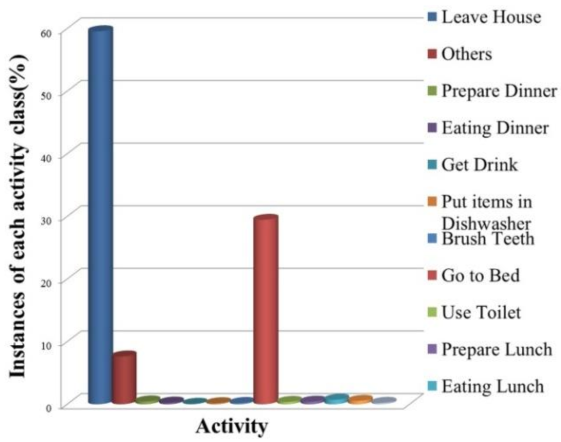
Table 1. Detailed summery of Kasteren datasets.

	House-A	House-B	House-C
Environment Type	Apartment	Apartment	House
Number of Rooms	3	2	6
Record Duration	25days	15days	20days
Number of Sensors	14	23	21
Number of Activities	10	13	16

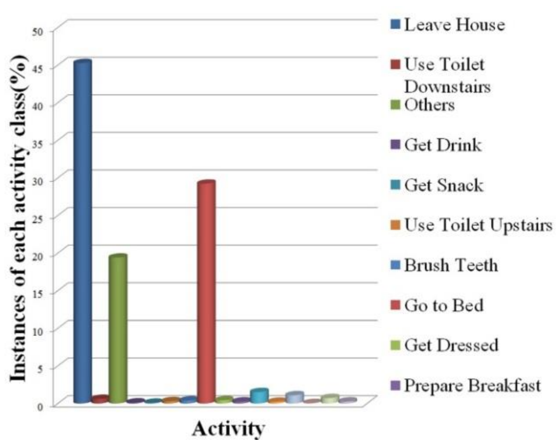
The list of activities for each one of the datasets is different. Figure 3 shows the percentage (%) of instances in each of the activity classes in three datasets.



(a)



(b)



(c)

Figure 3. Instances of each activity class in Kasteren dataset measured in percentage, a) House-A, b) House-B, c) House-C.

Sensor data were segmented in 60-second time slices. The number of time slices for House-A is 36000, House-B is 21600, and house-C is 28800. These time slices segmented data have been present in two different robust feature representations. The definitions of two types of features are presented in Table 2. Figure 4 shows the representation of features.

Table 2. Definition of Features.

Feature Name	Definition
Change Point (CP)	This feature indicates when a sensor changes the value. The value is 1 when a sensor state goes from zero to one or vice versa and 0 otherwise.
Last-fired (LF)	This feature indicates which sensor fired last. The sensor that changed state last continues to value 1 and changes to 0 when another sensor changes state.

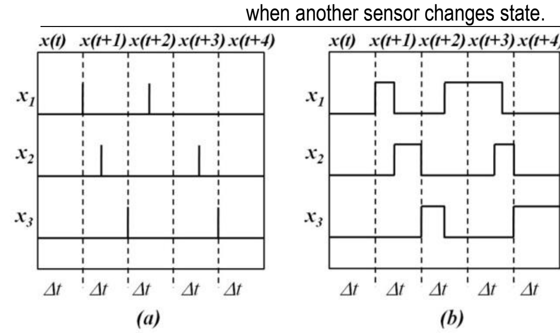


Figure 4. Feature representation: (a) Change Point (b) Last-fired

Another combined feature CP+LF is considered by concatenation of the two distinct feature matrices CP and LF.

4.2 Recognition Accuracy evaluation

4.2.1 Learning the rules for Modeling

The data were split into training and testing sets using a 'leave one day out' approach in which one day of sensor data is used for testing and the remaining days are used for training. The process was repeated for all the days. We used a RIPPER(Repeated Incremental Pruning to Produce Error Reduction) algorithm for rule learning rules. Rules for House-A are tabulated in Table 3.

Table 3. Learning rules for House-A.

	Rules of Activity for House-A
(i)	If (Current_Activity=others)∨(Current_Activity=Get snack)∧(Plates cupboard =1)∧(Microwave =1)∧(Fridge = 0) then Next_Activity=Get snack
(ii)	If (Current_Activity=others)∨(Current_Activity=Prepare Dinner)∨(Current_Activity=Get drink)∧(Fridge =1)∧(Cups cupboard =1) thenNext_Activity=Get drink
(iii)	If (Current_Activity=others)∨(Current_Activity=Prepare Breakfast)∧(Groceries Cupboard =1)∧ (Microwave =1)∨(Plates cupboard =1)∧(ToiletFlush =1) thenNext_Activity=Prepare Breakfast
(iv)	If (Current_Activity=others)∨(Current_Activity=Take shower)∧(Hall-Toilet =1)∧(Dishwasher =1) thenNext_Activity=Take shower
(v)	If (Current_Activity=Go to bed)∨(Current_Activity=others)∨(Current_Activity=Use toilet)∧(Hall-Bathroom =1)∧(ToiletFlush =1)∨(Hall-Bathroom =1)∧(Hall-Bedroom door =1)∨(Hall-Bathroom =1)∧(Hall-Toilet =1) thenNext_Activity=Use toilet
(vi)	If (Current_Activity=others)∨(Current_Activity=Get snack)∨(Current_Activity=Prepare Dinner) ∧(Fridge =1)∧(Groceries Cupboard =1)∨(Fridge =1)∧(Plates cupboard =1)∨(Fridge =1)∧ (Microwave =1) thenNext_Activity=Prepare Dinner
(vii)	If (Current_Activity=Take shower)∨(Current_Activity=Go to bed)∨(Current_Activity=others)∨ (Current_Activity=Leave house)∨(Current_Activity=Use toilet)∧(Hall-Bedroom door =0) ∧ (Frontdoor =0)∧(Hall-Toilet =0)∧(ToiletFlush =1)∨(Hall-Bedroom door =0)∧(Frontdoor =0) thenNext_Activity=others
(viii)	If (Current_Activity=others)∨(Current_Activity=Leave house)∧(Front door =1) thenNext_Activity=Leave house
(ix)	If (Current_Activity=others) ∨ (Current_Activity=brush teeth) ∨ (Current_Activity=Use toilet) ∨ (Current_Activity=Go to bed) ∨ (Hall-Toilet=1) ∨ (Hall-bathroom=1)∧(Hall-Bedroom door=1) thenNext_Activity=Go to bed
(x)	If (Current_Activity=Go to bed) ∨ (Activity=brush teeth) ∧ (Hall-Toilet=1) then Next_Activity=brush teeth

These rules are then translated into the linear model using the procedure described in section 3. The state-space base linear model for House-A can be expressed using equation (9) where L is the coefficient matrix which describe the relation between different attributes with instances of each activity class. The dimension of L is equal to 2^{10}-by-2^{14}. The activity state vector is represented by y and dimension of y is equal to 2^{10}-by-1. The sensor data vector is represented by x and dimension of x is equal to 2^{14}-by-1. Similarly, for House-B, the dimension of L is equal to 2^{13}-by-2^{23}, the dimension of y is equal to 2^{13}-by-1, and the dimension of x is equal to 2^{23}-by-1. Finally, for House-C, the dimension of L is equal to 2^{16}-by-2^{21}, the dimension of y is equal to 2^{16}-by-1, and the dimension of x is equal to 2^{21}-by-1.

4.3 Inferring the activity

The best activity state was selected using algorithm 1, as described in section 3.2. Testing was done by a ‘leave one day out’ approach, in which one day of sensor data was used for testing and the remaining days are used for training. The process was repeated for all day, and the average performance was measured. For performance measurement precision, recall and F-measure were used. The F-measure data were expressed as a mean standard deviation and significance were analyzed using Student’s t-tests. Statistical significance was considered as ($P<0.05$). F-measure, precision, recall, and accuracy could be calculated, as given below:

$$F-Measure=\frac{1}{\frac{1}{2}\left(\frac{1}{precision}+\frac{1}{recall}\right)}$$

$$\mathrm{Pr}ecision=\frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{TI_i}$$

$$\mathrm{Re}call=\frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{TT_i}$$

$$Accuracy=\frac{\sum_{i=1}^{N}TP_i}{Total\ instances} \tag{10}$$

where, TP=true positives, TI=total inferred, TT= total of true instances for each class of activity.

Using two distinct and one combined feature activity recognition were performed for three datasets. The highest accuracy was achieved using Change Point+Last Fired feature representation for each of the activities. The average F-measure value for three datasets using (CP+LF) features was also calculated separately and is shown in Figure-5. The results of the experiment for House-A and House-C were similar.

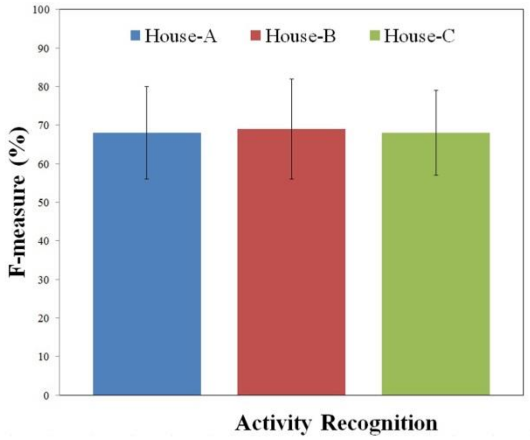


Figure 5. Performance Evaluation of the activity recognition system using linear Modeling.

To validate the performance of the proposed method, we compared the F-measure values with other methods, and comparison performance is shown in Figure 6. The proposed linear model had better recognition performance than other models: Naïve Bayes proposed by Tapia, et al. (2004) and HMM proposed byVan Kasteren, et al. (2011).

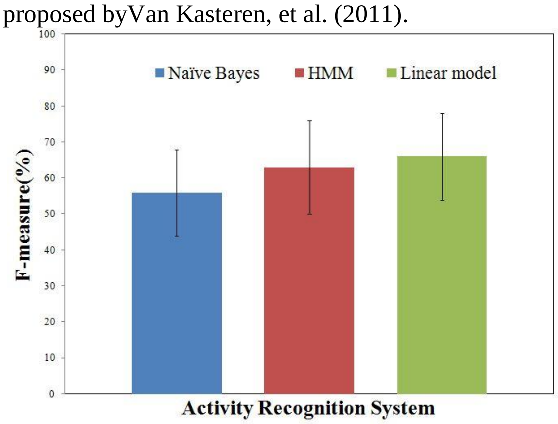


Figure 6. Performance comparison of the activity recognition system using linear Modeling.

5 CONCLUSION

IN this paper, we have presented a new approach to recognising human activity using a state, space-based linear model. This linear model uses sensor data in a smart space and describes the relation between activity state and sensor data. If current activity is known, then the next activity can be determined by using current activity and sensor data. This linear model can translate the activity problem by a linear algebraic equation which is easy to control. Three well-known real datasets were used to evaluate the recognition performance of the proposed model. A comparison was made with another model to validate the proposed model. For performance measures, F-measure was used, which considered the correct classification of each class as being of equal importance. F-measure data were expressed as a mean ± standard deviation and significance was analysed using Student's t-test. Statistical significance was considered as $p<0.05$. This state space based linear model could recognise human activity better than another well-known model. At present, we have applied this model to sensor network which generated binary values of data. In future, we will consider k-values of the sensor using a logic vector and multi-linear mapping with respect to its logical arguments.

6 ACKNOWLEDGEMENTS

THE work in this article was conducted on research grant of Kwangwoon University in 2018.

7 REFERENCES

M. Arif, A. Kattan, and S. I. Ahamed, (2017). "Classification of physical activities using wearable sensors", *Intelligent Automation & Soft Computing*, 23(1), 21-33.

P. Augustyniak, M. Smoleń, Z. Mikrut, and E. Kańtoch, (2014). "Seamless Tracing of Human Behavior Using Complementary Wearable and House-Embedded Sensors", *Sensors*, 14, 7831-7856.

W. W. Chen, (1995). "Fast Effective Rule Induction," *In Proceedings of the Twelfth International Conference on Machine Learning*, 9-12,115-123.

D. J. Cook, (2012). "Learning Setting-Generalized Activity Models for Smart Spaces," *IEEE Intelligent Systems*, 27(1), 32-38.

D. J. Cook, N. C. Krishman, and P. Rashidi, (2013). "Activity discovery and activity recognition: a new partnership," *IEEE Transactions on Cybernetics*, 43(3), 820-828.

I. Fatima, M. Fahim, Y.-K. Lee, and S. Lee, (2013). "Analysis and effects of home dataset characteristics for daily life activity recognition," *Journal of Supercomputing*, 66(2), 760-780.

A Jalal, S. Kamal, and D. Kim, (2014). "A Depth Video Sensor-Based Life-Logging Human Activity Recognition System for Elderly Care in Smart Indoor Environments", *Sensors*, 14, 11735-11759.

S. Karaman, J. B-Pineau, V. Dovgalecs, R. Mégret, J.Pinquier, R. André-Obrecht, Y. Gaëstel, and J.-F. Dartigues, (2014). "Hierarchical Hidden Markov Model in detecting activities of daily living in wearable videos for studies of dementia", *Multimedia Tools and Applications*, 69(3), 743-771.

S.-R. Ke, H. L. U. Thuc, Y.-J.Lee, J.-N.Hwang, J.-H.Yoo, and K.-H. Choi, (2013). "A Review on Video-Based Human Activity Recognition", *Computers*, 2, 88-131.

Ó. D. Lara & M. A. Labrador, (2012). "A Survey on Human Activity Recognition using Wearable

Sensors", *IEEE Communications Surveys & Tutorials*, 15(3), 1192-1209.

J. Li, Y. An, R. Fei, H. Wang and Q. Yan, (2017). "Activity recognition method based on weighted LDA data fusion", *Intelligent Automation & Soft Computing*, 23(3) 509-517.

L. Ljung and T.Soderstrom, (1982). Theory and Practice of Recursive Identification, The MIT Press, Cambridge, Mass, USA.

E. Nazerfard, B. Das, L.B. Holder, and D. J. Cook, (2010). "Conditional random fields for activity recognition in smart environments," In Proceedings of ACM International Symposium on Health Informatics, 282-286.

W. Nor Harizon, W. Mohamed, Mohd Najib, Mohd Salleh, and Abdul Halim Omar, (2012). "Comparative Study of Reduced Error Pruning Method in Decision Tree Algorithms", *IEEE International Conference on Control System, Computing and Engineering, Penang, Malaysia.*

F. J. Ordonez, P.de Toledo, and A. Sanchis, (2013). "Activity recognition using hybrid generative/discriminative models on home environments using binary sensors," *Sensors.* 13(5), 5460-5477.

P. Palmes, H. K. Pung, T.Gu, W. Xue, and S. Chen, (2010). "Object relevance weight pattern mining for activity recognition and segmentation", *Pervasive and Mobile Computing*, 6(1), 43–57.

J.-Y. Su, S.-C. Cheng and D.-K. Huang, (2015). "Unsupervised Object Modeling and Segmentation with Symmetry Detection for Human Activity Recognition", *Symmetry*, 7, 427-449.

E. M. Tapia, S. S. Intille, and K. Larson, (2004). "Activity recognition in the home using simple and ubiquitous sensors", In Proceeding of Second International Conference on Pervasive Computing, pp.158-175.

T. L. M. Van Kasteren, (2011). "Datasets for Activity Recognition," https://sites.google.com/site/tim0306/datasets.

T. L. M. Van Kasteren, G. Englebienne, and B. J. A. Kröse, (2011). "Human Activity Recognition from Wireless Sensor Network Data: Benchmark and Software", *Activity Recognition in Pervasive Intelligent Environments, Atlantis Press*, 165-186.

T. L. M. Van Kasteren, A. Noulas, G. Englebienne, and B. J. Korse, (2007). "Accurate Activity Recognition in a Home Setting", In Proceedings of the Conference on Autonomous Agents and Multiagent Systems (AAMAS2007), 1-9.

M. Vrigkas, C Nikou, and IA Kakadiaris, (2015). "A Review of Human Activity Recognition Methods", *Frontiers in Robotics and AI*, 2, 1-28.

D. Wilson and C. Atkeson, (2005). "Simultaneous Tracking and Activity Recognition (STAR) Using Many Anonymous, Binary Sensors," *Pervasive Computing*, 3468, 62-79.

S.-H. Yang, M. H. Kabir, and M. RobiulHoque, (2016). "Mathematical Modeling of Smart Space for Context-Aware System: Linear Algebraic Representation of State-Space Method based Approach", *Mathematical Problems in Engineering*, 2016, 1-8.

K. Yatani & K. N. Truong, (2012). "Body Scope: A Wearable Acoustic Sensor for Activity Recognition," In Proceedings of the 14th International Conference on Ubiquitous Computing.

8 DISCLOSURE STATEMENT

NO potential conflict of interest was reported by the authors.

9 NOTES ON CONTRIBUTORS

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