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HMM-Based Decision Model for Smart Home Environment

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Abstract

The smart home environment typically includes various systems with high level of heterogeneity characteristics. Smart home environment are configured in such a way that it comfort driven as well as achieving optimized security and task-oriented without human intervention inside the home. Smart home environment contain diversified systems ranging from entertainment to automation like devices that is heterogeneous in nature. For the reason that of systems heterogeneity, it is frequently challenging to execute interoperation around them and realize desired services preferred by the home occupants. The interoperation complexity stands at the bottleneck in ensuring various tasks executed jointly among diversified systems in smart home environment. In this paper, we present a Hidden-Markov Model (HMM) based decision model for smart home environment by providing decision support ability. The implementation has been carried out in such a way that quality information is acquired among the systems to demonstrate the effectiveness of interoperability among them. This proposed decision model is tested and proven that there is an elevated amount of reliability on this decision model in the smart home setting.

Keywords: *Smart Home, HMM, Interoperability, Feature selection*

1. Introduction

A "Smart Home" is frequently referred to as a home embedded with information and communication infrastructure that collaborates to the need of the home occupants [1]. Generally, smart home is seen as an entity integrated with diversified service function of automation, communication and control of its environment, and performing them in unified manner via intelligent tasks [3]. The field of smart home has been a multidisciplinary approach with variation in their architecture, dissimilar devices and systems, diverse application and services. In smart home, there is high interest and priority for low cost solutions with high performance technologies consolidated together. These technologies include the rise of high-speed communication structure and assured rapid increment of diversified systems in home environment. Those systems in smart home comprise of energy management devices, alarm and security systems and home automation system (HAS). In smart home environment, the interoperation unpredictability is one of the fundamental purposes behind uncertainty in interoperability among heterogeneous systems [4]. Interoperability is the procedure in which group of systems having diverse requirement exchanges information in a unified as well as federated routine [5]. These requirements are very much suited to the nature of smart home environment. Figure 1 below illustrates generic systems in smart home setting.

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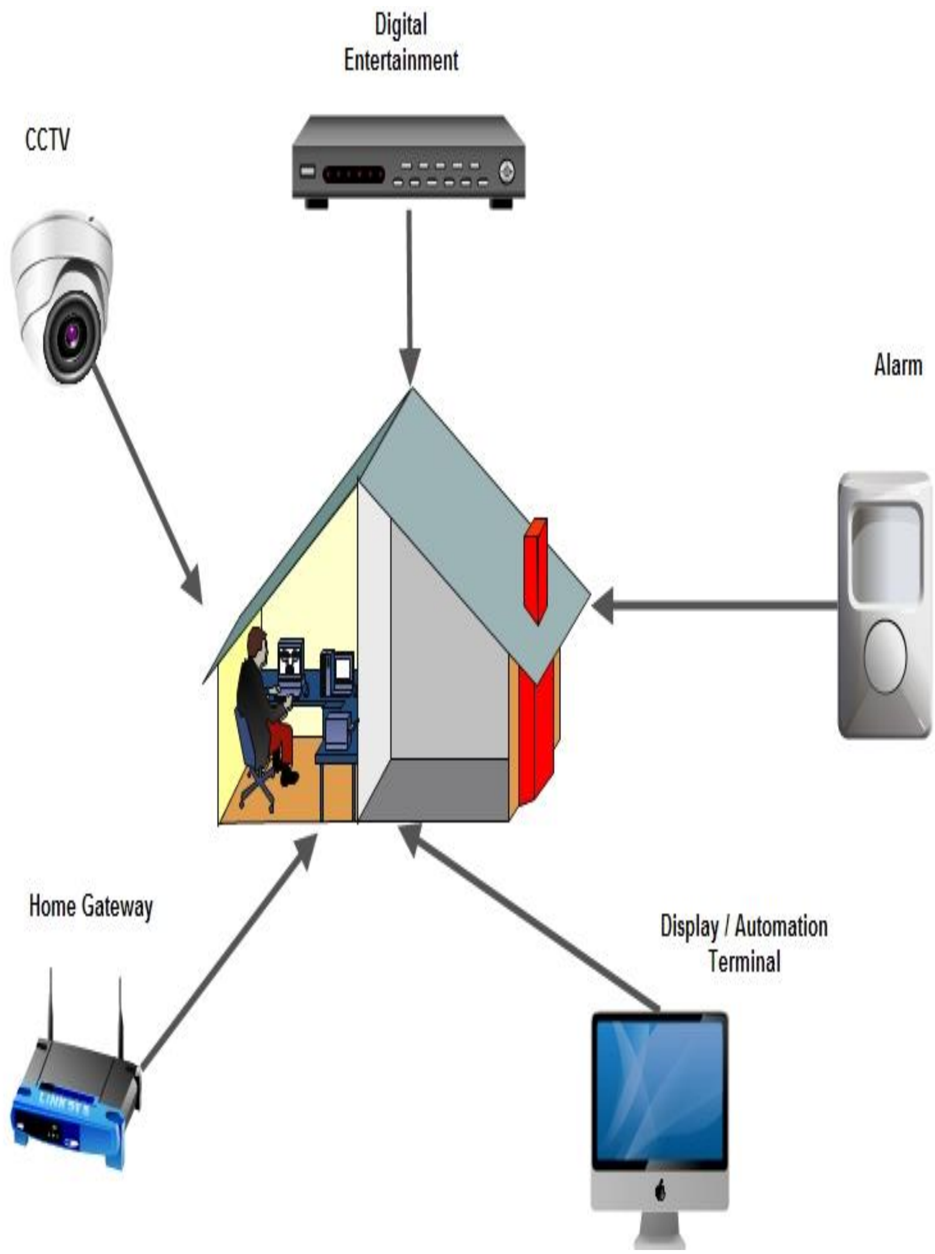

Figure 1. Heterogeneous Systems

A smart home comprises of heterogeneous systems where each system could be configured with many front-end devices, for example Closed Circuit Television (CCTV), alarm, occupancy sensor, audio devices and so forth, weaved together to provide interoperability in smart home. However, the focal issues of current research have been the advancement of effective decision making model for interoperation around heterogeneous system in the smart home environment. In this work, we focused primarily on achieving interoperability among subsystems utilizing Hidden Markov Model (HMM) technique. The HMM model represents the chance to give an equal opportunity for heterogeneous systems to achieve interoperability with other applications. In that capacity, we proposed an enhanced decision making model dependent upon HMM to solve the issue of interoperability among heterogeneous systems.

The paper begins with describing related works in Section 2. This is preceded with framework development elaborated in Section 3 and finally accompanied by conclusion in Section 4.

2. Related Works

In recent times, literatures as well work-in progress on smart home research suggested the importance of system integration as opposed to realizing overall interoperability utilizing decision making models. The importance to achieve interoperability in smart home can be seen from various perspectives. Available literatures on smart home research works highlighted the importance of applying HMM in different tasks before achieving overall interoperability using decision models. An important piece of work done by Freitag *et.al.*, describes a method, called "shrinkage" that improves the sampling as well as computing HMM architecture probabilities for training data [2, 6]. In this work, they deployed an optimization procedure for feasible selection of HMM architecture corresponding bespoke training data requirement for smart home.

Another important work presented by Cheng *et al.* provides a dominant inference engine based on HMM, known as ALHMM, combining the Viterbi and Baum-Welch algorithms measuring accuracy purposes and learning ability enhancement [8]. Similarly, another related research was conducted by Uddin *et al.*, on system development that extracts spatio-temporal attributes from a sequence of depth profiles of a variety of daily home tasks using Independent Component Analysis, also uses the trained HMMs, to recognize the activities from spatiotemporal features [7]. Their method has been enhanced for recognizing human gaits (normal and abnormal). On the other hand, Crandall *et al.*, introduced the implementation of wireless sensors implementing Hidden Markov Model for identifying individuals [9]. The obtained result is a low profile resource that carries single events to unique occupants attributes. Here, HMM is deployed for comparative analysis against Bayes solution on the same data sets. It is worth to highlight a work done by Rashidi *et al.*, on automated approach for activity tracking that naturally occurs in a smart home user lifestyle. Their work focuses on tracking the incident of regular tasks with intention to monitor health and identifying changes in a user patterns and lifestyle [10]. In addition, the mentioned work also detailed out on activity mining and tracking approach as well as validating (HMM) based algorithms applied on data collected in physical home environments. Research achievements stated in [2-10] are remarkable enough to be applied to real-world problems. However, it is worth to stress that interoperability is highly difficult due to the system's heterogeneity. Therefore the proposed model in this work is designed to overcome the disadvantages and provide a clear methodology to solve the difficulties of decision model among diverse systems in smart home environment.

3. Framework Development

3.1. System Architecture

The HMM-based decision model architecture consists of a set of heterogeneous systems is shown in Figure 2 below:

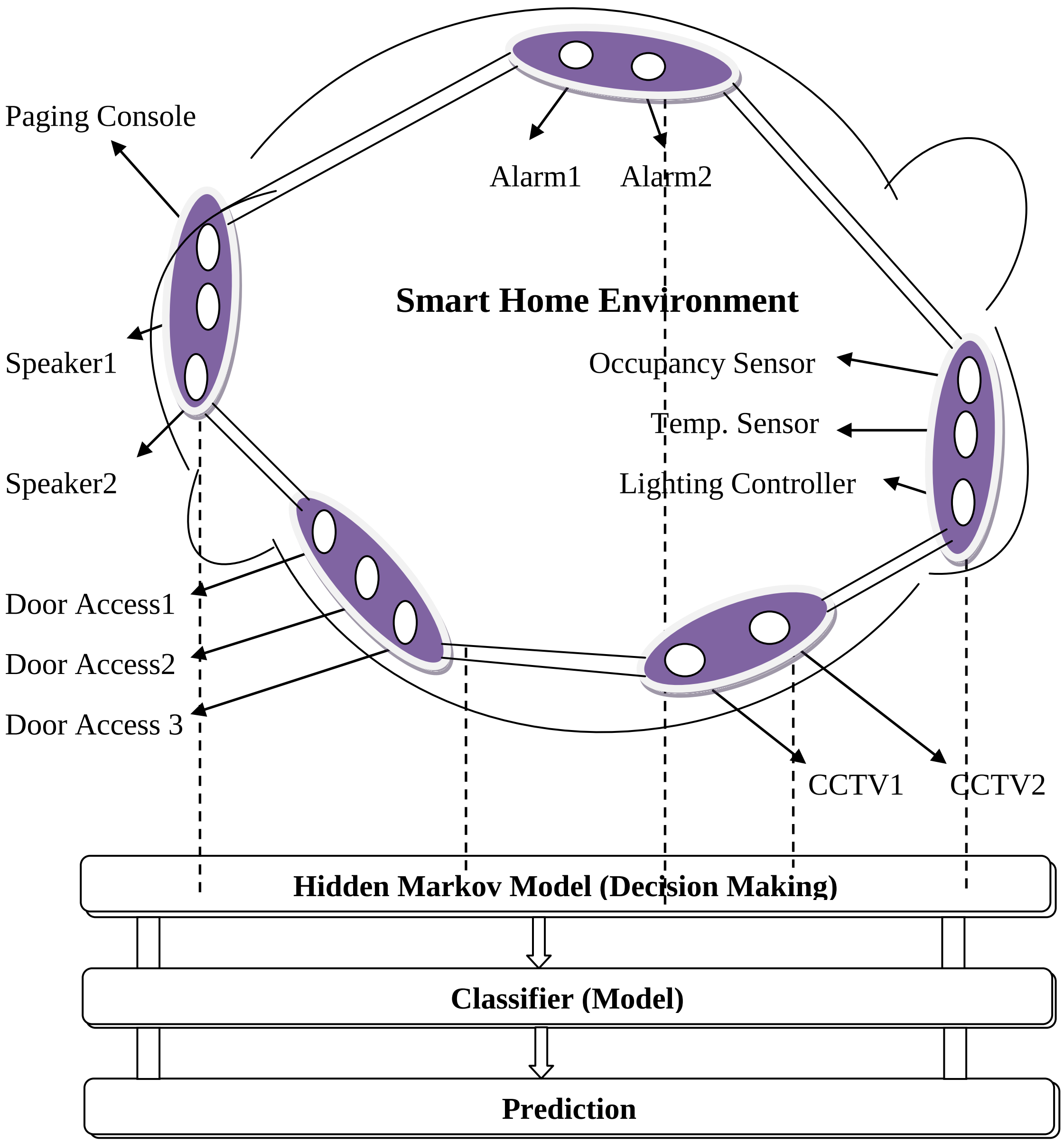

Figure 2. HMM-based Decision Making Framework

As shown in Figure 2 above, each subsystem is connected to each other in such a way that the functionality (interoperation) between them is determined by the HMM implementation. The interoperation between subsystems in the smart home environment is achieved from the HMM-based decision making model which serves as the building block that provide relationship among the devices in the home environment. The devices configured are CCTV, Home Alarm Management System, Audio Paging system, Energy Management System. The internal architecture of the HMM-based model is shown in Figure 3 below.

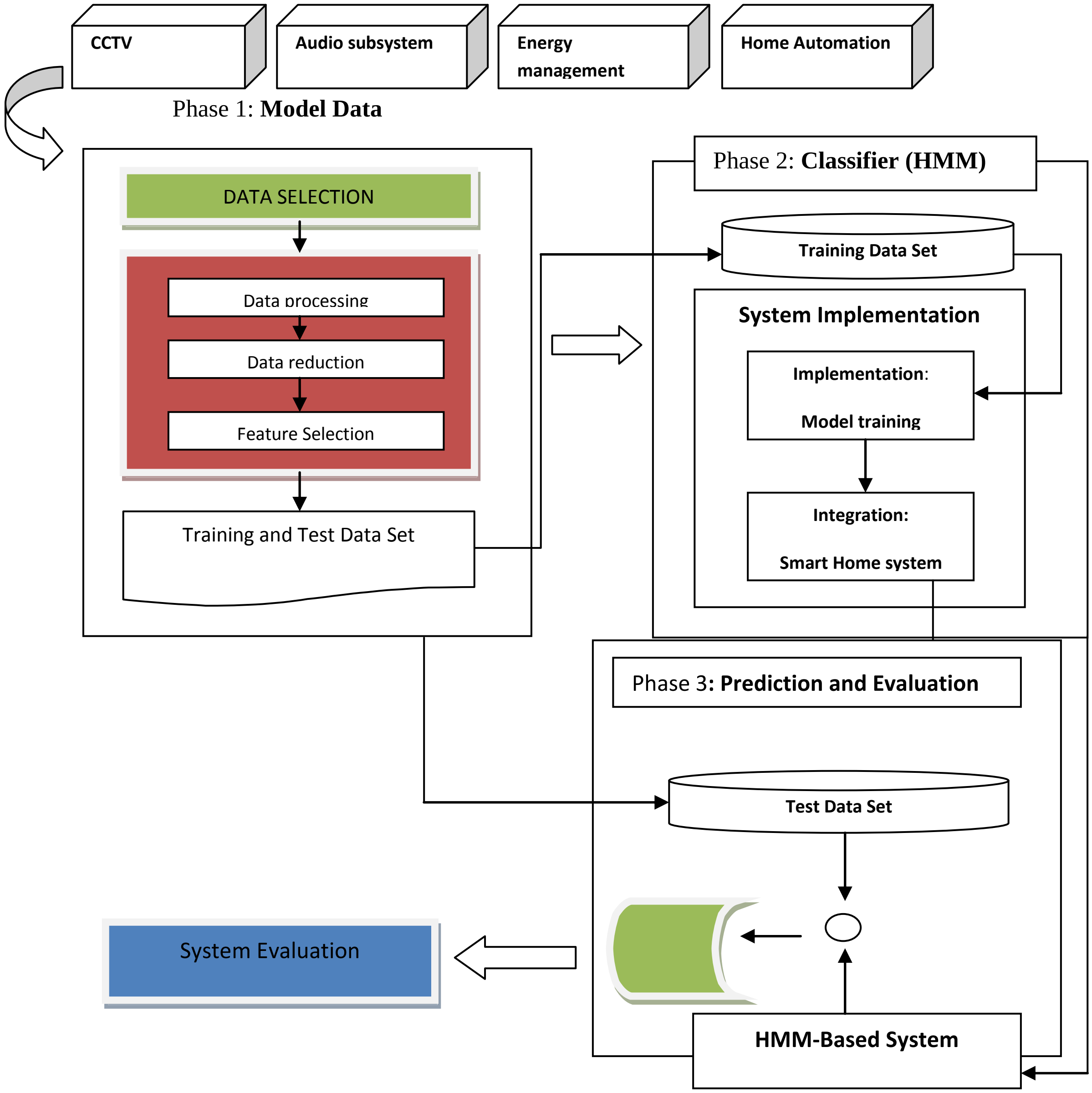

Figure 3. HMM based Model for Smart Home Environment

Figure 3 above describe about phases taken to accomplish the task of interoperability. The architecture comprises of three phases, namely – Model Data Phase, HMM implementation Phase, Prediction and Evaluation Phase. The HMM-based mechanism illustrated here defines the role of the architecture to perform cooperative execution of tasks among heterogeneous systems. During home events operation, each system linked with events is built during task execution based on home occupant's requirement. For instance, in the incident when a smoke alarm triggers smoke signal, the fire alarm system will instruct the audio distribution paging system to announce warning message immediately. In such scenario, the HMM-based mechanism due to its robustness and scalability would be able to handle sequential data as it is intended to provide higher accuracy in the part of decision making in home environment.

3.2. Data Description

The data sets presented in this work consists of the over 6000 events that occurred in the smart home building. Table I below shows the representation of the data sets.

Table 1. Data Sets Representation

Date	Time	Unique Identifier	Status	Action
2012-12-18	01:28:39	6	OFF	Alarm
2012-12-18	01:28:40	7	ON	Video
2012-12-18	03:20:58	12	ON	Light
2012-12-18	03:22:18	24	OFF	Alarm
2012-12-18	03:55:52	24	ON	Audio

The data obtained are arranged in sequence which makes it suitable for the HMM technique to perform decision making among subsystems. The description of the features is as follows:

1. Date
2. Time
3. Subsystems(unique identifier)
4. Status
5. Action

The preliminary fields are established by the data gathering setup. The end field named action describes the relationship between systems with the event occurred and the transition between them. The data sets are consigned to undergo some pre-processing stage to achieved quality data for the training. During the processing stage, the data set is limited to the required events of actions. It is then supplied as a training data for the machine learning algorithm. The machine learning algorithm learns the event of actions from the training set supplied and performs the interoperation.

3.3. HMM Technique and its Application

In principle, HMM is a compilation of fixed states joined by transitions. Each state is characterized by changes as well as representation of observation probabilities. Here, the HMM parameters are defined as such:

- N: *n* number on states
- M: *m* number of symbols being observed in respective states
- A: the state condition for each transition
- B: Observed symbol on probability distribution
- π: Initial state distribution

The illustration of the HMM architecture is shown below in Figure 4:

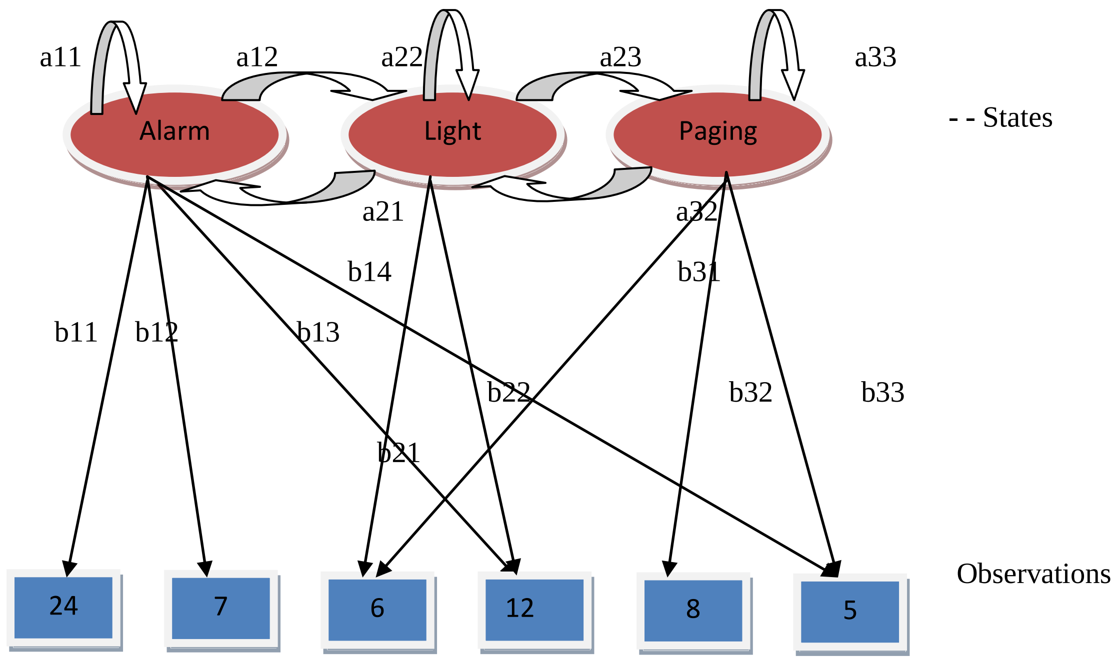

Figure 4. HMM-based Architecture

In the experiment, the parameters are related to certain functions. They are depicted as follows:

- The Hidden states represents the subsystem actions performed.
- The observations are the subsystem unique identifiers with their corresponding status.
- The transition probabilities signify the possibility of following event is triggered by the exact system or alternate one.
- The release probabilities are characterized by chances that an action triggered grounds any unique identifier with its corresponding status.

3.3.1. Learning Algorithm (Training Algorithm)

The training problem is important for most HMMs method as it allows the developer to become accustomed with model structures that observed data being trained and subsequently develop ideal model for real world applications [11].The training algorithm simply refers to the Baum – Welch Re-estimation method. The goal of the training is to obtain a model that extracts its statistical properties from a given set of training data and represent them. Now, for each event triggered by the subsystem, a HMM must be built and the model structures (A, B, π) are estimated using the Baum-Welch Re-estimation method that could enhance the chances of the training the observed vectors for the unambiguous event.

3.3.2. Viterbi Algorithm

Viterbi Algorithm is an eminent method that could resourcefully find the maximum posterior estimation of observations in sequence [12]. In HMMs, Viterbi Algorithm is adept to source the most probable hidden states sequence that could be generated. For each unknown event or action which is to be recognized, a calculation of model likelihoods of all possible models is performed using the Viterbi algorithm, followed by selection of the action or tasks whose most likelihood is the highest.

4. Result and Discussion

For the purpose of testing, data set for three home systems are obtained. It has been tested together to validate the capability of interoperation among them. Those systems are paging system, alarm system and closed-circuit-television (CCTV). For the performance metric, the interoperation deployment by HMM-based decision making technique is benchmarked using accuracy on actions performed. This decision model is to address the interoperability necessity in handling multiple data produced by heterogeneous systems. The accuracy of each action performed is depicted in Figure 5 below.

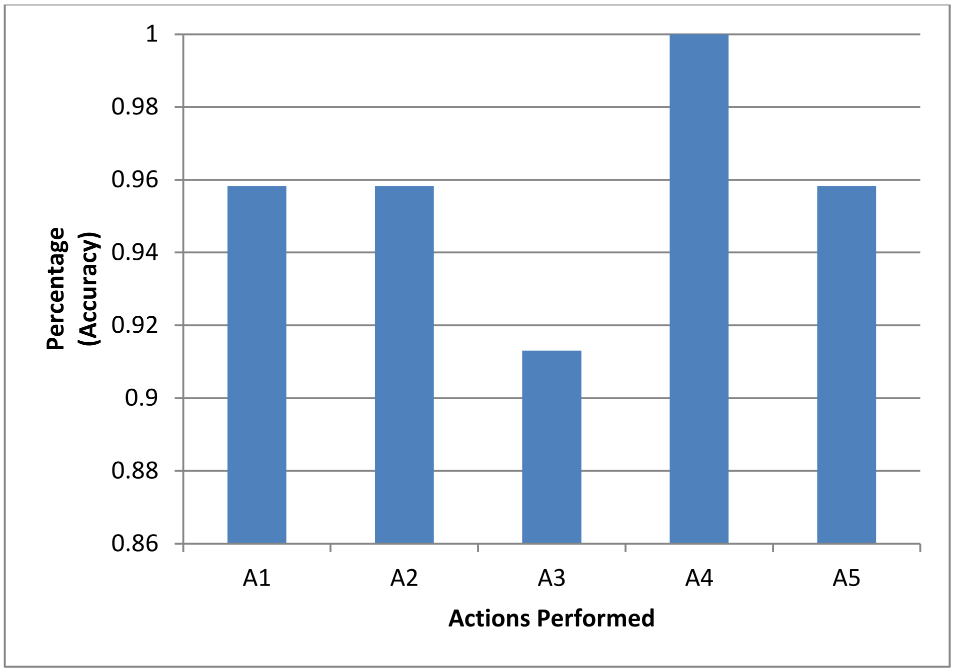

Figure 5. Accuracy of each Action Performed

From Figure 5 above, the HMM accuracy result for each action performed are promising. The initial hypothesis that the subsystems actions can be learned using HMM algorithm as a better option is verified by the obtained overall accuracy results. The behaviour pattern in HMM decision model is depicted in Table 2 below:

Table 2. Example Showing Behaviour Pattern in HMM

Event Number	Actual Class	Predicted Class	Success
1	A2	A2	Achievement
2	A1	A1	Achievement
3	A2	A1	Letdown
4	A3	A1	Letdown
5	A4	A4	Achievement

It is worth mentioning that during examination of the actual pattern of classification for smart home data, the way of handling of the HMM is a difficult chore to handle. As home events arrive simultaneously, it takes the HMM no more drawn out time and choosing the appropriate interoperation between the events. Table 2 above shows a modest part of how events are classified by the HMM. As seen in the Table 2, the left column indicates event number identification; the second column area is the actual class as provided by the training data set, the third column shows what the algorithm predicts and finally, the last column indicates the achievement indicator and let-down on the given events. In addition, the results indicates transition begin from A1 to A2 at event #3, yet the HMM obtains until event #5 before it has sufficient evidence to changing states. In such situation, those events transform starting with one event then onto the next have been termed a “transition” and are an essential characteristic that depicts on how HMM actually behaves. The obtained overall accuracy value as well as error rate are shown in Table 3 below.

Table 3. Overall HMM-Accuracy and Non-transition Confusion Error Rate

Overall Accuracy	Error rate
95.7%	4.3%

From Table 3, it is evident that the test result shows a high accuracy, given the complication of home data together with their respective service performed. The results also prove better reliability based on the condition of no given structure to their respective behaviour.

These contribute towards higher accuracy from the algorithm deployment and also verify its robustness. Similarly, classification errors occurred during HMM selection, but there was no substantial transition based action performed. Hence, the total error rates for such mis-interoperation between systems are summed up in Table 3 above. This also proves that the more the error rate, the more it leads to the reduction of accuracy.

5. Conclusions and Future Work

In this paper, we proposed a productive approach called HMM-based decision making model in smart home which has an exceptional learning ability around subsystems. The effectiveness of the model is tested in real phenomena. The technique gives rise to two algorithms – specifically, Viterbi and Baum-Welch algorithm. We have demonstrated the implementation of HMM based decision model for smart home environment that solves interoperability and measure the accuracy achieved as the core performance metric. The applicability of Viterbi is to develop the in all probability sequence of obtained results during the observation. On the other hand, the Baum-Welch is exploited to train the model to learn the decision model in smart home environment. The work done here has affirmed that the model can provide a reasonable solution as well as alternative mechanism for the smart home interoperability. It is evident that interoperability plays a significant role in smart home environment. A motivating development for future improvement would be assigning ontological or semantically linked decision model to achieve total complete interoperability in smart home environment.

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