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Hybrid Ontological Approach for Real Time Composite User Activity Recognition and Detection

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Abstract— Human activity recognition is an important parameter in the wide range of applications. To recognize the composite activities in the real and complex environments becomes difficult as monitoring the activities of multiple users cannot be done efficiently using conventional methods. The conventional methods mainly consist of knowledge driven and data driven approaches. In this paper a model for recognition of activities is proposed to detect the abnormal activities of the user. The model works in two modes i.e. learning mode and run mode. Initially, the model works on learning mode to get the sequence of activities and the detection of abnormal activities using hybrid ontological approach is done in the run mode. The simulation of this technique is presented and corresponding results are obtained to get the recognized activities. Thus, this paper calculates temporal relations between the series of actions termed into activity and later monitors this data with the real time data in the run mode.

Index Terms— Activity detection . activity recognition, composite activities, hybrid ontological approach, real time, temporal relations, user activity

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1 INTRODUCTION

In order to infer the activities, activity recognition should be accurate enough to get the efficient results. Activity recognition consist of three major tasks, namely, discovery, modelling and finding inference of the activities. Activity discovery mainly tracks the user, environment, and user activities using either sensors or the visual mediums like cameras. The conventional approaches for activity modelling mainly include a knowledge driven and data driven approach. Finally, activity inference processes sensory data against computational activity models to determine the ongoing activity.

Activity recognition mainly attempts to classify static states, dynamic states or transition states. For the real time dynamic environments, activity recognition can be further classified into static activity recognition and dynamic activity recognition. Static activity recognition mainly describes the self learning mechanism that gives series of interested actions. Another type is dynamic activity recognition which is also known as action spotting where it gets the ongoing activity.

The conventional approaches of knowledge driven and data driven activity modelling are mainly used to model simple activities. The composite activities are difficult to model using above approaches. In knowledge driven approach, the system consists of fixed set of objects with fixed sequence, location and time intervals thus defining a simple activity. The data driven approach mainly includes learning of activity and storage of the data for further inference. This approach cannot be used in real time activity monitoring as new sequences cannot be learnt. Thus, a hybrid approach combining both the learning mechanism of data driven approach and ontological reasoning for the knowledge driven approach for composite activity modelling in real time environments is proposed.

As described above, to implement this system in practical real scenario, the recognition system must detect variety of activities that are performed routinely in many different manners by different individuals under different environmental conditions. Thus, here we use hybrid temporal approach which mainly calculates time intervals between the activities to efficiently monitor the activities.

In this paper section 2 represents the related work on the activity recognition mainly focuses on techniques of vision based and sensor based activity recognition. Section 3 consists of comparative analysis of following techniques. Section 4 represents the circuit diagram and its description Section 5 explains the algorithms of these different modes of learning mode and run mode in detail. Section 6 displays simulation results of the proposed technique. Section 7 is the conclusion thus followed by references.

2 RELATED WORK

A growing number of users for the automated applications use a collaborative and interactive feature to avail the facility for eg in blog, wiki,etc. In order to generate the user generated content knowledge driven approach long with ontological feature is needed. Ontology mainly deals with logical computation of the data. Ontology matching and merging includes alignment and update the user data for analysis. This method uses knowledge management technique to manage the web based data.

Knowledge driven activity modelling mainly deals with fixed set of objects and their specific circumstance of time, location and space. Knowledge-driven approaches can be divided into those that encode temporal information and those that do not. Approaches that model temporal information include rule based and logic-based systems, e.g. spatio-temporal methods, spatio-temporal

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and context reasoning, temporal reasoning and active databases. Although most knowledge driven approaches assume that the user only performs one sequential activity, a spatio-temporal approach for composite activity modelling[13]. While the authors report success in applying their approach for recognizing interleaved and concurrent activities, no explicit model of these composite activities is provided.

The data driven approach for activity modelling mainly includes learning of new activities to provide flexibility. This approach has focus on identifying the context of a user for providing services based on the application. In order to cover maximum activities, a comprehensive set of sensors is defined. An interdisciplinary knowledge is required to relate set of activities with the sensors depending on the characteristics of the sensors. The learning mechanism introduced requires heavy resources for the execution of the machine learning algorithm which leads to requirement of backend server. Once the data is collected through sensors, it is sent to server for the training of the model. WEKA is a collection of machine learning algorithm for data mining used to train and test the model. The design is mainly to identify routine activities and provide flexibility to the system to add new sensors and thus new activities.Though it ensures flexibilty of implementation of new applications,there is an overlap among the activities and associated sensors.A single activity can be identified using multiple sensors but complex activities cannot be determined.

Daily activity recognition system aims to realize activities with inertial sensors, template matching which is the most commonly used to match the incoming sequence with the training sequence. Here, in order to improve the accuracy of recognition, raw data from sensors should be pre processed to reduce the dimension and to extract the important information.

In order to improve the accuracy of recognition, raw data from sensors should be pre processed to reduce the dimension and to extract the most important information. There are several features used in past articles, for example, the time domain features like means, variance and standard deviation, the frequency domain features etc. A feature evaluation method for template matching to select the most proper feature for certain activities and thus improve the overall accuracy of recognition. In template matching method, the raw sensor data features are used to represent the primary ones. Then those pre processed data are used to create template. This kind of template creation is done during training phase. For one certain class of activity, the similarity between each training sample of that class is calculated and one which has the highest average similarity with other samples is chosen to be the template and the value of minimum similarity is the threshold.

In recognition phase, the similarity between test sample and the template is calculated, if it is higher than the threshold, the test sample will be classified as that class of gesture.

3 Methodology

The following model to be constructed aims to recognize the activities and detect the abnormal ones. The model is divided into two stages namely hardware design and flowchart which describes the stages of the activity recognition. Firstly, we describe a circuit diagram which is constructed according to the aim of the model which mainly consists of sensors, microcontroller, lcd display, real time clock and related circuits. The second stage of programming is further divided into two stages as learning mode and run mode. The corresponding algorithms in the respective mode will be described and related simulation results are obtained. Thus, we describe the plan of project work as shown in fig.1.

Fig.1. Stages of the work

4 Circuit Diagram

The system consists of set of sensors, microcontroller, RTC (Real Time Clock), EEPROM (Memory chip), LCD display, and buzzer. The circuit diagram is constructed as per the block diagram. Fig 2. shows the following circuit diagram of the system.

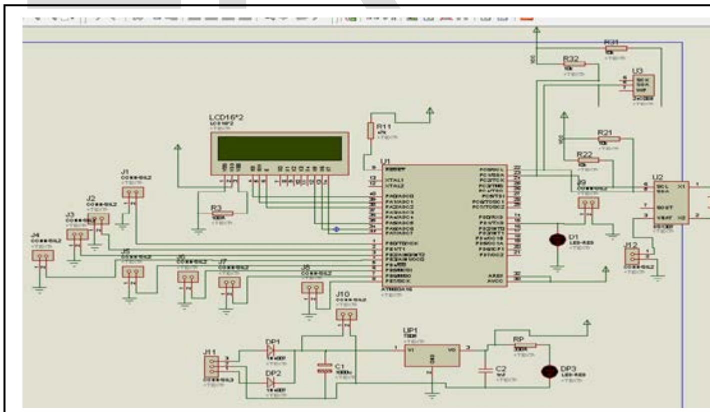

Fig.2. Circuit diagram

Sensors are the devices converting the sensed physical quantities into electrical signals. These signals will be sensed and further recognition process will be carried forward. In order to cover maximum possible activities we consider total five sensors in a room. The door sensor at the entrance, another at the cupboard, window sensors mainly three in number. The activities will be monitored according to these sensors.

The microcontroller will be programmed accordingly with corresponding pins to get the sequence and timing of the actions carried over. Here two controls will be given for to enable learning mode and run mode. The microcontroller will

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switch the modes accordingly and store the data in its memory. All the operations within the microcontroller are performed at high speed and quite simply. As the ATmega16A is a low-power CMOS 8-bit microcontroller based on the AVR enhanced RISC architecture, it is well suited for our application. It has 16K bytes of In-System Programmable Flash Program memory with Read-While-Write capabilities, 512 bytes EEPROM, 1K byte SRAM. ATmega16A has throughputs at 1 MIPS per MHz.

Real time clock IC DS1307 is used for our application to get the real timestamps of the actions. It has a 3V battery separately to enable the working of the clock even if the system is switched off. The battery life is about ten years. So, it is well suited for system. A real-time clock (RTC) is an integrated circuit that keeps track of the current time,date, and year with leap-year compensation. The real-time clocks (RTC) are ultra low power clock/date devices with programmable time-of-day alarms and programmable square-wave outputs.

A liquid-crystal display (LCD) is a flat panel display that uses the light modulating properties of liquid crystals. Here we use the LCD that is 16 characters wide with 2 rows. The status of the activities will be displayed accordingly in order to model the activities.

In order to store the time stamps of the user activities, we require this memory chip connected to microprocessor in order to recognise the activities and further detect the abnormal activities. EEPROM (electrically erasable programmable read-only memory) is user-modifiable read-only memory (ROM) that can be erased and reprogrammed (written to) repeatedly.The chip does not have to be removed to be rewritten.It has a limited life - that is, the number of times it can be reprogrammed is limited to tens or hundreds of thousands of times. Thus, the life of the EEPROM can be an important design consideration

5 ALGORITHMS

The circuit diagram shown above is modified for simulation results keeping the components as it is. The system will be working in two modes of operation i.e. in learning mode and run mode. The corresponding sub stages of each mode are shown in fig.3.

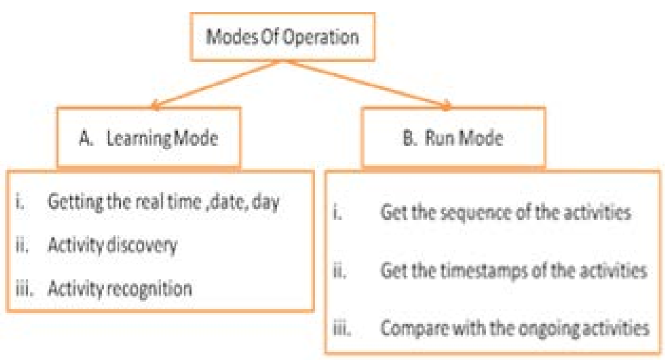

Fig.3. Modes of Operation

A] Learning Mode: The learning mode will consists of above listed three stages of getting the real time, day and date, activity discovery and recognition. The following algorithm explains this stage of getting the real time, day and date.

1. Start
2. Ensure the satisfactory turning ON of the hardware by ensuring a “welcome” and blinking of LED.
3. Set the date, time and day when the system is used for the first time.
4. while(1)
5. {
6. rtc_get_time// to get current time
7. rtc_get_date // to get current date
8. }

In the first sub stage of this mode, in order to get the real time information we use RTC for the operation. The microcontroller is programmed to initiate the RTC. Further, once it is initiated the clock is running throughout even if the supply is not given. The 3V battery to the RTC helps in maintaining the accurate operation.

1. Start
2. Initialize all the pins where sensors(Here switches are taken into consideration) for demonstration
3. While(1)
4. {
5. Check the status of all the pins into consideration
6. If(change found)
7. {
8. Record the action number
9. Record its sequence
10. Do
11. {

    Record the start time

12. }while(Status changed)
13. }
14. }

The timestamps of the activities obtained in the discovery stage are used for taking the time difference between them in order to get the exact time of the actions. The activity recogni-

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tion aims to recognize the activities in two ways that is by

- Sequence
- Time duration

In the run mode, for accurate abnormal detection of activities, the sequences as well as timestamps are verified. Here, separate arrays of the sequences and timestamps are created. When the system enters the run mode, the data in these arrays will be checked with the incoming data that is simultaneously the sequence and the timings of the actions will be checked. If random sequences found, it will term it as an abnormal activity.

B] Run Mode: The run mode monitors the sequence of activities using hybrid ontological approach. Here, the abnormal activities are stated for recognition, terming it as knowledge driven approach. The real time data is obtained that is the sequence of actions and time stamps in learning mode describes the data driven approach including the self learning mechanism. The ontology is the logically classifying the activities which is done by calculating temporal relations. Thus, the run mode completely describes hybrid approach that is combination of both knowledge driven and data driven approach and the ontology using the temporal relations.

An algorithm is described to illustrate the matching of real time sequences and timings with the ones obtained in the learning mode as follows:

1. Start
2. Initialize RUN mode
3. Get the sequence number, timings of the ongoing activities
4. Simultaneously store the sequence numbers in the array sequence_r []and compare it with the one obtained in learning mode
5. If (equal) then display "Sequence match"
6. Else display "Sequence mismatch"
7. The temporal relations are calculated again in the run mode and stored in the array timings_r[]
8. Compare with the array in learning mode
9. If (equal) then display "timing match"
10. Else display "timing mismatch"
11. End of RUN mode

From above, the mismatched sequences and their timings can be found. In order to detect the abnormal activity, the sequence obtained is to be compared with the sequences in the abnormal sequences list. If any of the sequence found, then would be termed as abnormal activity. The following algorithm explains the same.

1. Start
2. Mismatch found
3. Check the list of abnormal activity sequences provided as per the application
4. If found one of them display as an "abnormal activity"
5. If not found, include as a new activity in learning mode with users permission
6. End

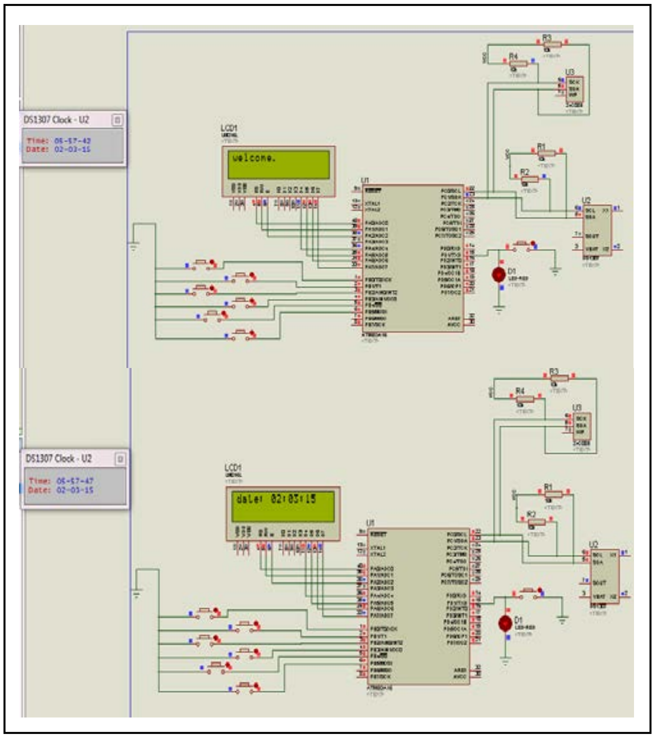
Thus, this mode separates regular activities from the new ones as well as detects the abnormal activities found. Also, a new activity can be if not found abnormal can be added as new activity with user's permission adding to the accuracy of recognition and detection of activities.

6 Simulation Results

For the simulation of above modes, the hardware module is considered which consists of five sensors denoted as switches to symbolize the on off activity of the sensors, microcontroller, EEPROM memory chip, LCD display and RTC clock. These sensors are referred to as switches as per the limitation of simulating software used Proteus circuit design suite. Here, the various sub stages of learning mode are shown in the following figures.

A] Learning Mode

The first stage of the learning mode to get the real time, date and day is shown in fig.4.



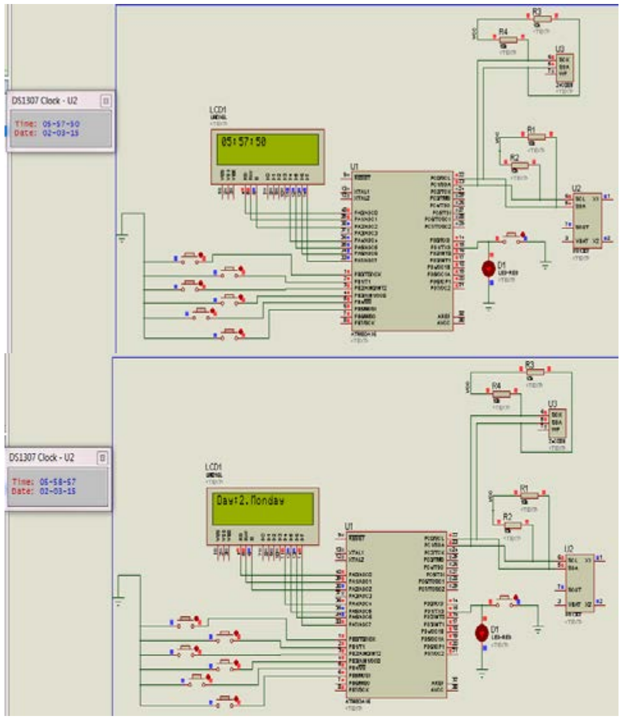
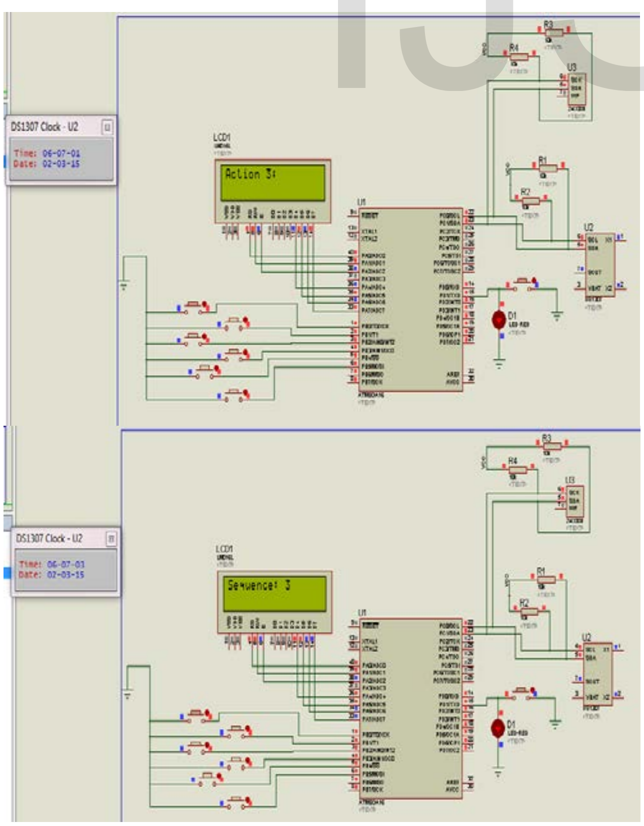


Fig.4.Getting the real time, date and day

The second stage of learning mode is the activity discovery. It mainly includes getting the action number, its sequence and the start time of the activity. All the three sub stages are as shown in fig. 5.



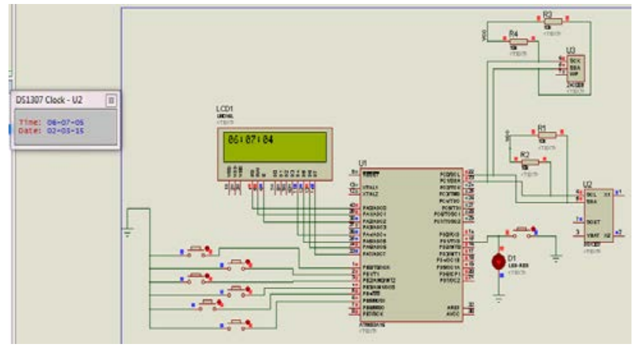


Fig.5. Activity discovery

The third stage in learning mode is activity recognition. Firstly, the learning mode is initiated. The sequence of activities and its timings are stored in the memory chip. Then the time difference between the actions is calculated to mark the temporal relations. The corresponding sequence of actions and its timestamps are stored in EPROM memory in the microcontroller.

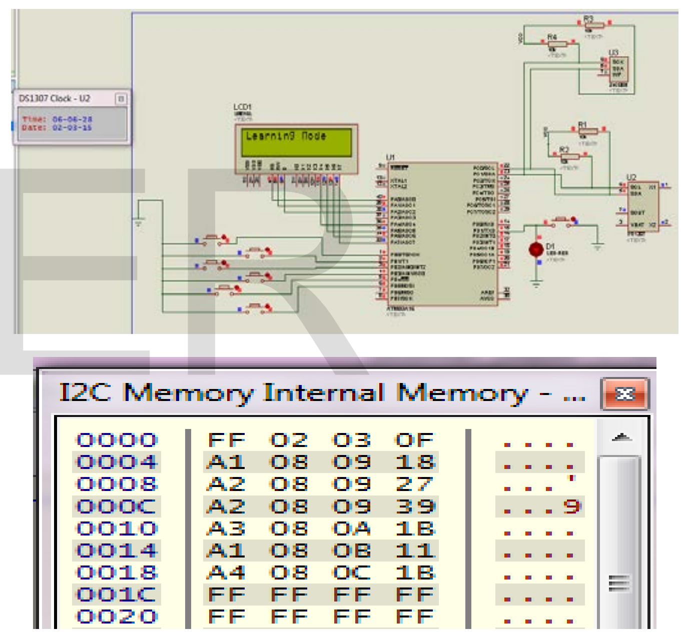


Fig.6. Activity Recognition

The sequence array from the above is shown in fig.7 which gives the order of actions performed to define a activity. Here, the activity consists of sequences of A1 A2 A2 A3 A1 A4.

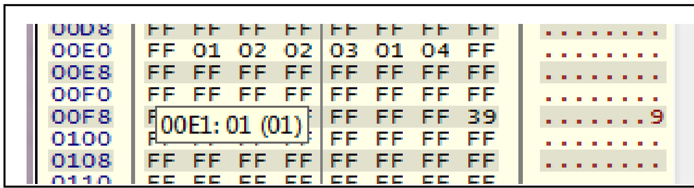


Fig.7. Action sequence

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The time array from the above is shown in fig.8 which gives the timestamps of actions performed to define an activity. The timing is described in hours, minutes and seconds respectively.

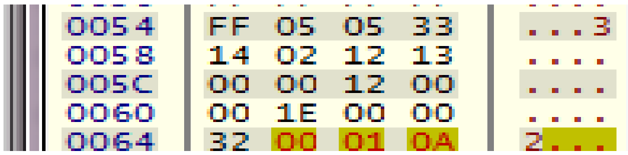

Fig.8. Timing sequence

Thus, the data obtained in the learning mode is described in the following table.

TABLE 1
LEARNING MODE

Se-quence	Action no.	Time(in decimal)	Timings (Hex)		Timings (Decimal)	
			Min	Sec	Min	Sec
1	A1	09:24:48		12		18
2	A2	09:25:06		12		18
3	A2	09:25:24		1E		31
4	A3	09:25:55		34		52
5	A1	09:26:47	01	0A	01	10
6	A4	09:27:57	XX	XX	XX	XX

B] Run Mode: The initialization of run mode is as shown in fig.8. Here, we obtain sequence of actions and the ones obtained in run mode are compared with the ones in learning mode. The comparison of actions is done based on two parameters that are sequence and timings. If both the parameters are matched, the action is matched. If either of the parameters are not matched, it is compared with the list of abnormal sequences an if found, termed as abnormal activity and if not it is added as new sequence. The timings error can be tolerated till 5 seconds due to simulation limitations. But if exceeded beyond, then termed as abnormal activity.

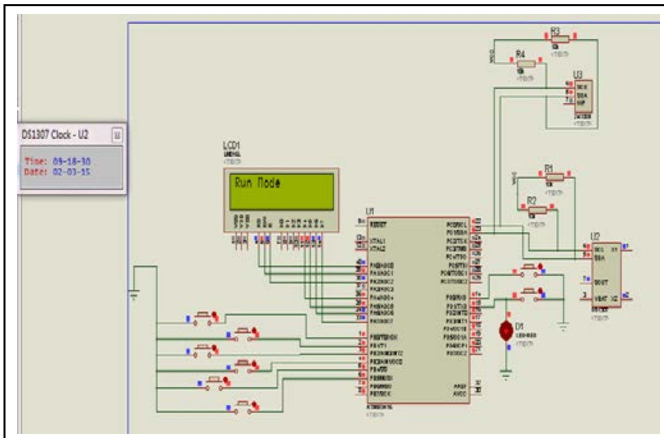

Fig.8. Run mode

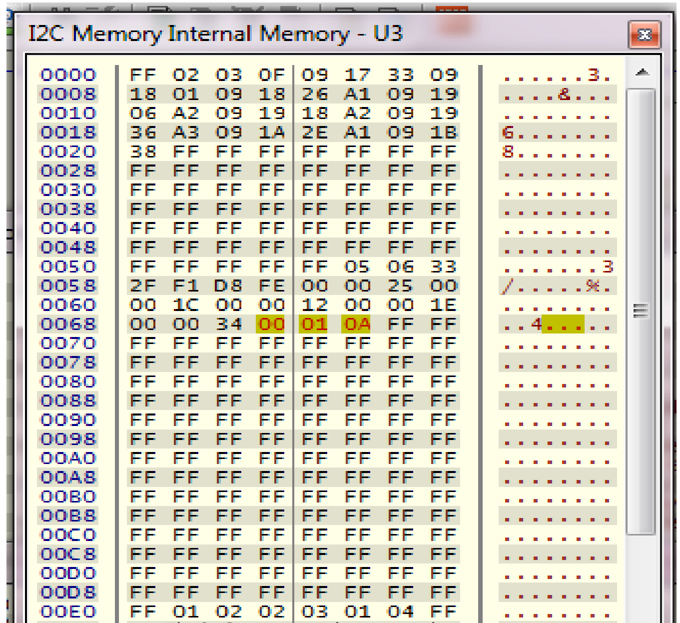

Fig.9. Sequences in run mode

The sequences in run mode are obtained as shown. Thus, the data obtained is explained in the following table.

TABLE 2
RUN MODE

7 HARDWARE RESULTS

Se-quence	Action no.	Time(in decimal)	Timings (Hex)		Timings (Decimal)	
			Min	Sec	Min	Sec
1	A1	08:09:24		13		19
2	A2	08:09:39		12		18
3	A2	08:09:57		1E		31
4	A3	08:10:27		32		50
5	A1	08:11:17	01	0A	01	10
6	A4	08:12:27	XX	XX	XX	XX

The temporal relations among the real time activities are calculated for accurate activity recognition. This method calculates the difference time of the activities where the timestamps obtained are using real time clock. Thus, this difference acts as temporal relation between the activities to determine the recognition of activity as valid or invalid.

A] Learning Mode: To model the activities, first the real time clock IC DS 1307 is interfaced with microcontroller ATMega 16. Also LCD is interfaced with the ATmega 16 to get the display of real time and date.

Activity modelling algorithm creates the patterns of the sensed activities. From above, various activities will be sensed and their corresponding timings will be stored in memory. Modelling focuses on sequence of the actions being performed to generate the pattern.

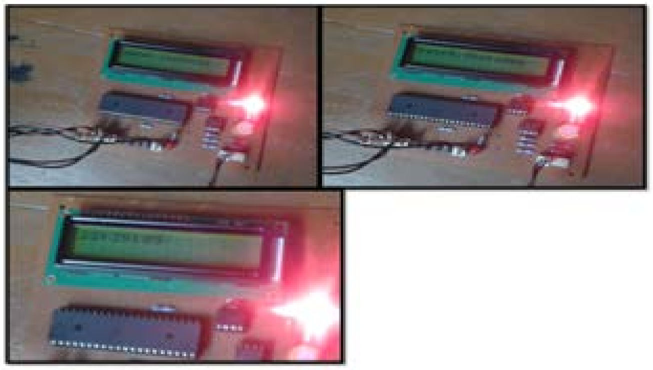

Fig.10. Display of real time, day and date

It represents the learning mode of the system where all the patterns of the activities performed will be generated for further making an inference as shown in fig.11.

Fig.11. Activity recognition

B. Run Mode: In this mode real time activities are compared with the ones obtained in learning mode. This gives the inference of activity match or mismatch as shown in fig.12.

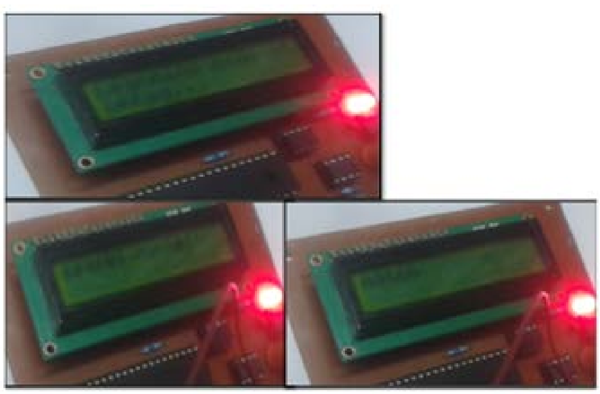

Fig.12. Run Mode

8 Result Analysis

From above tables, the data in the learning and run mode is obtained. The accuracy of the sequence is 100% as shown in the following table whereas time intervals may vary till 5 seconds owing to simulation constraints. Also, the sequence matching is done accurately in the hardware. The timestamps matching is done using the ranges of the observed timestamps of the activity as the exact timestamp cannot be obtain as the simulation considering the hardware constraints.The following tables give the comparison of sequences and timings in learning and run mode. The graph shows the overall accuracy and plot of the above data obtained.

TABLE 3
Sequence Matching

Sequence Matching	
Learning Mode	Run mode
A1	A1
A2	A2
A2	A2
A3	A3
A1	A1
A4	A4

TABLE 4
Timestamps Matching

Action sequences	Timestamps Matching				Accuracy
	Learning Mode		Run mode		
	Min	Sec	Min	Sec	
A12		19		18	52.63%
A22		18		18	100%
A23		31		31	100%
A31		50		52	40%
A14	01	10	01	10	100%

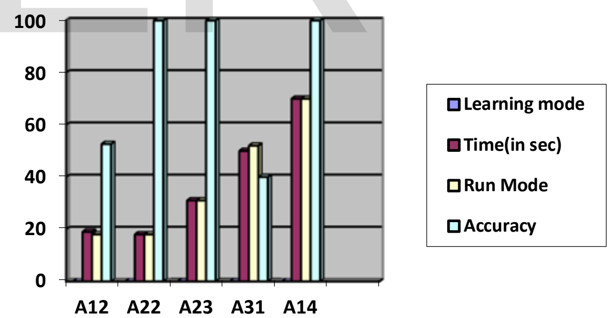

Fig.13. Result Analysis

Thus, overall accuracy of 78% can be seen.

Conclusion

A system for composite user activity recognition and abnormal activity detection using hybrid ontological approach is proposed. Here, activity is recognized on the two parameters mainly on the sequences and the timings. Also the hybrid ontological approach is used where knowledge driven approach for the abnormal activity detection and data driven approach with self learning mechanism for activity recognition. The ontological approach is mainly used to logically find the temporal relations between the activities. The accuracy for the sequence matching is 100% whereas for timestamps matching

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is 78% from the results above. The system efficiency can be increased further by making the system learn more sequences in learning mode.

FUTURE SCOPE

This technique being developed can be applied for the application of home security. Home security is always been a crucial need of the hour. Though the ways of security varied from tricks to keep valuables in the farms to lockers and now various security systems. Developing a self learning system to monitor the activities of the habitats and also detection of abnormal activity can definitely add to more secure homes. Moreover, also these systems can be useful for industries thus changing the parameters as per requirements. For e.g. in banks, the security focus is mainly for the lockers and the safe where the cash is kept. Similarly, in factories more focus would be on poisonous gas leaks and fires. As per the requirements mentioned above, banks would definitely need high quality motion sensors and door /window sensors in order to get most accurate detection of activity. Similarly, in factories high precision smoke detectors to get exact percentage of gases in the air are required to detect gas leaks and also fire alarms. Also, this system can be implemented as health monitoring system by taking into consideration the need of the application as human activity monitoring. The sensors like accelerometers, motion detectors, etc will be implemented to implement above application. Thus, this technique is developed for the "smart society".

REFERENCES

[1] George Okeyo ,Liming Chen, Hui Wang, Roy Sterritt,"A Hybrid Ontological and Temporal Approach for Composite Activity Modelling" ,2012, *IEEE 11th International Conference on Trust, Security and Privacy in Computing and Communications,* 978-0-7695-4745-9/12 $26.00 © 2012

[2] Muhammad Arshad Awan,Zheng Guangbin,Shin-Dug Kim,"Activity Recognition in WSN: A Data-driven Approach",*National Research Foundation of Korea,*2012081659

[3] Chao Chen, Haibin Shen," A Feature Evaluation Method for Template Matching in Daily Activity Recognition," 978-1-4799-1027-4/13/$31.00 ©2013 IEEE

[4] Shuwei Chen,Jun Liu,Hui Wang,Juan Carlos Augusto,"A Herrarchical Human Activity Recognition Framework based on Automated Reasoning",2013 *IEEE International Conference on Systems, Man and Cybernetics,*978-1-4799-0652-9/13 $31.00 © 2013 IEEE

[5] L. Chen, C. Nugent and H. Wang, "A Knowledge Driven Approach to Activity Recognition in Smart Homes," *IEEE Trans. Knowledge and Data Eng.*, vol. 24(6), pp.961-974, 2011.

[6] Liming Chen,Chris Nugent, and George Okeyo," An Ontology-Based Hybrid Approach to Activity Modeling for Smart Homes", *IEEE Transactions On Human-Machine Systems*, Vol. 44, No. 1, February 2014

[7] S. Saguna, A. Zaslavsky and D. Chakraborty, "Complex activity recognition using context driven activity theory in home environments," *Proc.11th Int.Conf. and 4th Int. Conf. on Smart spaces and next generation wired/wireless networking* (NEW2AN'11/ruSMART'11), 2011.

[8] T. Gu, L. Wang, Z. Wu, X. Tao and J. Lu, "A Pattern Mining Approach to Sensor- Based Human Activity Recognition," *IEEE Trans. Knowledge and Data Eng.*, vol. 23, pp. 1359-72, 2011.

[9] S. McKeever, J. Ye, L. Coyle, C. Bleakley and S. Dobson, "Activity recognition using temporal evidence theory," *Journal of Ambient Intelligence and Smart Environments,* vol. 2, pp. 253-269, 2010

[10] L. Chen, J.Hoey, C. D. Nugent,D.Cook, andZ.Yu, "Sensor-based activity recognition,"*IEEE Trans. Syst.,Man, Cybern. C, Appl. Rev.*, vol. 42, no. 6, pp. 790–808, Nov. 2012.

[11] D. Lymberopoulos, A. Bamis, T. Teixeira and A. Savvides, "BehaviorScope: real-time remote human monitoring using sensor networks," *Proc. 2008 Int. Conf. On Information Processing in Sensor Networks* (IPSN 2008), pp. 533-4, 2008.

[12] Mirza Adipradhana, I.G.B. Baskara Nugraha, Suhono Harso Supangkat,‖ Intervention of Non-Inhabitant Activities Detection in Smart Home Environment"