A Multi Agent Approach to Facilitate the Identification of Interleaved Activities

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ABSTRACT

This paper presents a Multi-agent approach to identifying interleaved activities in a smart environment. The use of binary contact sensors was explored to identify Activities of Daily Living with assistance from a system made up of agents. Activities were identified when an activity trigger event was detected. Upon detection, a time window would activate around the trigger event, prompting the activity agents to identify which of their events were present within the set time window, thus enabling them to calculate a percentage of likeliness that the activity was their own. As a result, the highest percentage of activity matches would be displayed as having occurred. To evaluate this approach, 36 interleaved activities were processed and compared with a single agent system in addition to 28 non-interleaved activities. As a benchmark, the results were compared to that of another study. Results presented a precision, recall and F-measure of 0.69, 0.81 and 0.74. This paper concluded that the Multi Agent System (MAS) is a promising approach for identifying interleaved activities when compared to methods that fail when presented with data that is not in a set order. However, several limitations are present which need to be overcome to make the results more accurate when compared to other approaches.

KEYWORDS

Multi Agent System; Ambient Assisted Living; Aging in Place

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1 INTRODUCTION

As the use of pervasive computing is becoming more popular in healthcare it is beginning to bridge the gap between technology and the physical world [1]. With the growing ageing population and the need to reduce healthcare costs, encouraging the ageing to live independently for longer has placed more demand on the need for robust and scalable smart environments. As a result, it is now possible to perform automated human activity recognition and in return identify changes in activity patterns that may be linked to long term health issues [2]. Activity recognition can be used to identify activities of daily living (ADLs) performed by occupants of smart environments [3]. ADLs are recognized more easily when they are scripted, step by step in a set order, so ensuring a more realistic set of results would require using more complex scenarios such as interleaved activities [4]. This paper proposes a Multi Agent approach to the identification of interleaved ADLs within the context of a smart environment with the aim to provide monitoring of the elderly with cognitive declines such as dementia. Using binary contact sensors to monitor the opening or closing of doors or the movement of objects, and a Multi Agent System (MAS) activity recognition is carried out; with results being displayed according to the percentage of likeliness that agents, within the MAS, decide matches each ADL. This is achieved using a temporal algorithm, generating custom time windows based on the available sensor data. Time windows were triggered by an activation "trigger" sensor, with each ADL having their own unique 'trigger' assigned, generating a time window that will encompass the preceding N seconds of sensor data and the ensuing N seconds of sensor data. The use of a MAS facilitates these time windows to be considered simultaneously subsequently allowing for the detection of multiple activities at the same time. This paper presents the outcome of this approach and highlights the limitations found in comparison to a benchmarking method. The remainder of the paper is structured as follows. Related Work will highlight similar research within the areas of activity recognition, MAS and interleaved activities. The Methodology section presents an overview of the MAS and the algorithms used whilst highlighting each ADL and set of interleaved activities involved in the study. Experimental Results and Discussion present and discuss the findings from this study in comparison to a similar approach and highlights limitations. Finally, the Conclusion and Future Work section provides a critique of the findings and outlines the plans for future work.

2 RELATED WORK

Previous studies have investigated interleaved activities, activity recognition using agents and using multi-agent systems, however, none have combined these, especially using a MAS for the purpose of ambient assisted living. A study by Helaoui *et al.* looked at recognizing interleaved activities using a Markov logic method [5]. They took into consideration the start and end times of activities and evaluated it against activity recognition algorithms. The authors ensured the data they used included activities that were more complex such as overlapping and alternating events to provide a more realistic result. Nevertheless, their limitations made their work differ from this study. Firstly, they made assumptions about their activity recognition, where if an activity's start point is not detected then they did not consider this activity in their results. Therefore, if an activity was carried out as expected, with only the 'start point' missing, this activity was not acknowledged at all. Furthermore, they used wearable RFID tags to collect a proportion of their data, despite wearable technologies being a growing area in healthcare, it still produces many challenges. Wearable technology can be expensive to implement in addition to being difficult to gain trust with the elderly or persons intended for use [6]. Within their study the results of precision, recall and F-measure were 0.71, 0.99 and 0.82. Hamid *et al.* aimed to recognise ADLs from sets of events in a smart environment where 'One agent' activities were focused on and events were performed one at a time [7]. Strain gages were placed throughout their smart environment which collected data when walked over. They relied on the start and end event of activities to identify what the activity is and similar to the proposed method in this paper, activities were made up with local events, for example, if the fridge was opened then milk must be have been lifted out. They did not take in to consideration that some events may take longer than others and therefore did not test their approach with event duration in mind. A further study by Lu *et al.* [8] investigated interleaved activities using a location-aware activity recognition approach. They used RFID tags and a smart floor to collect data which they then used to identify activities based on the location of the participant. Limitations with this method again included costs of installation of a smart floor in addition to the complications that came with requiring the participant to wear an RFID device [8]. This method was also quite complex in that multiple types of intrusive sensors were required, some such as cameras causing ethical issues mainly with privacy. Generally, limitations found included using an approach that did not take time in to consideration when carrying out activities and sensors that were pricey or intrusive to privacy having been used to collect data. The method presented in this paper did not possess any of these limitations; all events that took place were acknowledged as having taken place and all sensors used were contact sensors, so no major expense, trust or privacy issues had potential to arise.

3 METHODOLOGY

Nexa LMST-606 contact sensors [1] were placed around a smart environment, to detect actions which were then translated and identified as activities by set algorithms. 16 sensors were placed around the smart environment's bedroom (with en suite) and kitchen in specific areas to detect the opening and closing of doors, movement of appliances or to mimic the use of appliances and furniture such as the bed and kettle. Locations of each sensor are presented in Fig. 1, showing the overview of the smart environment with an 'x' marking the location of each Nexa sensor. Each sensor opening or closing represented an event, for example using the kettle or a cupboard opening or being closed.

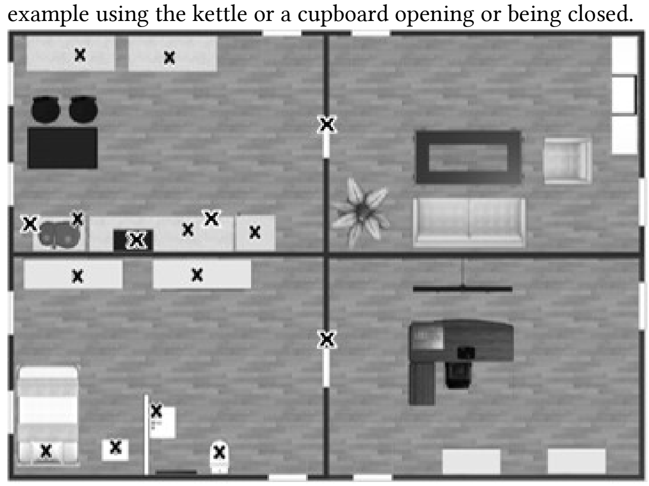


Figure 1: Image showing the layout of the smart environment where the approximate location of each of the 16 Nexa sensors have been marked with an 'X'.

Events were grouped together to form seven single activities and nine interleaved activities, all of which are listed in Table 1.

Table 1: List of activities in each Dataset

Activity	Dataset
Dressing	Non-Interleaved
Sleeping	Non-Interleaved
Toileting	Non-Interleaved
Preparing a Hot Drink	Non-Interleaved
Preparing a Cold Drink	Non-Interleaved
Preparing Food	Non-Interleaved
Cleaning	Non-Interleaved
Dressing & Sleeping	Interleaved
Dressing & Toileting	Interleaved
Sleeping & Toileting	Interleaved
Preparing a Hot Drink & Preparing Food	Interleaved
Preparing a Hot Drink & Preparing a Cold Drink	Interleaved
Preparing a Cold Drink & Preparing Food	Interleaved
Preparing a Hot Drink & Cleaning	Interleaved
Preparing a Cold Drink & Cleaning	Interleaved
Preparing Food & Cleaning	Interleaved

Interleaved activities were devised by pairing single activities together, with events within an interleaved activity carried out in a specific order to ensure that the activities would be properly interleaved within each other. As an example of this, Table 2 presents the order of events in the interleaved activity of Dressing & Sleeping, where their events are amalgamated.

Table 2: Table showing the formation of the interleaved activities of dressing and sleeping

Event Order	Event	Activity
1	Open bedroom door	Dressing & Sleeping
2	Open bedside drawer	Sleeping
3	Open Wardrobe	Dressing
4	Use the bed	Sleeping
5	Open Dresser	Dressing

To collect data, one researcher carried out each single activity and interleaved activity four times, creating two datasets: a non-interleaved (112 instances) and an interleaved (232 instances).

3.1 Multi Agent System (MAS)

The MAS used as part of this activity recognition system was created using Java. Each single activity had its own agent; there were seven activity agents in total: Dressing, Sleeping, Toileting, Hot Drink, Cold Drink, Food and Cleaning. Raw data was collected through sensor readings and stored within a database.

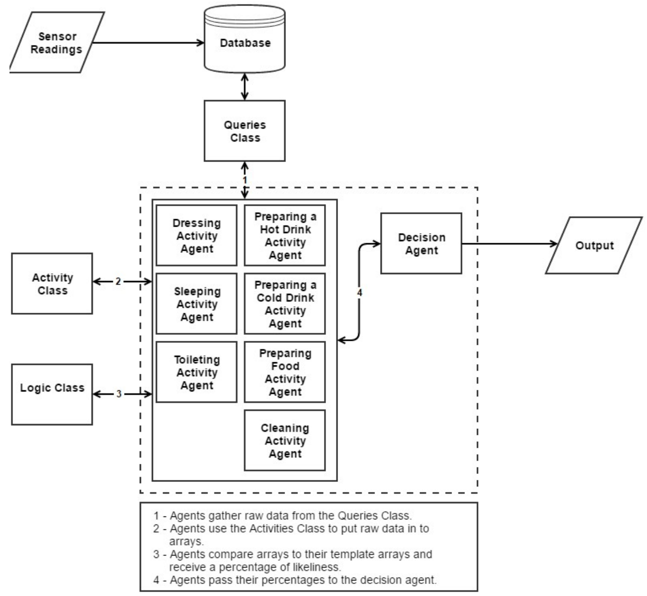


Figure 2: Image showing the relationship and communication flow between agents within the MAS.

The Queries Class accessed the data in the database so it could be used by the activity agents. Each agent looked for their assigned trigger event and set a time window around the trigger so that they would know what data was required from the Queries Class. Agents took the raw data and used the Activity Class to sort it in to arrays. Activity Agents used the Logic Class to compare and match the arrays to their own template arrays. By matching events, the agents worked out a percentage of likeliness of their activity being carried out and would inform the Decision Agent; who would then decide which percentages were the highest two, and display them as having taken place. Fig. 2 illustrates this process and shows the communication flow between these agents.

3.2 Time Windows

Activities were recognized when their events were carried out within a set time window. Time window parameters were set when a uniquely assigned event was found: these were known as Trigger Events, these are listed in Table 3.

Table 3: List of Trigger Events

Unique Trigger Event	Activity
Wardrobe	Dressing
Bed	Sleeping
Toilet	Toileting
Kettle	Preparing a Hot Drink
Crockery Cupboard	Preparing a Cold Drink
Microwave	Preparing Food
Cleaning Cupboard	Cleaning

Each time the MAS detected a Trigger Event, a set time would be set before and after the timing of the Trigger Event. Through ad hoc testing the optimal time window was found to be 120 seconds long, with 60 seconds preceding and proceeding the trigger event, and was applied for all activities. As an example, when the 'Kettle' Trigger Event was detected, the parameter was set around this and events within the time window set were noted: This is illustrated in Fig. 3.

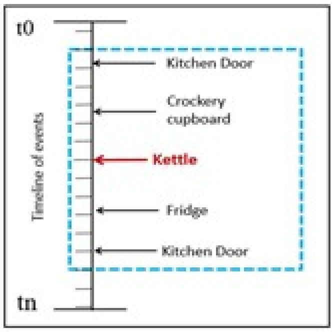


Figure 3: Image showing how a time window is set when the Trigger Event 'Kettle' is detected.

Once the events within the time window were noted, they were entered one by one in to an array. This array was then compared against set arrays within each activity agent in the MAS. The output consisted of how much (as a percentage) the activity found matched the activities in the MAS. For example, if 4 out of 5 of the events were found to match then this would be an 80% match. An example of pseudocode showing how percentages were calculated is presented in Fig. 4.

```
Algorithm    calculatePercentage(int[] template, int[] data, double
totalPositives)
Create result variable
Create counter variable
For
      Loop through template array
          for
              Loop through data array (sensorIDs)
              If data == template
                  Counter +1
              End if
          End for
End for
Calculate percentage and assign to result
Return result
```

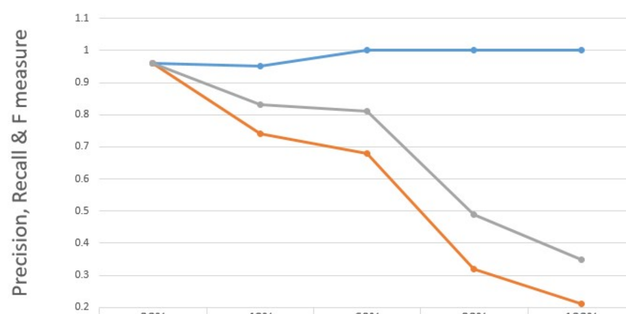
Figure 4: Example of pseudocode showing how percentages are calculated within the MAS.

3.3 Single Agent System

As a benchmark, a single agent system was created to compare with the MAS approach. This system was only able to read events in the order they occurred. The MAS differed from this as agents within it ran in parallel, looking for their own activities independently and working together to output their results. For example, when dressing and toileting were carried out, the single agent system identified the dressing events, until it recognized a toileting event in which case it decided that dressing must no longer be taking place and did not report a result.

4 EXPERIMENTAL RESULTS & DISCUSSION

This Section presents the results from this study, compares two different systems, a single agent system and the MAS, on their ability to identify interleaved activities, and states limitations found. Accuracy was determined through measuring the precision, recall and F-Measure of results. Two experiments were carried out, one as a benchmark which was the single agent system, the second with the MAS. All agents in both the single and MAS implemented the same algorithm within the context of their individual activities. In each experiment, two sets of data were tested, the first being single activities carried out in order and repeated four times, the second being the interleaved dataset made up of nine pairs of activities, also repeated four times. In total, this resulted in 344 sensor events being recorded. For each experiment, the precision, recall and F-Measure were calculated at thresholds set in 20% increments. Each percentage increment represents the likeliness of the activity taking place, for example, if the system predicts that there is a 60% or higher chance that sleeping is taking place, this is marked as having happened. In the first experiment, the single agent system could detect all the activities as they were carried out in a precise order and all fell within the set time windows, results of this are presented in Fig. 5.



	20%	40%	60%	80%	100%
precision	0.96	0.95	1	1	1
recall	0.96	0.74	0.68	0.32	0.21
f	0.96	0.83	0.81	0.49	0.35

Threshold Percentage

Figure 5: Line graph illustrating the thresholds in increments used to get the optimal Precision, Recall and F-Measure for identifying single activities in the single agent system.

When the interleaved dataset was tested with this system it was unable to identify any activities as no single activities were present in the interleaved dataset. Within the second experiment, the MAS identified the single activities, results of which can be seen in Fig. 6. Through ad hoc testing the optimal threshold was found to be 60% when identifying interleaved activities in the MAS; with a precision, recall and F-measure of 0.69, 0.81 and 0.74, respectively. Fig. 7 shows how the breakeven point of the results was at the threshold percentage of 80%, due to the recall and F-measure beginning to drop, as a result illustrating that 60% provided the most accurate results of thresholds tested.

As this MAS could identify the interleaved activities this was viewed as a success. A benefit of using a MAS was that agents all ran in parallel meaning if any changes or new implementations needed to take place it would have been easy to add in new agents or modify the specific agents as desired. The

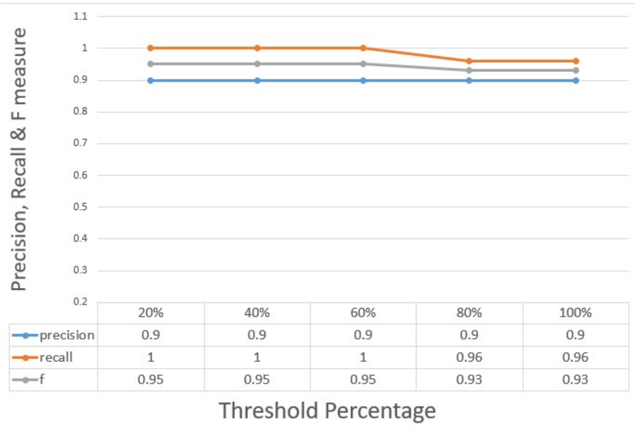


Figure 6: Line graph illustrating the thresholds in increments used to get the optimal Precision, Recall and F-Measure for identifying single activities in the MAS.

single agent system failed at identifying the interleaved activities as it read each event sequentially. With more agents, the MAS had the increased ability to assign each agent with their own roles, and thus provided them with the additional functionality to look for their own activities taking place, regardless of the order.

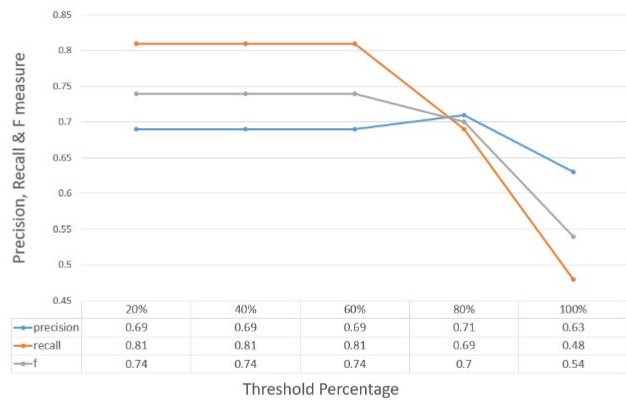


Figure 7: Line graph illustrating the thresholds in increments used to get the optimal Precision, Recall and F-Measure for identifying interleaved activities in the MAS.

By reading each activity in order the system would have been assuming that an activity had ended as soon as it detected an event from another activity, using the MAS removed this limitation.

5 CONCLUSION & FUTURE WORK

A Multi Agent approach has been used to develop an activity recognition method to identify interleaved activities in a smart environment. Time windows were used to allow agents to read events and decide upon a likelihood that their activity was being performed based on percentages estimated. This approach was tested and compared against a benchmark single agent system which could not identify if more than one activity was taking place at the same time. Thus, supporting that a MAS approach is successful at fulfilling the task of interleaved activity identification due to its ability to run the agents in parallel, all looking for their own activities. When results were compared to that of the study by Helaoui *et al.* [5] it was found that the proposed methods' results were comparable to their study with a precision, recall and F-measure of 0.69, 0.81 & 0.74 as to their results of 0.71, 0.99 & 0.82. Their results were based around the assumptions that if the first sensor event is missed then the activity is not registered as happening. The study in this paper does not make any assumptions and performs almost as accurately. Limitations were however found within the proposed method. Within the MAS, each algorithm displayed a result every time the system was ran, therefore when an interleaved activity was carried out, the system identified most activities in that room as having taken place. To improve upon this a future study will be carried out to assign each ADL with a unique trigger id as before, only ensuring if this trigger is identified, only the percentage for that ADL will be displayed. As an example, when the activities of dressing and sleeping are carried out, results will only display results for these two activities and will not output the percentages of likeliness for all other activities. This would in turn result in a smaller false positive, thus producing more desirable precision, recall and F-measure results. In future, a larger dataset and/or a public dataset collected outside of this study could also be used to further benchmark against other data, this would be completed to gain a wider view into the accuracy and benefit of this method. Furthermore, future studies could also facilitate the identification of more than two activities occurring at once rather than limiting the system to a maximum of two.

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