Revisiting Human Activity Frameworks*

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Abstract. A classical activity theory has for long been established as a de-facto framework on which many human activity models and recognition algorithms are based. We observed several limitations to the classical activity theory, mostly attributed to its inability to discern among seemingly similar concepts and artifacts. We discuss these limitations and introduce a generic activity framework that addresses these issues. We provide a comparative analysis to quantify the effect of our proposed framework on the accuracy of activity recognition using a benchmark of activities of daily living. We report significant improvement of the recognition accuracy.

Keywords: Human Activity, Human Activity Model, Human Activity Recognition, Activity Theory, Generic Activity Framework

1 Introduction

Activity recognition (AR) is an important sensing science in pervasive computing because it can be applied to many ubiquitous applications including health care and elder care [1][2][3][4]. A significant body of research has been established in the past decade in areas such as activity recognition algorithms, activity recognition systems, and activity datasets [5][6][15][16][17][18][19]. Creating activity frameworks is a prerequisite for enabling AR algorithms and systems, to explain, if activities are recognized through artifacts that a person uses, an artifact-usage based activity framework must first be constructed so that the AR system can recognize activities based on their relationships with the artifacts. For example, if an activity system detects that a person uses toothpaste and a tooth brush, then the system interprets that the person is doing the activity "*brushing teeth*". Since an activity framework forms the basis for effective activity recognition, it is important to ensure that such frameworks can represent many real-world human activities.

So far, several sensor based activity recognition projects have been based on and inspired by a well known activity theory [13][14][15]. However, we encountered some limitations of this theory while attempting to represent specific real world

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activities. To illustrate, for the *eating* activity, there are many similar activities such as *having lunch, chewing food,* or *having a meal*. Even though they are similar, they are not the same. Some AR systems may classify all these activities separately while other AR systems may regard them as equal. We found that the traditional activity theory is not sufficient to support the recognition of similar activities. Another limitation is that the activity theory does not distinguish between the tool used for an activity and a target object of an activity. This can cause incorrect recognition of activity. For example, it is difficult to distinguish *eating* and *washing dishes* because both activities involve similar artifacts such as dishes, forks or spoons. Some research projects tried to overcome this limitation by combining motion and artifact [16][17]. Motion is useful to determine the relationship between an artifact and an activity. For instance, the scooping action of a spoon can be used to determine *eating* activity more definitively as compared to a spoon whose action is not specified. However, this approach is not sufficient either because it does not distinguish tool and object. For example, without connection between scooping spoon and food, it is still confusing whether the activity is *eating*. Besides tool, motion, and object, there are several other elements to consider in recognizing activities (e.g., subject, action order, time, location, or context). These elements should be included in any activity framework. Therefore, we propose a generic activity framework, which improves on the aforementioned problems.

The rest of this paper is organized as follows. In section 2, we discuss the traditional activity theory and its limitations. The proposed approach is explained in section 3. A comparison and analysis are presented in section 4. Finally, section 5 concludes the paper.

2 Background

In this section, we describe the well known activity theory and analyze its limitations in recognizing human activities.

2.1 Activity Theory

Activity theory was founded by L. S. Vygotsky at The Cultural-Historical School of Psychology during 1920s and 1930s. It was developed by A. N. Leontjev and A. R. Lurija and coined the term "activity" [7][8]. Activity theory was first applied to human-computer interaction (HCI) in the early 1980s [7]. Today, it is applied implicitly or explicitly in much of the vast body of activity recognition research. The definition of activity theory is described in [7] as: "Activity Theory is a philosophical and cross-disciplinary framework for studying different forms of human practices as development processes, both individual and social levels interlinked at the same time."

The activity theory utilizes four components (subject, tool, objective, and outcome). In [7][8], the authors used *object* originally instead of *objective*. But, since *object* has multiple meanings (something material or goal), we chose *objective* to avoid conflict with target *object* of an activity. A subject is a participant of an activity. An objective is a plan or common idea which can be shared for manipulation and transformation by the participants of the activity. Tool is an artifact a subject uses to fulfill an objective. Outcome is another artifact or activity. Transforming the objective into an outcome motivates the existence of an activity. For example, having ones own house is an objective and the purchased house is the outcome. Transforming the *object* into the *outcome* requires various tools. These relationships between components are presented with lines in Fig. 1. Bold line indicates direct relationship between components while a gray line represents a mediated relationship. In Fig. 1, subject and tool have a direct relationship because a subject uses a tool in person. The relationship between an objective and subject is mediated by a tool because subjects achieve their objective using tools.

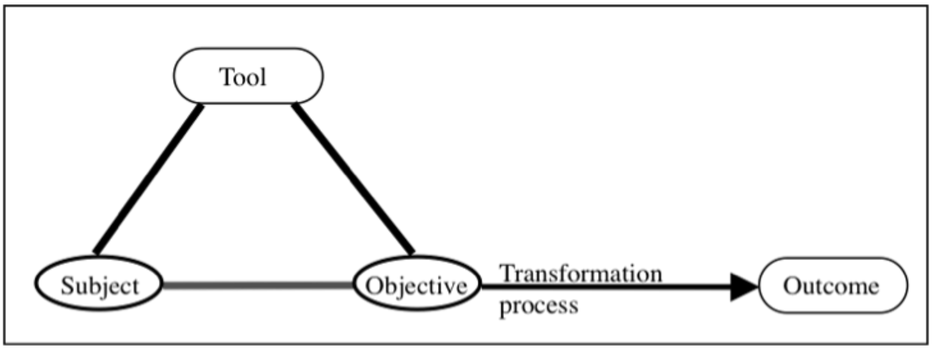

Fig. 1 Basic structure of activity theory [**7**].

Activity theory has a hierarchical structure. Because objectives of an activity are transformed into outcomes through several steps, activities are regarded as long-term formations. As shown in Table 1, activity is composed of actions and an action consists of operations [7].

Table 1. Hierarchical level of an activity and an example of activity, action, and operation.

Levels	Related Purpose	Example of purpose
Activity	Motive	Completing a software project
Action	Goal	Programming a module
Operation	Conditions	Using an operating system

Activities are composed of cooperative actions or chains of actions. These actions are all related to the motive of an activity. Each action has a goal and consists of operations to reach the goal. Operation is a unit component and it depends on the faced condition where the operation performs. The detailed description of each level is as follows:

Activities. Activities are realized as chains and networks of individual and cooperative actions. These actions are related to each other by the same objective and motive.

Actions. Actions participate in an activity. An action has a goal. However, without a frame of reference created by the corresponding activity, the actions cannot really be understood.

Operations. Actions consist of chains of operations, which are well-defined routines used subconsciously as answers to conditions faced during the performing of the action. In the above example in Table 1, operating system and computer will be conditions.

2.2 Limitations of Models based on Activity Theory

Even though activity theory is well-known and is often used in activity recognition research, it is not sufficient for real world activity recognition. Activity theory is created and developed by psychologists who wanted to understand human activity. On the other hand, modern activity recognition techniques are being employed to understand human activities automatically by intelligent systems. Since AR systems are less flexible than humans, it is necessary to improve the theory in order to use it in machine systems. The following are the limitations of activity theory for intelligent systems.

Firstly, the border between hierarchical layers is blurred. As described in [7], an activity can lose its motive and become an action, and an action can become an operation when the goal changes [7]. For less flexible computer based system, this unclear border makes automated activity recognition difficult because the change of motive of activity and goal of action are not easy to detect. Therefore, it is necessary to find clearer ways to determine each layer.

Secondly, *tool* and *object* need to be distinguished. The same item may be used as tool or object. It is important to distinguish such items in order to recognize and interpret human activities accurately. For example, there is cough syrup in a bottle. The bottle is a tool for containing the medicine. Therefore, if a subject operates the bottle, it may be for taking cough syrup. But, it is not true if the bottle is a target object of some activities such as *moving a bottle*. Combining motion and tool is helpful to recognize activities in this case. However, it is not sufficient. For instance, for the same tool and motion, it may be possible to have different activities for different target objects. For example, the motion *pouring* is combined with the medicine bottle. However, pouring the medicine bottle is not enough to determine the *taking medicine* activity because the target object of the activity is not clear. If a cup is a target object, the subject might take the medicine. But if the target object of the activity is sink or no object, it might mean the medicine was thrown away because of a sour taste. Activity framework should support representation of these cases.

Last but not least, many human activities are too complicated to be represented by a single activity name. For example, eating has several similar activities such as *having food or meal, having breakfast, lunch or dinner, or having snack*. Since the top layer is *activity* in activity theory, the activity layer includes everything. This makes AR system design cumbersome and difficult to conceptualize. This difference in granularity is not conducive to sharing or modularizing AR systems.

To solve the aforementioned limitations, we propose a generic activity framework in the next section.

3 Proposed Generic Activity Framework

In this section, we explain the proposed generic activity framework.

3.1 Generic Activity Framework Composition Design

The generic activity framework has a hierarchical structure. The hierarchical structure has several advantages. Firstly, it makes the activity recognition system more tolerant to sensor environment change. For instance, even if more sensors are inserted in the AR system, the upper layers in the hierarchy will not be seriously influenced. In other words, the additional sensors will cause changes to the motion, tool, and operation layers. But, the operation layer will not be affected directly from the sensor change. Secondly, activity recognition using hierarchical structure is analogous to the way people recognize, so it is easier to design more natural and intuitive AR algorithm. To illustrate, when people observe an event, they accumulate it, and compose the unit observations until they find what it is.

Each layer of the structure consists of activity components. In total, there are eight components in the generic activity framework. We chose the eight components according to 5W1H framework and we also found the eight is the most influential. 5W1H is well known method to represent knowledge for many applications including web or newspaper because of its capacity to describe knowledge. It was created by Rudyard Kipling, the Nobel Laureate of Literature in 1906 [9]. 5W1H framework deals with six keywords (‘who', 'what', 'where', 'when', 'why' and 'how'). We split ‘how’ into two components (tool and order) for more detailed information. We also add *context* because it is important to understand activities. It is not necessary that every activity contains all eight components as long as the activity is recognized clearly. For example, the walking activity does not require any object. Also some components such as motive are difficult to know. The detailed description of the eight components is given below:

Subject. A subject is an actor of the activity. Subject has an important role as an activity classifier especially when there are multiple people. In other words, a different subject means a different activity.

Time. This is the time when an activity is performed. It consists of start time and end time. We can also calculate the duration of an activity with time. Time and duration are useful to recognize more detailed activities. For example, if an *eating* activity is performed around noon; it is *having lunch* instead of just *eating*. Also depending on the duration of the *eating*, we can classify the *eating* to *having a meal* or *having a snack*.

Location. Location is the place where an activity is performed. If an activity is performed in several places, location will have multiple values. Location is also a crucial classifier of activities. In other words, since location has a particular function such as *sleeping* or *cooking*, it gives important information for recognizing activities.
Motive. Motive is the reason why a subject performs a specific activity. Motive is the objective in activity theory as shown in Fig. 1. To determine motive, some artificial intelligent reasoning technique may be required.

Tool. Tool is an artifact that a subject uses to perform an activity. Tool provides essential information to classify activities. For example, a spoon or a fork is a tool for eating or cooking. Therefore, an AR system can expect those activities when it detects that a user uses a spoon or fork.

Object (Target). An *object* can also be any artifact like *tool*. However, *object* is the target of an activity while as a *tool* is used by a subject. Distinction between tool and object is important for accurate activity recognition because some artifacts are both tool and object depending on an activity.

Order. Order is the sequence in which actions of an activity are performed. Usually order does not matter for many activities. But, order is important for some activities. For example, to have food, we should serve food first and cut, pick, scoop food.

Context. Context is information, which is used to determine the situation where an activity is performed. Some contexts such as temperature or humidity are directly sensed by installed sensors. On the other hand, some contexts like motive of activity need some artificial intelligent techniques such as reasoning or pattern recognition to elicit them.

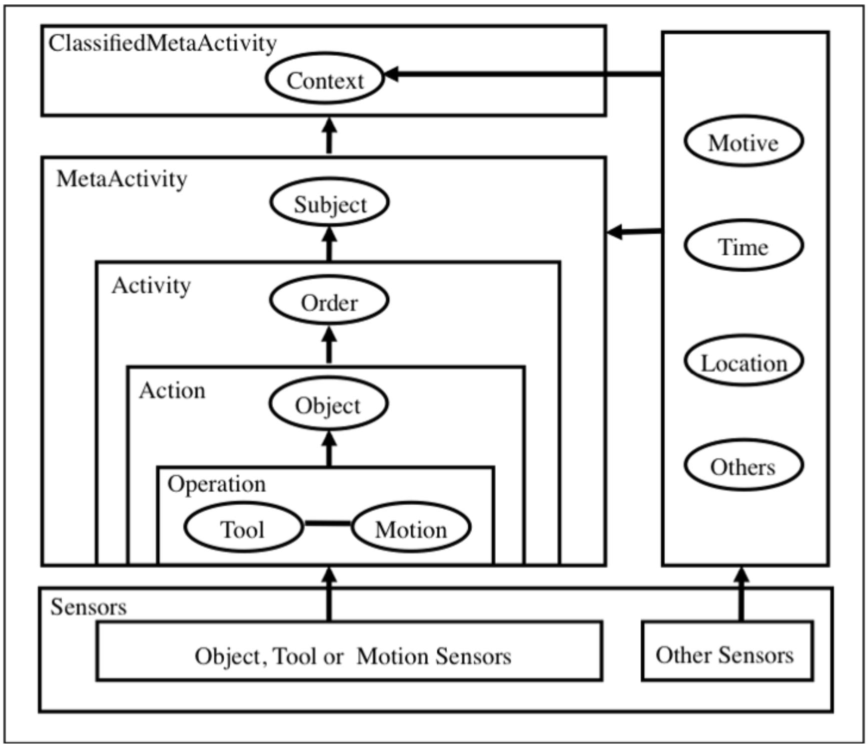

Fig. 2 Composition diagram of generic activity framework. It is composed of several hierarchies and each hierarchical layer contains classifier components.

Fig. 2 shows a composition diagram of the generic activity framework. In Fig. 2, rectangles are layers and ellipses present components. According to the composition of components, the activity framework has a hierarchical structure that is similar to activity theory. Activity theory has three layers—operation, action, and activity. In our generic activity framework, meta activity and classified meta activity layers are added. Also it clearly defines the components of each layer. The detailed description for each layer is given below:

Sensors. Sensors are installed in the pervasive space (e.g. a smart home) to collect event information of the space. Based on the source of sensor data, sensor is classified into four types: motion, tool, object, and context sensor. A motion sensor is about peoples' movements such as *raising an arm* or *turning body*. Nowadays, gyro sensors or accelerometer sensors are used to sense human motion. Tool sensor data is from sensors attached to equipment which is used by people. Object sensor data is from sensors installed on passive objects such as groceries or frozen food packets [1]. RFID readers and tags are representative sensors to recognize tools and objects. Sound sensors, vibration sensors or pressure sensors are also used to recognize activities.

Operation. Operation is a composition of tool and motion. The user operates tools with specific motion. For example, if computer is a tool, some hand or finger motion will be performed for typing a keyboard.

Action. Action is determined by combination of operation and object. For example, if a user types a command to open a file, typing on the keyboard is an operation and the file is an object and this combination is *open file* action. Object is important to recognize actions. However, some actions do not have an object. For instance, in *sleeping* activity, the action is *lying down* on the bed. A bed is a tool for sleeping, but no object is involved in sleeping. Moreover, some activities like walking do not require tools. Therefore, although tool and object are important, they are not mandatory components.

Activity. Activity is a collection of actions. Activity may involve multiple actions that occur in a certain order. For example, for laundry activity, we should put clothes into the washer first. Otherwise, it is difficult to say it is laundry activity even though the washer runs. But for many activities, the order of actions varies a lot according to the user. For example, there are several actions such as *scooping, picking,* and *cutting food* for *eating*. The order of these actions is totally up to a person. Therefore, we consider the relationship between activity and action unless the order is critical for recognizing activity.

Meta activity. A meta activity is a collection of activities. When an activity is complicated, it is composed of several simple activities. For example, to prepare a meal, people obtain food material from refrigerator and wash, cut or chop the materials. Sometimes, microwave is used, and people may also wash dishes to serve food. In this example, preparing a meal is a meta activity. Other activities such as *preparing food material, washing, cooking*, and *microwaving* are simple activities.

Classified meta activity. When meta activity is combined with context information including time or location, meta activity can be more specialized.

Classified meta activity is the specific meta activity which contains more context information. For example, having a meal meta activity is classified into several meta activities such as *having breakfast, lunch,* or *dinner* according to time of the activity performed.

3.2 UML Diagram of generic activity framework

In this section, a Unified Modeling Language (UML) diagram shows activity components and their relationships. Each activity component and layer is an entity in Fig. 3.

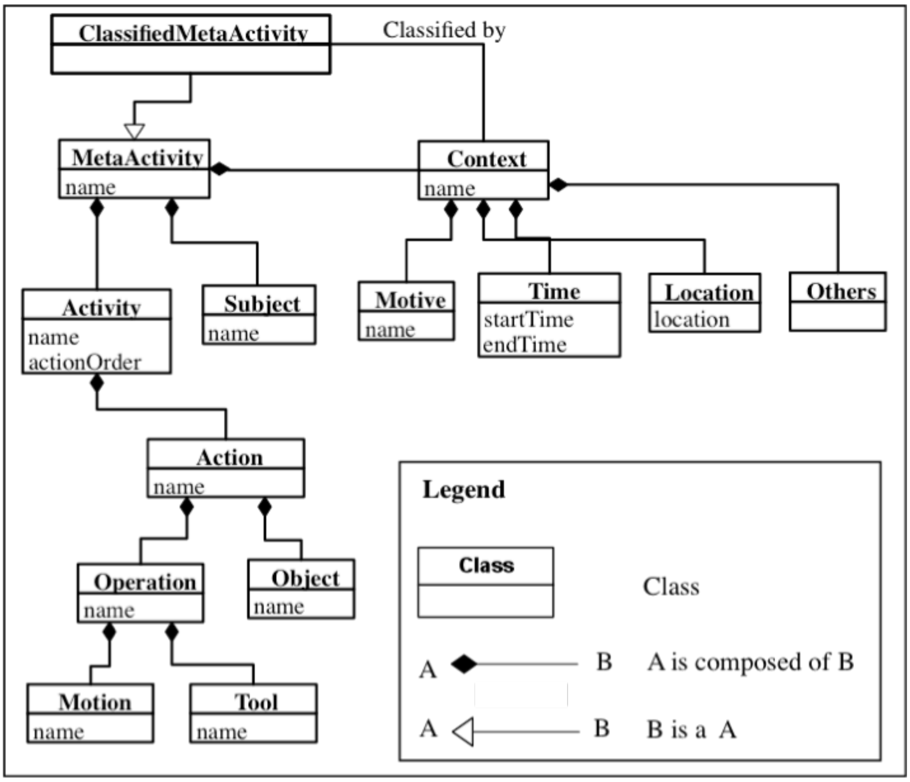

Fig. 3. UML diagram of generic activity framework

These entities are connected to each other with two relationships such as Is-Composed-Of and IS-A. The detailed descriptions of two activity relationships are given below:

Composition (Whole-part) relationship. Composition relationship is a whole-part relationship between activity and component. In Fig 3, terminal entities represent activity components such as subject, tool, motion, object, time, or location. Internal entities are operation, action, activity, and context. Root entity is meta activity.

IS-A (Inheritance or general-special) relationship. Is-A relationship shows the relationship between general entity versus special entity. This is also called inheritance relationship because special entities inherit characteristics of general entity. To illustrate, having a meal is a general meta activity which indicates having food. When having a meal meta activity combines with time, location, etc., the meta activity is specialized. For example, if having a meal is performed at lunch, it is having lunch. If having lunch is performed at a restaurant, it will be eating out. Since having lunch or eating out is having a meal meta activity, it inherits features of the meta activity (e.g. component of the meta activity).

3.3 Example of generic activity framework

In this section, we will show a nested diagram of our generic activity framework including a simple example.

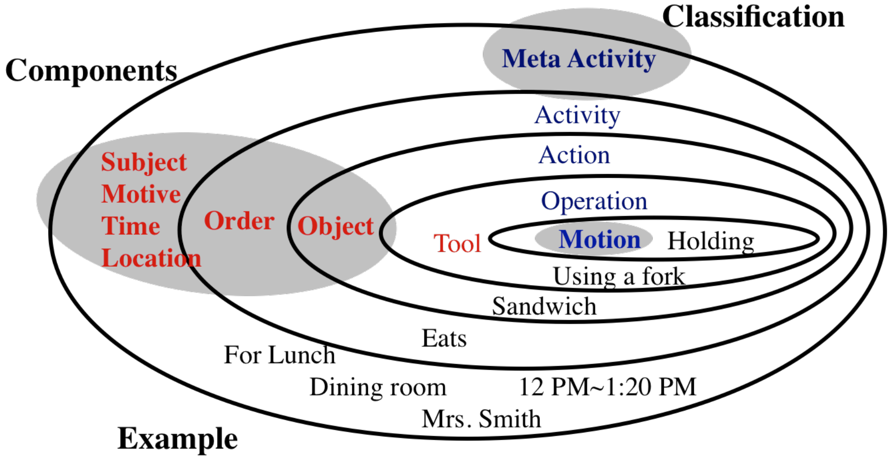

Fig. 4. Nested diagram of our generic activity framework. Shade ellipses indicate new components in the generic activity framework.

The classification shows composition hierarchy in Fig. 4. The composition is performed from the motion layer to the meta activity layer. To illustrate, an action is composed of several operations, and activity is composed of several actions. Components are additional classifiers for each classification layer. For instance, an action is classified based on objects involved and related operations. The components of an activity are actions and the order of those actions. Examples of each component are shown in the diagram.

4 Comparison and Analysis

In this section, our generic activity framework is compared with activity theory. We used an activity scenario for the care of the elderly from [4]. From the scenario, we retrieved meta activities, activities, actions, operations, motions, tools, objects, and related components such as time or location. Table 2 shows the result of retrieved components. In the generic activity framework, there are 11 meta activities, 13 classified meta activities, and 33 activities while as there are 32 activities when we applied activity theory. This result implies that our generic activity framework can recognize more activities than activity theory.

Table 2. Meta activity and activity list of eldercare scenario. It shows meta activities, activities, actions and their corresponding tools and objects.

Meta Activities	Activities (Location)	Actions		
		Operations	**Tool**	**Object (Target)**
Rest	Sleeping (Bedroom)	• Lying down • Getup	• Bed	• Body
	Relaxing (Living room)	• Sitting down • Getup	• Sofa	• Body
Hygiene	Taking a bath (Bathroom)	• Turning on/off water faucet	• Water faucet	• Body
	Brushing teeth (Bathroom)	• Moving brush	• Tooth brush • Toothpaste	• Teeth
	Toileting (Restroom)	• Pushing toilet flush	• Toilet flush	
Grooming	Combing hair (Bathroom)	• Moving comb	• Comb	• Hair
	Getting dressed (Bedroom)	• Open / Close dresser, closet	• Dresser • Closet	• Clothes
Preparing a meal • Breakfast • Lunch • Dinner • Snack	Cooking (Kitchen)	• Cutting, • Chopping • Stirring • Serving	• Knife • Utensils • Plate	• Food
		• Boiling • Baking	• Range or Oven	• Food
	Microwave (Kitchen)	• Starting program	• Microwave • Dish	• Food
	Refrigerator (Kitchen)	• Open/Close	• Refrigerator	• Food
	Freezer (Kitchen)	• Open/Close	• Freezer	• Frozen food
	Washing dishes by hand (Kitchen)	• Scrub	• Sink • Water faucet	• Plates • Utensils • Spoon, Fork • Knife •

Meta Activities	Activities (Location)	Actions		
		Operations	Tool	Object (Target)
(Ingesting) Having a meal • Breakfast • Lunch • Dinner • Snack	Eating (Dining room)	• Cutting • Picking • Scooping	• Plates • Spoon, • Fork • Knife	• Food
		• Serving	• Plates • Dining mat	• Food
	Drinking	• Holding a cup • Drink	• Cup	• Water • Juice, Tea
Medication	Taking medicine (Anywhere)	• Taking medicine • Drink water	• Medicine bottle • Cup	• Medicine
Laundry	Washing clothes (Laundry Room)	• Turning on/off • Choosing an option	• Washer	• Clothes
	Drying clothes (Laundry Room)	• Turning on/off • Choosing an option	• Dryer	• Clothes
	Keep clothes in dresser or closet (Bedroom)	• Open dresser • Close dresser	• Dresser knob	• Clothes
Entertain-ment & Information	Watching TV (Living room)	• Turning on/off • Choosing program	• TV remote control	• TV
	Listening to music (Living room)	• Turning on/off • Choosing program	• Audio player	• CD
	Access Internet (Living room)	• Open browser	• Computer	
	Reading a book (Anywhere)	• Reading a book		• Book
	Reading newspaper (Anywhere)	• Reading newspaper		• Newspaper
Cleaning • Bedroom • Kitchen • Bathroom • Living room • Dining room • Laundry room	Vacuum (Anywhere)	• Turning on/off • Moving arm • Moving hand	• Vacuum cleaner	• Bedroom • Kitchen • Bathroom • Living room • Dining room • Laundry room
	Mopping (Anywhere)	• Moving arm • Moving hand	• Mop	• Mop • Bathroom floor
	Sweeping (Anywhere)	• Moving arm • Moving hand	• Broomstick	• Bedroom • Kitchen • Bathroom • Living room • Dining room • Laundry room

Meta Activities	Activities (Location)	Actions		
		Operations	Tool	Object (Target)
Cleaning (continued from the previous page) • Bedroom • Kitchen • Bathroom • Living room • Dining room • Laundry room	Wiping	• Moving arm • Moving hand		• Dresser • Sofa • Desk • Front door
	Washing dishes (Kitchen)	• Starting program	Dish washer	• Plates • Utensils • Spoon, Fork Knife
	Ordering (Anywhere)	• Moving arm • Moving hand		Most artifacts • Bed • Desk, Chair • Plates • Refrigerator • Toothbrush • Toothpaste
Getting Out	Leaving Home (Entrance)	• Open front door • Close front door		• Front door
	Arriving Home (Entrance)	• Open front door • Close front door		• Front door
Moving	• Walking (Anywhere)	• Stepping		• Body
	• Motion (Anywhere)	• Moving		• Body

In Table 2, we can see that many artifacts are used as tools or object in activities. When an artifact is used for several activities, it is difficult to classify activities accurately using activity theory because it regards artifacts as tools only. For example, in Table 2, for activities *cooking, eating*, *ordering or washing dishes*, a dish is an artifacts and it is a tool for *cooking and eating* and an object for *ordering or washing dishes*. Since activity theory consider dishes as tool, *using dish* information is not sufficient to determine which activity is performed. In contrast, generic activity framework determines activities considering both tool and object. Most artifacts have their own function. Usually, when the artifact is used for the particular function; it is a tool of the corresponding activity. On the other hand, the artifacts are maintained by the user. In the management activities such as *ordering* or *cleaning*, the artifacts are objects.

Table 2 also shows the relationships between meta activities, activities, actions and operation. Some meta activities such as *preparing a meal, having a meal* or *cleaning* are classified into several specialized meta activities according to context such as time, location etc. For example, *preparing meal* may involve *preparing breakfast, lunch*, or *dinner* according to the time at which it is performed. *Cleaning* specifies several activities like *cleaning bedroom* or *cleaning kitchen* depending on the location. Since these meta activities are obviously different from each other, they should be clearly determined as shown in Table 2.

The generic Activity Framework can recognizes more activities than activity theory because it classifies activities from sensor data with more classifiers such as motion, tool, object, order, subject and context. For example, bed is a tool for sleeping. Therefore, sleeping activity is retrieved from an artifact *bed* in activity theory where artifacts are considered as tools only. On the contrary, bed is also a target object for the *ordering bed* activity. Also even though a subject is lying down on a bed, if the activity happens too short time, it may not be sleeping. With considering eight components, generic activity framework can classify more activities. Fig. 5 shows the number of related activities for each artifact. The number of activities is inferred from Table. 2. For example, plate is a tool for *eating* and *cooking* in Table. 2. Also plate is an object of *washing dishes* and *ordering plates* activities. Therefore, the number of activities is two and four respectively.

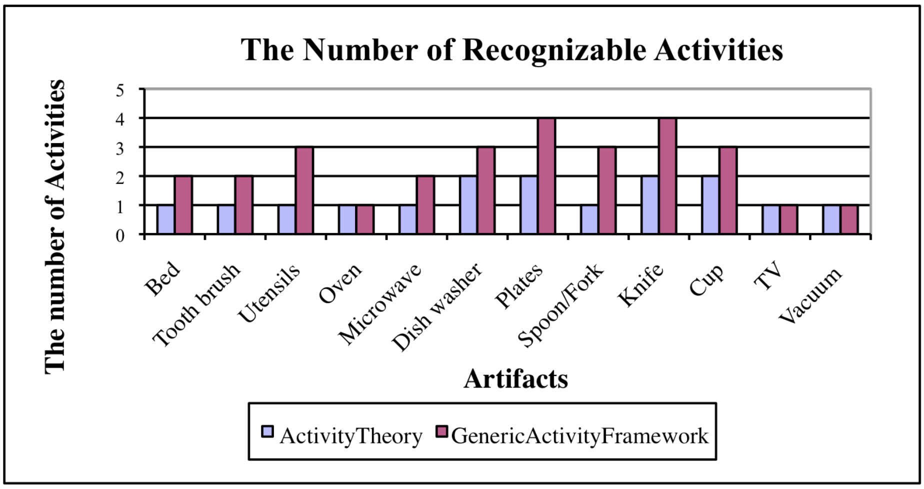

Fig. 5. This graph shows the number of correctly recognizable activities for each artifact.

Since a practical activity recognition systems must account for the uncertainty in real-world situations, we need to manage the uncertainty of the system. Theories such as Bayesian probability can address the problem of uncertainty. Even though Bayesian probability is a well-established technique, it has several difficulties such as requiring large volume of data or enumeration of all possibilities and it is cumbersome for practical applications [11]. To overcome the disadvantages of Bayesian probability, the certainty factor was developed and it outperforms for several areas such as diagnostics and medicine [11]. The value of certainty factor ranges from -1(very uncertain) to +1(very certain) through zero (neutral). Certainty factor is obtained from MB (Measure of belief) and MD (Measure of disbelief) using equation (1)

CF (H, E): certainty factor from hypothesis H influenced by evidence E. CF value is from –1 to 1. CF (H, E) is determined by MB (H, E) – MD (H, E).

$$CF(H,\ E) = MB(H,E) - MD(H,E) \tag{1}$$

MB (H, E): MB is the measure of increased belief in hypothesis H influenced by evidence E. p(H) and 1-p(H) are the probabilities of that hypothesis being true or false respectively. The evidence, E, reduces uncertainty due to the absence of the evidence. In other words, E increases p(H) and decreases (1 - p(H). If the evidence is very weak, then p(H|E) - p(H) is almost zero, and the uncertainty remains about the same. On the other hand, if the evidence, E, is very strong, p(H|E) - p(H) will equal 1 - p(H) and MB will be 1, therefore, no uncertainty is left. The function *max* is used to normalize the MB value positive (between 0 and 1).

$$\mathrm{MB(H,\ E)} = \begin{cases} 1 & \text{if } \mathrm{p(H)} = 1 \\ \dfrac{\max\left(\mathrm{p(H \mid E),\ p(H)}\right) - \mathrm{p(H)}}{1 - \mathrm{p(H)}} & \text{otherwise} \end{cases} \tag{2}$$

MD (H, E): measure of increased disbelief on hypothesis H influenced by evidence E. If the evidence is very weak, then p(H) – p(H|E) is almost p(H), and the uncertainty will be close to 1. On the other hand, if the evidence, E, is strong, p(H) – min(p(H|E), p(H)) will equal 0 and MD will be 0. The purpose of function *min* is to make the MD value positive.

$$\mathrm{MD(H,\ E)} = \begin{cases} 1 & \text{if } \mathrm{p(H)} = 0 \\ \dfrac{\mathrm{p(H)} - \min\left(\mathrm{p(H \mid E),\ p(H)}\right)}{\mathrm{p(H)}} & \text{otherwise} \end{cases} \tag{3}$$

The probabilities of hypothesis, p(H), are assigned according to Table 2. Since we consider all 33 activities to be equally probable, we assigned the same probability (1/33) to each activity. The conditional probability of H given evidence E, p(H|E), is calculated based on Table 2. We counted activities for each evidences. The time was chosen to be the time duration for each activity. To find reasonable duration for each activity, we used a real world data set, which is provided by University of Amsterdam [20]. This data set records activities of daily living performed by a man living in a three-bedroom apartment for 28 days [19]. If we could not find a dataset for an activity, we assigned the duration based on common sense. After finding every conditional probability, we summed them up according to the addition rule of probability. Table 3 shows an example of Sleeping. The probabilities of other activities are calculated with same method.

Table 3. The probabilities of *Sleeping* activity for each evidence.

Evidence (E)	p(Sleep and E)	p(E)	p(Sleep| E)	Sum of p(Sleep| E)
tool	1/33	2/33	0.50	0.50
motion	1/33	2/33	0.50	0.75
object	2/33	5/33	0.40	0.85
order	1/33	0.25	0.12	0.87
subject	1/33	1	0.03	0.87
time	11/33	0.5	0.68	0.96
location	1/33	10/33	0.10	0.96

Using the estimated probabilities, we computed the certainty factor. Fig. 6 shows the certainty factor for each activity. Generic activity framework shows higher certainty than activity theory for every activity in Fig. 6. The main reason is that unlike activity theory which considers artifacts as tools only, generic activity framework accounts for eight components including both tools and objects. For instance, there are many activities related to bed. If the AR system recognizes sleeping when it detects bed, the certainty of the activity is low because there is high probability that some activity other than sleeping is being performed.

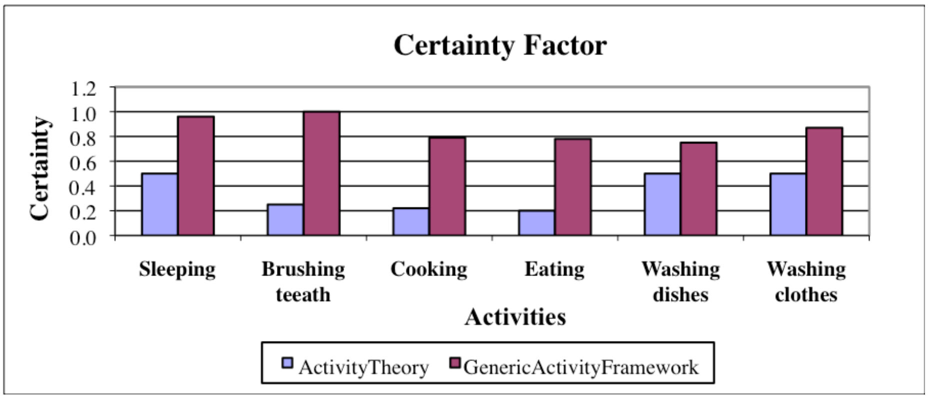

Fig. 6. Certainty factor of activities. For every activity, generic activity framework shows higher certainty factor value.

Conclusion

Despite the many achievements and progress of activity recognition research, accurate recognition remains a very challenging and dynamic problem due to the complexity and diversity of human activities. In order to address some of the challenges; we propose a generic activity framework, which is a refinement of the classical activity theory. The generic activity framework allows researchers to create an activity model for complex and diverse human activities. The generic activity framework defines eight components of human activity and based on the components it creates a hierarchical activity structure.

A major advantage of the proposed approach is that it can represent real world activities better by using the eight components and by distinguishing tools from objects. This advantage implies reduced false recognition of activities due to misinterpretation of object use. Another important advantage is that it can classify activities according to context. Therefore, better representation of human activity is possible.

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