# Measuring Functional Independence of an Aged Person with a Combination of Machine Learning and Logical Reasoning

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### Abstract

Various approaches to human activity recognition have been proposed to achieve better management of human health and wellness. However, there are few approaches that measure the levels of activity in an accountable way. In this paper, we propose a novel approach to measure the functional independence of an aged person with a combination of machine learning and ontology-based logical reasoning. As to combining the two different approaches, we utilize semantic contexts as the interlayer and dummy contexts as a way of handling the difficulty in reasoning with incomplete data. The Functional Independence Measure (FIM) is used to build an ontology to evaluate an aged person's functional independence. Evaluation experiments using data collected in the laboratory environment of the authors' are conducted, and the results of which show the effectiveness of the proposed approach.

## Introduction

As the world's population is aging rapidly, the importance of maintaining elderly people's health and wellness is rising. Ambient Assisted Living (AAL) has been gathering a great deal of interest under such circumstances. AAL is a concept to support elderly people to live independently for as long as possible and improve their quality of life with ambient intelligence techniques including AI and IoT. In the AAL community, human activity recognition is one of the most attention-getting topics (Monekosso, Florez-Revuelta, and Remagnino 2015) and is necessary for making intelligent systems to be proactive and adaptive to each user.

Numerous previous studies have proposed various approaches to human activity recognition. However, there is insufficient research conducted on measuring activity levels in an accountable way, even though it is essential to conduct long-term observation of changes in Activities of Daily Living (ADL) for assisting elderly people to stay active longer. With regard to the activity recognition approaches, there are two mainstreams, data-driven approaches and knowledge-driven approaches (Chen et al. 2012).

In this paper, we propose a novel approach to measure the functional independence of an aged person with a combination of machine learning and ontology-based logical reasoning. The proposed approach possesses an explainability derived from ontology-based logical reasoning while keeping data-driven approaches' flexibility and robustness to individual differences of activities. When combining the two different approaches, we use semantic contexts as the interlayer between them. The machine learning layer applies machine learning techniques to data collected from various sensors such as object sensors (RFID, contact sensor), wearable sensors (smartwatch, RFID-attached cloth), and environment sensors (temperature sensor, light sensor). It extracts various context information such as inhabitants' actions, postures, and relatively low-level activities, and spatial relations between human and objects. The recognized context information is then organized as semantic contexts to derive higher contextual activities and their activity levels by ontology-based logical reasoning. In addition, we propose to utilize dummy contexts as a way to handle the difficulty in reasoning with incomplete data. It makes the system calculate a confidence value for each possible class even when context information obtained at machine learning layer is incomplete.

We use the Functional Independence Measure (FIM) to design an ontology for scoring aged person's functional independence level. The ontology is written in OWL/RDF format following the W3C standards. The FIM is widely used in medical and nursing care fields and now the Japanese government uses it to determine the amount of nursing care insurance. Thus, development of automatic FIM scoring method is highly desired. The FIM consists of 18 items: 13 items of motor and 5 items of cognitive. Each of the 18 items has a maximum score of 7 which indicates a patient's independence level with 7 being the highest (independent) and 1 the lowest (most dependent). The score decreases as the level of assistance the patient requires increases. The list of the 18 items is shown in Table 1. A characteristic of the FIM is that the score should be based on what a patient actually does and not on what a patient should or might be able to do. Hence, the FIM matches sensor-based activity recognition.

The rest of this paper is organized as follows. Section 2 introduces the related works. Section 3 describes the proposed approach's architecture, the semantic contexts, the ADL/FIM ontology, and the usage of dummy properties in detail. Section 4 presents results and analysis of the experiments of this study. Section 5 concludes the paper with future work.

Table 1: List of the FIM items

| | | | |
|---|---|---|---|
| Motor | Self-Care | Eating | / 7 |
| | | Grooming | / 7 |
| | | Bathing | / 7 |
| | | Dressing Upper Body | / 7 |
| | | Dressing Lower Body | / 7 |
| | | Toileting | / 7 |
| | | Subtotal Score | /42 |
| | Sphincter Control | Bladder | / 7 |
| | | Bowel | / 7 |
| | | Subtotal Score | /14 |
| | Transfers | Bed, Chair, Wheelchair | / 7 |
| | | Toilet | / 7 |
| | | Tub, Shower | / 7 |
| | | Subtotal Score | /21 |
| | Locomotion | Walk, Wheelchair | / 7 |
| | | Stairs | / 7 |
| | | Subtotal Score | /14 |
| | Motor Subtotal Score | | /91 |
| Cognitive | Communication | Comprehension | / 7 |
| | | Expression | / 7 |
| | | Subtotal Score | /14 |
| | Social Cognition | Social Interaction | / 7 |
| | | Problem Solving | / 7 |
| | | Memory | / 7 |
| | | Subtotal Score | /21 |
| | Cognitive Subtotal Score | | /35 |
| Total FIM Score | | | /126 |

# Related Works

In this section, we review the pros and cons of both machine learning-based activity recognition approaches and ontology-based activity recognition approaches.

## Machine Learning-based ADL Recognition

One of the most important advantages of machine learning-based approaches is that they can handle noises, uncertainties, and incompletenesses that sensor data potentially possesses. Their major drawback is that a large number of sensor data is required to create activity models, which results in its cold-start problem and model applicability and reusability. Despite that, in recent years, the advancement of deep learning makes it possible to perform automatic and high-level feature extraction (Wang et al. 2017) and achieves higher performances than conventional techniques. However, while deep learning's remarkable performance is gathering great interests, its insufficient explainability is now considered an urgent issue (Gilpin et al. 2018). Also, many of the activities recognized using machine learning techniques are relatively less contextual, have distinct, and often periodic, motion patterns such as standing, walking, brushing teeth, and ascending/descending stairs.

## Ontology-based ADL Recognition

In real-world settings, intelligent systems are required to be able to recognize considerably complex activities such as eating, dressing, and social interactions. In those situations, ontology-based approaches have been gaining increasing interest to recognize such complicated activities in an explainable way by using its comprehensive reasoning mechanism. Ontologies have been actively used in object-based and location-based activity recognition communities. In object-based activity recognition, activity models are constructed using detected human-object interactions and/or objects in the space detected in a combination with object sensors. Yamada et al. proposed to detect semantics of location by exploiting WordNet to handle unlearned things and their multiple name representation (Yamada et al. 2007). There are more features that ontology-based activity recognition approaches provide: machine-processable rich domain knowledge, multi-level reasoning, flexible and easily customizable nature, and integration and interoperability between contextual information and ADL recognition (Chen and Khalil 2011). However, ontology-based reasoning has difficulties in handling uncertainty and incomplete data. There are several approaches tackling the weaknesses of the ontology-based reasoning with uncertainty. For instance, Noor et al. integrated ontological reasoning based on Description Logic with Dempster-Shafer theory to handle uncertainty derived from imperfect observations (Noor, Salcic, and Wang 2016).

# Combination of Machine Learning and Ontology-based Reasoning

In this paper, we propose a novel approach to measure the functional independence of an aged person cum patient with a combination of a machine learning-based approach and ontology-based logical reasoning. By adding ontology-based reasoning function on top of machine learning-based techniques, an ADL recognition system becomes more explanatory and more context-aware while keeping data-driven approaches' flexibility and robustness to noises and uncertainties in sensor data. Figure 1 shows the overview of the proposed approach from sensor data collection and semantic context extraction to ADL recognition and FIM scoring. Collected sensor data is to be processed in the data-driven phase to extract semantic contexts, then possible activity classes and FIM scores are inferred by ontology-based logical reasoning using the obtained semantic contexts.

## Semantic Context Extraction

The lower part of the middle section of Figure 1 shows the process of semantic context extraction from low-level sensor data using data-driven approaches. In this study, semantic contexts include action, posture, activity, interacting object, surrounding object, location, and time. In order to extract the semantic contexts, various types of sensors can be utilized. The left section of Figure 1 shows the list of sensors which can be used. Wearable sensors are often used to detect a person's actions, postures, and simple activities (Morales and Roggen 2016; Jin et al. 2018). Object sensors such as RFID-tag and contact sensor can capture where the objects are, the objects' status of usage, and spatial relation between the objects (Bouchard, Bouchard, and Bouzouane 2011). Wearable sensors can also be considered as one kind of object sensors which are attached to humans. Such information like what objects are in the target place, what the interacting objects

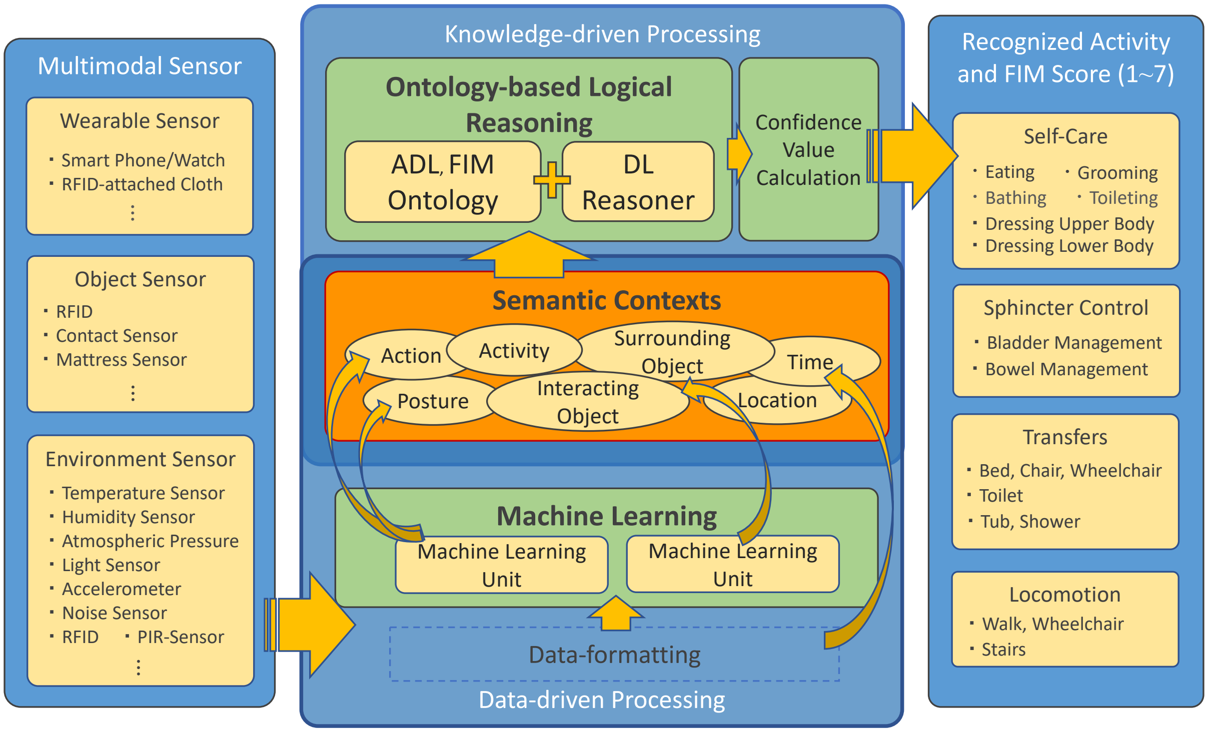


Figure 1: Overview of the proposed approach

are, and if a staff or a helper is around the patient can be obtained by using object sensors. Environment sensors such as temperature sensor and humidity sensor are used to monitor the conditions of the room.

Interacting object contexts especially have an important role in the proposed approach. We take advantage of the semantic information to express the level of assistance that a helper provides for a patient. The Egenhofer's topological spatial framework (Egenhofer and Franzosa 1991) is referenced to express a spatial relation between objects. Figure 2 shows the visual representation of the spatial relations between a patient and a helper and their rough correspondence with different assistance levels. It can be considered that the closer the distance between the helper and the patient, the higher the level of assistance.

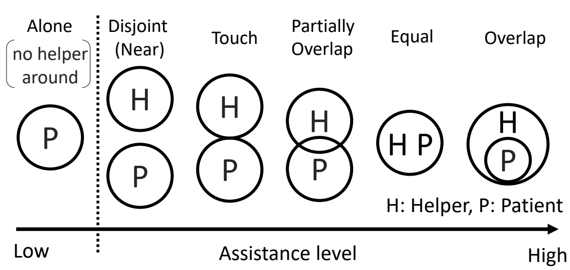


Figure 2: Visual representation of patient-helper spatial relations and their correspondence with assistance levels

Note that applying machine learning is not always necessary when extracting semantic contexts. For example, context information of the objects in a room can be extracted by applying a simple filter program to the read RFID tags data. It is also worth noting that data formatting is a necessary process before applying machine learning techniques since a large amount of data collected from various kinds of sensors comes at different timing in different formats. Noises and variations of sensor data resulted from individual differences are handled in this phase. Subsequently, recognized semantic contexts are sent to the next logical reasoning phase to be processed.

## ADL Recognition and FIM Calculation

The top part of the middle section of Figure 1 shows the process from ontology-based logical reasoning and confidence value calculation to ADL recognition and FIM scoring. An OWL DL reasoner such as the pellet (Sirin et al. 2007) infers pairs of a possible activity class and a FIM score based on the pre-defined ADL/FIM ontology and the semantic contexts obtained from the previous phase. Then the most likely pair of activity class and score is chosen after the confidence value calculation. This process is required because dummy contexts are utilized to make the reasoner output possible classes even if the previously obtained semantic contexts are incomplete. In this phase, modifying the semantic contexts come from the data-driven layer may be needed if the type or the semantic level of the obtained context is not the required one. In the case that the type fails to be the required one, the type will be converted whenever possible. For example, when a posture context is needed but only the action context of *isSittingOn(Context, Chair)* arrives from the data-driven layer, it will be converted to *hasPosture(Context, Sitting)* using SWRL or in an external program through OWL API. Similarly, when the semantic level of a context is different from what is required, it will be adjusted as specified in SWRL or external programs. For example, the spatial relationship between a helper and a patient will be converted to assistance level since the level from the previous phase.

**ADL/FIM Ontology** Web Ontology Language (OWL) and Semantic Web Rule Language (SWRL) are used to construct ADL/FIM ontologies. An OWL ontology consists of individuals, properties, and classes. Individuals represent objects in the domain of interest. In this case, an individual is, e.g. a person, an artifact, or an activity. Properties are binary relations on two individuals. For example, the property *hasCurrentActivity* may link the individual *Person1* and the individual *Person1CurrentActivity*.

In the ADL/FIM ontology, every person has one's own activity individual, and extracted semantic contexts are linked to the activity individual with *hasContext* properties. An example is shown in Figure 3. Also, a sequence of contexts can be expressed using *hasPrecedentContext* or *hasSubsequentContext* property as shown in Figure 4. This example illustrates transitions from a living room to a restroom and then to a private room. Since *hasPrecedentContext* is transitive property, the contexts at both ends are implicitly linked with *hasPrecedentContext*.

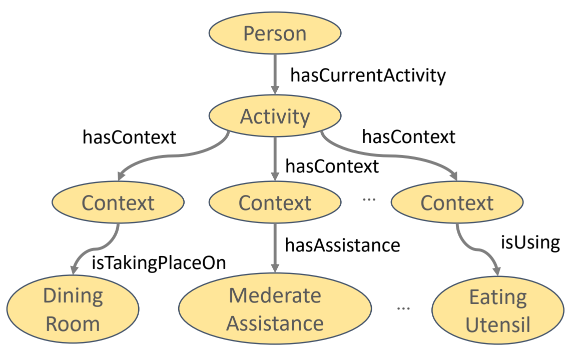


Figure 3: Example relation representation of Person, Activity, and Context class in the ADL/FIM ontology

The FIM part of the ontology is constructed with reference to the IRF-PAI Training Manual[1]. Figure 5 shows the actual definition of Eating-6 in the ADL/FIM ontology.

**Dealing with Incomplete Semantic Contexts** In sensor-based ADL recognition, as mentioned in (Tiberghien et al. 2012), missing or falling sensor readings resulted from running out of battery, packet loss, and wifi disconnection are common but severe issues. However, an OWL DL reasoner does not provide any results when the required semantic contexts are incomplete. It is obvious that such an approach

[1]https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/InpatientRehabFacPPS/Downloads/IRFPAI-manual-2012.pdf

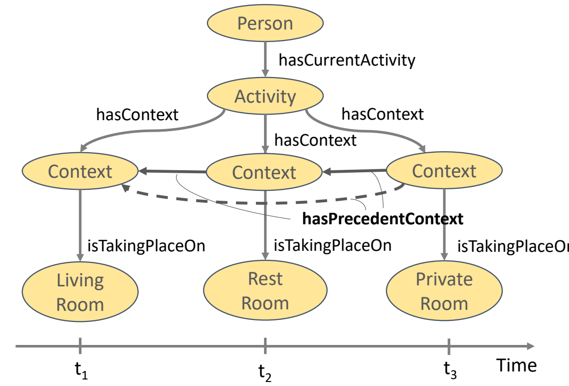


Figure 4: Example representation of time-ordered contexts

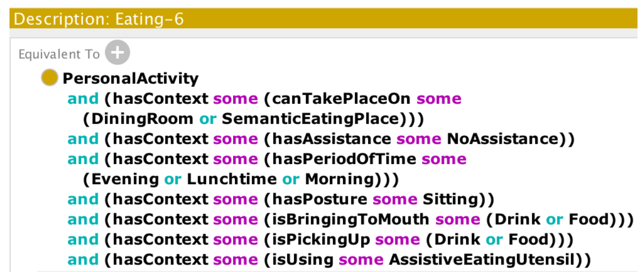


Figure 5: The definition of the Eating-6 class

lacks in efficiency and effectiveness especially in real-life settings where the environment is more unsatisfactory and where some levels of results from even incomplete data are in greater needs. Hence, we introduce dummy contexts to make a reasoner output candidate classes. Using this design, we hope that the most likely results can be obtained by calculating a confidence value for each class.

A dummy context can be expressed by adding an *isDummy* property to a context. By linking dummy contexts with the activity of a person as its initial state, a reasoner can output candidate classes even if some semantic contexts cannot be reached. In the simplest case, a confidence value can be obtained by calculating the proportion of non-dummy contexts among the contexts required to be the activity class. Figure 6 shows that an individual's class in the Activity class would be inferred to be Eating-6 due to dummy contexts. This inference is made based on the assumption that a smartwatch's battery has run out and the data cannot be collected while the other contexts have reached as expected. In this case, confidence value would be $5/7(=0.71)$ since its 5 contexts out of 7 are valid contexts.

# Evaluation Experiments

## Implementation and Data Preparation

We implemented an ADL recognition and FIM scoring system which the proposed methods were applied, and conducted experiments. An ADL/FIM ontology was created using the Protégé 5.2, which is a widely used ontology editor. Figure 7 shows an excerpt of the ontology. It shows a part

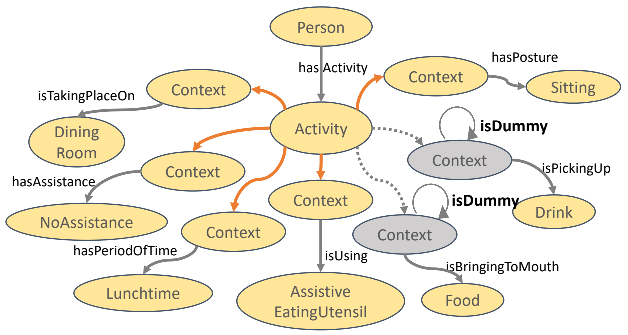


Figure 6: Activity(Eating-6) with dummy contexts

of Classes, Object properties, and Individuals from left to right. The system was implemented in Java with the OWL API and the JFact reasoner.

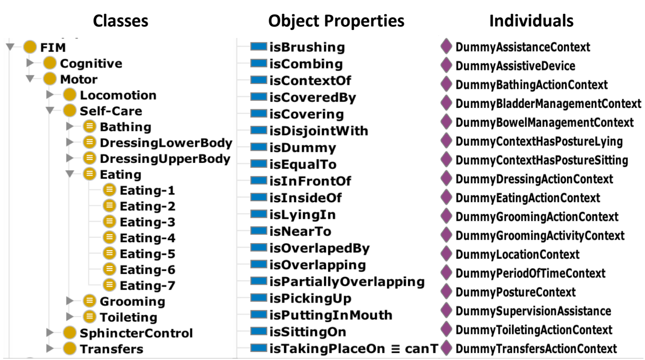


Figure 7: FIM ontology (excerpt)

We also created a dataset in our laboratory (Numao Lab) environment. As shown in Figure 8, a subject wears smartwatches and RFID-attached shirt, pants, and slippers. Furthermore, RFID tags are attached to things and environments such as the floor, tables, eating utensils and grooming utensils. We asked three subjects to act in accordance with the prepared scenarios. FIM items of Eating, Grooming, Transfer-BedChair were chosen for the experimental scenarios. We recorded their performances with a 360-degree camera and later labeled the videos' segments manually using the labels listed in Table 2. The scenarios used are as follows:

- **Eating-7**: The subject eats and drinks all by himself in a safe and timely manner.
- **Eating-4**: The subject sometimes needs assistance when scooping small pieces of the food.
- **Eating-2**: The helper gives hand-over-hand assistance to scoop the food and bring the spoon to the subject's mouth so the subject can chew and swallow the food.
- **Grooming-7**: The subject does all grooming tasks by himself in a safe and timely manner.
- **Grooming-4**: The subject is independent with three of the four tasks (washing hands, combing, washing face) after setup assistance by a helper.
- **Grooming-2**: The subject washes his hands by himself but needs help with the rest of grooming activities.
- **Transfers-BedChair-7**: The subject safely gets up to a standing position from a regular chair then the subject safely transfers from chair to bed independently. Also, the subject safely gets up from the bed and sits on a regular chair independently.
- **Transfers-BedChair-4**: The subject transfers into and out of the bed to an armchair. The subject needs light support in order to keep himself steady.
- **Transfers-BedChair-2**: The subject requires lifting and lowering assistance to stand up and sit down.

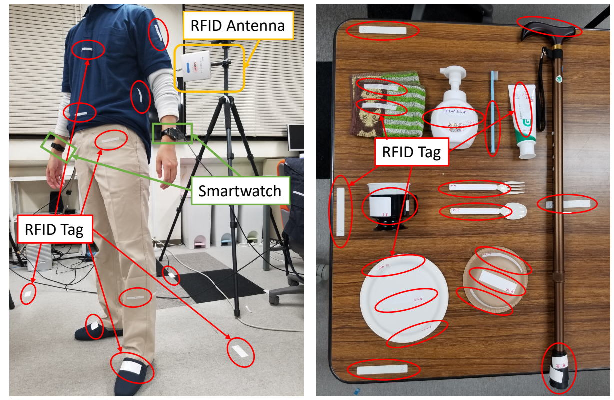


Figure 8: Data collection setup

Although we actually collected sensor data, in these experiments, we only used the labeled data which had been created by labeling the recorded videos as input for ontology-based logical reasoning, assuming that semantic contexts had been obtained by machine learning-based approaches for the sake of simplicity.

In this experiment, assistance levels were calculated based on the proportion of assistance time among the entire mealtime. When there were no helpers around the subject, it would be considered to be independent state. When a helper was close to the subject, it would be considered to be setup or supervision assistance. If a helper was touching the subject, assuming the two had distance shorter than an arm's length, it would be considered to be minimal contact assistance. On the other hand, if a helper was caught by the sensor to be closer to the subject by an arm's length or looking as if the two partially overlapped, it would be treated as more assistance than touching. Confidence values were calculated based on the proportion of non-dummy contexts among the contexts required to be that activity class.

At the end of the experiments, we compared the inferred results in both cases of with and without dummy contexts. Dummy contexts were applied for all possible semantic contexts except the location context. We also tested and compared the cases where the semantic contexts which should be obtained from a smartwatch were missing and checked how the dummy contexts deal with it.

Table 2: Property List and its Range class (Domains are Concept class)

| Eating | | Grooming | | Transfers-BC | |
|---|---|---|---|---|---|
| Property List | Property's Range | Property List | Property's Range | Property List | Property's Range |
| hasPeriodOfTime | Evening | hasAction | BrushingTeeth | hasPosture | Sitting |
| | LunchTime | | Combing | | Slouching |
| | Morning | | WashingHands | | Lying |
| hasPosture | Sitting | | WashingFace | isHolding | Armrest |
| isBringingToMouth | AssistiveEatingUtensil | hasPosture | Sitting | | GrabBar |
| isPickingUp | BasicEatingUtensil | | Slouching | isLyingIn | Bed |
| isSittingOn | Chair | | Standing | isSittingOn | ArmChair |
| | Wheelchair | isInFrontOf | Sink | | Bed |
| isTakingPlaceOn | DiningRoom | isSittingOn | Chair | | Chair |
| isUsing | Spoon | | Wheelchair | | WheelChair |
| | Fork | isTakingPlaceOn | Bathroom | isTakingPlaceOn | Bedroom |
| | Cup | isUsing | Comb | hasNoHelperAround | Helper |
| hasNoHelperAround | Helper | | Cup | isNearTo | |
| isNearTo | | | Hand Towel | isTouching | |
| isTouching | | | Teethbrush | isPartiallyOverlappedBy | Patient |
| isPartiallyOverlappedBy | Patient | hasNoHelperAround | Helper | isOverlappedBy | |
| isOverlappedBy | | isNearTo | | | |
| | | isTouching | | | |
| | | isPartiallyOverlappedBy | Patient | | |
| | | isOverlappedBy | | | |

## Results and Analysis

Table 3 shows the inferred results when dummy contexts are not used. It correctly classifies the six scenarios including Eating-7, Eating-4, Grooming-7, Transfers-BC-7, Transfers-BC-4, and Transfers-BC-2 out of the nine scenarios, but cannot correctly classify the Eating-2 scenario and cannot output any results for the Grooming-4 and Grooming-2 scenarios. The Eating-2 scenario is misclassified because it fails at the assistance level calculation phase. In this experiment, assistance level calculation is simply based on the proportion of assistance time among the entire mealtime. Due to the significantly long time of conversation between the helper and the subject, it has resulted in long mealtime and sparse assistance even though the subject of the Eating-2 has required hand-over-hand assistance in scooping food and bringing the food to the mouth. Regarding the latter two grooming scenarios, subjects have not performed at least one grooming activity. It results in missing contexts and no outputs by the reasoner.

Table 3: Inferred results without dummy concepts

| Scenario (to-be) | Inferred Class |
|---|---|
| Eating-7 | Eating-7 |
| Eating-4 | Eating-4 |
| Eating-2 | Eating-3 |
| Grooming-7 | Grooming-7 |
| Grooming-4 | - |
| Grooming-2 | - |
| Transfers-BC-7 | Transfers-BC-7 |
| Transfers-BC-4 | Transfers-BC-4 |
| Transfers-BC-2 | Transfers-BC-2 |

Tables 4, 5, and 6 show the results inferred with dummy contexts after confidence value calculation. We are able confirm that the correctly classified results in Table 3 are also classified in the correct class when dummy contexts are applied. In addition, the scenarios of Grooming-4 and Grooming-2 which are not classified to any class in Table 3 generate inferred results, though the Grooming-4 scenario was misclassified.

Table 4: Results inferred with dummy contexts of Eating class

| | Scenario-1 (Eating-7) | Scenario-2 (Eating-4) | Scenario-3 (Eating-2) |
|---|---|---|---|
| Eating-7 | **1.0** | 0.857 | 0.857 |
| Eating-6 | 0.857 | 0.857 | 0.857 |
| Eating-5 | 0.857 | 0.857 | 0.857 |
| Eating-4 | 0.857 | **1.0** | 0.857 |
| Eating-3 | 0.857 | 0.857 | 0.857 |
| Eating-2 | 0.857 | 0.857 | **1.0** |
| Eating-1 | 0.857 | 0.857 | 0.857 |

Table 5: Results inferred with dummy contexts of Grooming class

| | Scenario-1 (Grooming-7) | Scenario-2 (Grooming-4) | Scenario-3 (Grooming-2) |
|---|---|---|---|
| Grooming-7 | **1.0** | 0.75 | 0.5 |
| Grooming-6 | 0.875 | 0.625 | 0.375 |
| Grooming-5 | 0.875 | 0.75 | 0.5 |
| Grooming-4 | 0.875 | 0.75 | 0.5 |
| Grooming-3 | 0.875 | **0.875** | 0.5 |
| Grooming-2 | 0.875 | 0.75 | **0.625** |
| Grooming-1 | 0.875 | 0.75 | 0.5 |

Tables 7, 8, and 9 show the results when semantic contexts derived from smartwatch's sensor data are removed. Dummy contexts are also used. These results indicate that dummy contexts function effectively even if some of the contexts are missing.

Table 6: Results inferred with dummy contexts of Transfers-BedChair class

| | Scenario-1 (Transfers-BC-7) | Scenario-2 (Transfers-BC-4) | Scenario-3 (Transfers-BC-2) |
|---|---|---|---|
| Transfers-BC-7 | **1.0** | 0.833 | 0.833 |
| Transfers-BC-6 | 0.714 | 0.714 | 0.714 |
| Transfers-BC-5 | 0.833 | 0.833 | 0.833 |
| Transfers-BC-4 | 0.833 | **1.0** | 0.833 |
| Transfers-BC-3 | 0.833 | 0.833 | 0.833 |
| Transfers-BC-2 | 0.833 | 0.833 | **1.0** |
| Transfers-BC-1 | 0.833 | 0.833 | 0.833 |

Table 7: Inferred result for Eating class without contexts from smartwatch

| | Scenario-1 (Eating-7) | Scenario-2 (Eating-4) | Scenario-3 (Eating-2) |
|---|---|---|---|
| Eating-7 | **0.5** | 0.429 | 0.429 |
| Eating-6 | 0.375 | 0.286 | 0.286 |
| Eating-5 | 0.375 | 0.429 | 0.429 |
| Eating-4 | 0.375 | **0.571** | 0.429 |
| Eating-3 | 0.375 | 0.429 | **0.571** |
| Eating-2 | 0.375 | 0.429 | 0.429 |
| Eating-1 | 0.375 | 0.429 | 0.429 |

Table 8: Inferred result for Grooming class without contexts from smartwatch

| | Scenario-1 (Grooming-7) | Scenario-2 (Grooming-4) | Scenario-3 (Grooming-2) |
|---|---|---|---|
| Grooming-7 | **0.5** | 0.375 | 0.375 |
| Grooming-6 | 0.375 | 0.25 | 0.25 |
| Grooming-5 | 0.375 | 0.375 | 0.375 |
| Grooming-4 | 0.375 | 0.375 | 0.375 |
| Grooming-3 | 0.375 | **0.5** | 0.375 |
| Grooming-2 | 0.375 | 0.375 | **0.5** |
| Grooming-1 | 0.375 | 0.375 | 0.375 |

Table 9: Inferred result for Transfers-BedChair class without contexts from smartwatch

| | Scenario-1 (Transfers-BC-7) | Scenario-2 (Transfers-BC-4) | Scenario-3 (Transfers-BC-2) |
|---|---|---|---|
| Transfers-BC-7 | **0.667** | 0.5 | 0.5 |
| Transfers-BC-6 | 0.429 | 0.429 | 0.429 |
| Transfers-BC-5 | 0.5 | 0.5 | 0.5 |
| Transfers-BC-4 | 0.5 | **0.667** | 0.5 |
| Transfers-BC-3 | 0.5 | 0.5 | 0.5 |
| Transfers-BC-2 | 0.5 | 0.5 | **0.667** |
| Transfers-BC-1 | 0.5 | 0.5 | 0.5 |

From these results, it can be said that using ontology-based logical reasoning in combination with machine learning-based approaches is promising for FIM measurement; and that using dummy contexts is effective to deal with incomplete contexts. However, improvements are needed for treating the details of the FIM ontology to handle more specific situations and the calculation method of the assistance level.

## Conclusion and Future Work

In this study, we propose a novel approach to measure the functional independence of an aged person with a combination of machine learning and ontology-based logical reasoning. The combination makes a system more explanatory and more context-aware while keeping flexibility and robustness to noises and uncertainties in sensor data. The proposed approach uses semantic contexts as the interlayer for connecting machine learning techniques and ontology-based logical reasoning. Furthermore, we explore the utilization of dummy contexts when handling the difficulties in reasoning with incomplete data. The evaluation experiments indicate the effectiveness of our proposed approach that can infer activity classes and FIM scores based on even incomplete semantic contexts. Considering the fact that the experiments of our proposed approach are limited to only research laboratory settings, it is essential to test the same proposal in real-life environments and to reconfirm its effectiveness. This study has been approved by the Human Research Ethics Committees of the University of Electro-Communications (registration number: 18042) and conducting a demonstration experiment in this spring at a nursing home with the cooperation of St. Marianna University School of Medicine.

## Acknowledgement

This work was supported by JSPS KAKENHI Grant Number JP17H01823 “Development of Watching System by Integration of Non-Restrictive Sensors”.

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