Ontological Sensor Selection for Wearable Activity Recognition

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Abstract. Wearable activity recognition has attracted very much attention in the recent years. Although many contributions have been provided so far, most solutions are developed to operate on predefined settings and fixed sensor setups. Real-world activity recognition applications and users demand more flexible sensor configurations, which may deal with potential adverse situations such as defective or missing sensors. A novel method to intelligently select the best replacement for an anomalous or nonrecoverable sensor is presented in this work. The proposed method builds on an ontology defined to neatly describe wearable sensors and their main properties, such as measured magnitude, location and internal characteristics. SPARQL queries are used to retrieve the ontological sensor descriptions for the selection of the best sensor replacement. The on-body location proximity of the sensors is considered during the sensor search process to determine the most adequate alternative.

Keywords: Ontologies · Activity recognition · Wearable sensors · Sensor selection · Sensor placement · Human anatomy

1 Introduction

The recognition of human activity by means of wearable systems has lately attracted much attention. These systems consist of mobile and portable devices normally worn on diverse body parts to quantify physical activity patterns. Although many solutions have been provided to this respect [4,7,8,10], most of them are designed to operate in closed environments, where the sensors are predefined, well-known and steady. However, these conditions cannot be guaranteed in practical situations, where sensors may be subject to diverse types of anomalies, such as failures [3] or deployment changes [5,6]. Hence, the support of anomalous sensor replacement is seen to be a key requirement to be met by realistic activity recognition systems in order to ensure a fully functional operation. To enable sensor replacement functionalities in an activity recognition system, mechanisms to

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abstract the selection of the most adequate sensors are needed. To that end, a comprehensive and interoperable description of the available sensors is required, so that the best ones could be selected to replace the anomalous ones. For an accurate sensor selection during runtime use of the recognition systems, practical definitions such as sensor location or availability are required. Consequently, there is a clear need of models that may integrate these heterogeneous sensor descriptions, as well as techniques that may enable the discovery and selection of the most adequate sensors.

This work proposes the use of ontologies to comprehensively describe the wearable sensors available to the user. This fairly reflects an innovative utilization of ontologies in the activity recognition domain, which goes beyond their typical use to detect activities in a knowledge-based recognition approach. Moreover, an iterative search mechanism is also defined to determine the best replacement for a given sensor based on the analysis of the on-body location of the existing ones and their proximity to the anomalous sensor.

2 Related Work

Ontologies have been primarily used in human behavior recognition to detect activities in a knowledge-based oriented fashion. Concretely, ontologies are utilized to describe the activities, while reasoning and inference methods are considered for the recognition process. This is the case of [9], in which ontologies are used to both represent and reason activities based on the analysis of the user interaction with smart objects in pervasive environments. Similarly, in [11] the authors use ontologies to detect office activities based on the analysis of the outputs of binary sensors. Another example is reported in [1], which presents an ontology-based smart home system that discovers and monitors activities of the daily living. Binary or very simple sensors are considered in related works to detect primitives or atomic activities, which are described in an ontological model and used for ontological reasoning to detect high level activities. However, they do no exploit the potential of data-driven approaches in activity recognition, where the sensor data is analyzed using machine learning techniques to detect patterns matching known activities. Therefore, and in order to move one step forward, knowledge-driven approaches have been combined with data-driven approaches to recognize activities. For example, a hybrid model using machine learning techniques applied to body motion data and reasoning based on the ontological representation of the activities is defined in [2]. Ontological reasoning is also used in [12] to recognize complex activities based on simple actions, which are detected via supervised learning algorithms building on data from wearable sensors.

3 SS4RWWAR Ontology

The Sensor Selection for Real-World Wearable Activity Recognition Ontology (SS4RWWAR Ontology), firstly introduced in [13], is an extensible and evolvable ontology that describes heterogeneous wearable sensors in order to enable the selection of replacements for anomalous sensors in activity recognition systems. The SS4RWWAR Ontology comprises an upper ontology defining the basic common concepts for the description of wearable sensors and several plugable domain ontologies which inherit from the concepts in the upper ontology and define them in more detail.

The SS4RWWAR Upper Ontology (see Fig. 1) specifies the sensor description through the *WearableSensor* class. This class links to the *Magnitude* class which lists the magnitudes measured by the sensor -acceleration or rate of turn in inertial measurement units- via the *measures* property; the location where the sensor is placed (*Location*) via the *placedOn* property; the sensor internal characteristics (*Characteristic*) via the *hasInternalCharacteristic* property; and a human readable description (*rdfs:Literal*) via the *hasReadableDescription* property.

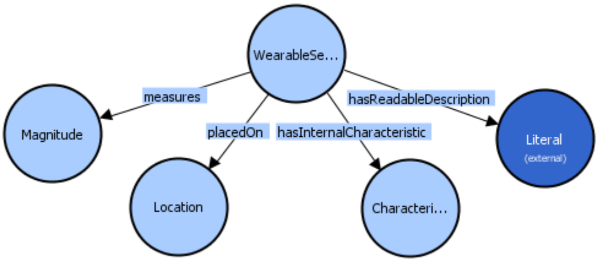

Fig. 1. SS4RWWAR Upper Ontology representing the description of wearable sensors

The SS4RWWAR Human Body Ontology describes the human body parts and uses them as sensor locations, by defining the *HumanBodyPart* class as a subclass of the *Location* class. Fig. 2 shows how the division of the body is done through the subclasses of *HumanBodyPart* -*Head*, *Trunk*, *UpperLimb* and *LowerLimb*- and their subclasses representing the subdivisions of each body part. The different body parts are linked to others through the *connectedTo* property and its eight subproperties defining the connections according to the standard human directional terminology: superior or inferior, anterior or posterior, medial or lateral, proximal or distal. Since the head has located the trunk below, the *Head* is defined as *inferiorlyConnectedTo some Trunk*; and inversely, the *Trunk* is defined as *superiorlyConnectedTo some Head*. The connections between the *Trunk* and the *UpperLimb* are also established via the *inferiorlyConnectedTo* and the *superiorlyConnectedTo* properties. The *Trunk* is also defined as *lateralyConnectedTo some UpperLimb* and the *UpperLimb* as *mediallyConnectedTo some Trunk* since the upper limbs are in a lateral position from the trunk. Similarly, the subdivisions of the main body parts are also linked via the subproperties of *connectedTo*. The face is the anterior part of the head and the scalp the posterior part of it; thus, the *Face* is defined as *posteriorlyConnectedTo some Scalp* and the *Scalp* as *anteriorlyConnectedTo some Face*. The subdivisions of the trunk, *Thorax*, *Back* and *Abdomen*, are also linked through the *anteriorlyConnectedTo*, the *posteriorlyConnectedTo*, the *inferiorlyConnectedTo* and the *superiorlyConnectedTo* properties. Last, to link the subdivisions of the upper and lower limbs the *distallyConnectedTo* and the *proximallyConnectedTo* properties are used. For example, the elbow is connected to the arm in the direction of the main body mass and to the forearm in the opposite direction. Thus, the *Elbow* is defined as *distallyConnectedTo some Forearm* and *proximallyConnectedTo some Arm*.

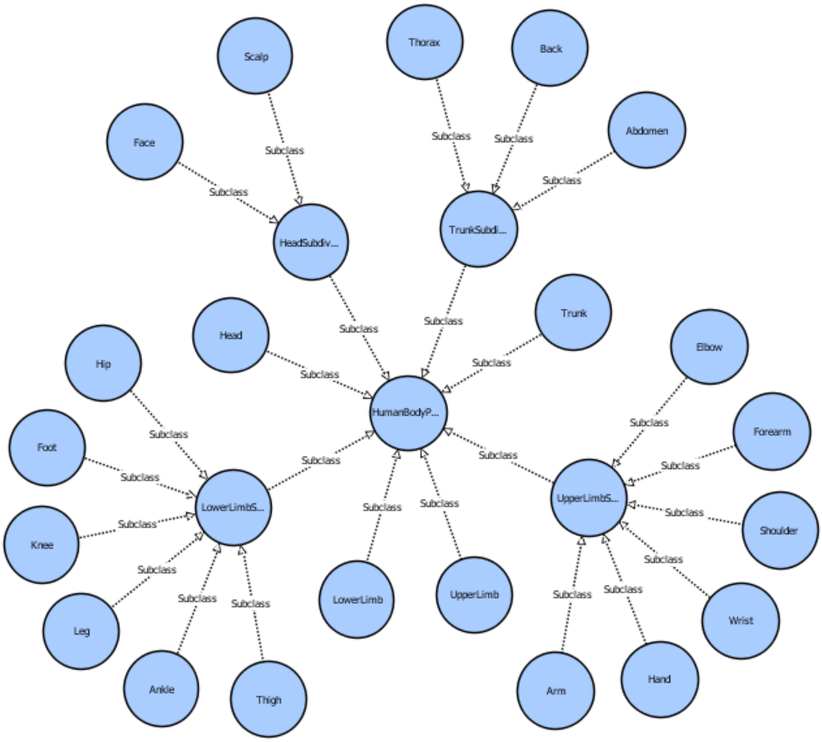

Fig. 2. SS4RWWAR Human Body Ontology defining the human body parts where the wearable sensor can be located

4 SS4RWWAR Ontology-Based Sensor Selection Method

Sensor selection to enable the replacement of anomalous sensors in the activity recognition system can be supported by the usage of the previously presented SS4RWWAR Ontology. The sensor selection method is based on the inference features provided by the SS4RWWAR Ontology and requires that all the available wearable sensors are described using this ontology. Posing the adequate SPARQL queries on the wearable sensor descriptions will allow finding the best sensors which could replace the ones suffering from anomalies.

The novel selection method for the replacement of anomalous sensors proposed in this work is based on an iterative query process triggered once a sensor is detected to have failed. The first option in order to replace an anomalous sensor would be trying to find another sensor located on the same body part. Under this condition, the measurements of the two sensors would be very similar and the activity recognition system would continue working with a similar performance after replacing the anomalous sensor with the other one in the same body part. Hence, the first step of the method is posing to the SS4RWWAR Ontology a SPARQL query to select a replacement sensor located on the same body part. This query, shown in Listing 1.1, is generic and applies to any sensor located on any body part. This abstraction is possible since the query does not require to include where the anomalous sensor is located. The sensor location is inferred from the ontology; thus, only the identifier of the anomalous sensor is needed. In fact, the `<sensor-id>` string in the query must be replaced with the actual identifier of the anomalous sensor as indicated in the SS4RWWAR Ontology. In case no sensor is found on the body part where the anomalous sensor is located, no results would be returned. In this scenario, it would be logical trying to replace the sensor with another one located on any of the adjacent body parts. If two parts are connected, one could expect that their movements are similar and the activity recognition system could still work with the sensor on the adjacent body part. Therefore, the second step of the method is posing to the SS4RWWAR Ontology a SPARQL query to select a replacement sensor located on an adjacent part. This generic query is shown in Listing 1.2, where the `<sensor-id>` string must be replaced with the identifier of the anomalous sensor. In case no sensor is found on the adjacent parts, one could think of trying to find the sensor placed on the closest body location. The closest sensor should be the one that could provide the most similar measurements and therefore be the best to replace the anomalous one. Thus, the third step of the method is posing to the SS4RWWAR Ontology a SPARQL query to select a replacement sensor located on a part directly connected to the adjacent part. This generic query is shown in Listing 1.3, where the `<sensor-id>` string must be replaced with the identifier of the anomalous sensor. This query process would be repeated increasing the number of hops on the body anatomy until a sensor is found. The SS4RWWAR Ontology would exploit the power of inference to find the replacement sensor placed in the closer body part.

```
SELECT ?replacementsensor
WHERE { <sensor-id> ss4rwwar:placedOn ?part.
    ?replacementsensor ss4rwwar:placedOn ?part.
    FILTER (<sensor-id> != ?replacementsensor) }
```

Listing 1.1. SPARQL query for the selection of a replacement sensor located on the same body part where the anomalous sensor is worn.

```
SELECT ?replacementsensor
WHERE { <sensor-id> ss4rwwar:placedOn ?part.
    ?part rdf:type ?parttype.
    ?parttype rdfs:subClassOf ?restriction.
    ?restriction rdf:type owl:Restriction.
    ?restriction owl:onProperty ?connected.
    ?connected rdfs:subPropertyOf body:connectedTo.
    ?restriction owl:someValuesFrom ?conparttype.
    ?conpart rdf:type ?conparttype.
    ?bodypart body:hasPart ?part.
    ?bodypart body:hasPart ?conpart.
    ?replacementsensor ss4rwwar:placedOn ?conpart }
```

Listing 1.2. SPARQL query for the selection of a replacement sensor located on a body part adjacent to where the anomalous sensor is worn.

```
SELECT ?replacementsensor
WHERE { <sensor-id> ss4rwwar:placedOn ?part.
    ?part rdf:type ?parttype.
    ?parttype rdfs:subClassOf ?restriction1.
    ?restriction1 rdf:type owl:Restriction.
    ?restriction1 owl:onProperty ?connected1.
    ?connected1 rdfs:subPropertyOf body:connectedTo.
    ?restriction1 owl:someValuesFrom ?conparttype1.
    ?conpart1 rdf:type ?conparttype1.
    ?conparttype1 rdfs:subClassOf ?restriction2.
    ?restriction2 rdf:type owl:Restriction.
    ?restriction2 owl:onProperty ?connected2.
    ?connected2 rdfs:subPropertyOf body:connectedTo.
    ?restriction2 owl:someValuesFrom ?conparttype2.
    ?conpart2 rdf:type ?conparttype2.
    ?bodypart body:hasPart ?part.
    ?bodypart body:hasPart ?conpart1.
    ?bodypart body:hasPart ?conpart2.
    ?replacementsensor ss4rwwar:placedOn ?conpart2.
    FILTER (<sensor-id> != ?replacementsensor) }
```

Listing 1.3. SPARQL query for the selection of a replacement sensor located on a body part directly connected to a part adjacent to where the anomalous sensor is worn.

In order to provide a clearer view of the functioning of the proposed sensor selection method, let us imagine a sensor setup where the user is wearing six acceleration sensors: S1 and S2 on the left wrist, S3 on the thorax, S4 on the abdomen, S5 on the right thigh, and S6 on the right leg. This scenario and therefore the wearable sensors are described using the SS4RWWAR Ontology. The sensor descriptions are actually instances of the *WearableSensor* class, concretely *S1*, *S2*, *S3*, *S4*, *S5* and *S6* in this example. The links between the sensors and their locations are established through the *placedOn* property. Therefore, the *S1* and *S2* instances are asserted to have the property *placedOn* with value *UserLeftWrist* which is an instance of the *Wrist* class. The *S3* instance is asserted to have the property *placedOn* with value *UserThorax* which is an instance of the *Thorax* class. The *S4* instance is asserted to have the property *placedOn* with value *UserAbdomen* which is an instance of the *Abdomen* class. The *S5* instance is asserted to have the property *placedOn* with value *UserRightThigh* which is an instance of the *Thigh* class. Last, the *S6* instance is asserted to have the property *placedOn* with value *UserRightLeg* which is an instance of the *Leg* class. Let us suppose that S1 is detected to suffer from some anomaly and the proposed sensor selection method is triggered. Therefore, the ontology is retrieved with the SPARQL query presented in Listing 1.1 where the string `<sensor-id>` is replaced with the string `S1` which is the actual identifier of the anomalous sensor. This query returns S2 as replacement for S1 since the two sensors are located on the same body part, concretely on the left wrist. This result is produced because the ontology describes that both the *S1* and the *S2* instances have the same value *UserLeftWrist* for the property *placedOn*. Let us now suppose that it is S3 which suffers from an anomalous behavior. In this case the SPARQL query presented in Listing 1.1 (replacing `<sensor-id>` with `S3`) does not produce any results since there is no other sensor on the thorax. Therefore, the query presented in Listing 1.2 (replacing `<sensor-id>` with `S3`) is posed to the ontology. S4 is returned as a result since this sensor is located on the abdomen which is a body part adjacent to the thorax where S3 is worn. This query result can be explained thanks to the structure of the ontology. The property *placedOn* has value *UserThorax* for the *S3* instance. The *UserThorax* is an instance of the *Thorax* class, and any member of this class is *inferiorlyConnectedTo* a member of the*Abdomen* class. Since the *S4* instance asserts the property *placedOn* to have the value *UserAbdomen*, which is an instance of the *Abdomen* class; then, the *UserThorax* is *inferiorlyConnectedTo* the *UserAbdomen*. Therefore, it can be concluded that the *S3* and the *S4* instances have for the property *placedOn* values that are instances of adjacent body parts, concretely *UserThorax* and *UserAbdomen*. Finally, let us suppose that S5 behaves anomalously. In this case, the first and the second SPARQL queries presented in Listing 1.1 and in Listing 1.2 (replacing `<sensor-id>` with `S5`) do not produce any results since there is no sensor on the thigh neither on the hip or the knee which are the two parts adjacent to the thigh. Therefore, the query presented in Listing 1.3 (replacing `<sensor-id>` with `S5`) is posed to the ontology. S6 is returned as a result since this sensor is located on the leg which is a body part directly connected to the knee, that is an adjacent part to the thigh. Like in the other examples, the explanation of this result is based on the logical of the ontology definition. For the *S5* instance, the *placedOn* property has asserted the value *UserThigh* which is an instance the *Thigh* class. Any member of *Thigh* class is *distallyConnectedTo* a member of the *Knee* class, and any member of this class is *distallyConnectedTo* a member of the *Leg* class. Moreover, the *S6* instance asserts for the property *placedOn* the value *UserLeg*, which is an instance of the *Leg* class. Therefore, the *UserThigh* is *distallyConnectedTo* the *UserKnee* which is *distallyConnectedTo* the *UserLeg*. So, it can be concluded that the *S5* and the *S6* instances have for the property *placedOn* values that are instances of close by body parts, concretely *UserThigh* and *UserLeg*.

5 Conclusions

Wearable activity recognition systems operating in realistic conditions are subject to malfunctioning due to changes suffered by body-worn sensor devices. Hence, mechanisms to support the selection of adequate alternative sensors are required. This work has presented an innovative use of ontologies in the activity recognition domain, which goes beyond their typical use to detect activities in a knowledge-based recognition fashion. Concretely, ontologies are used here to enhance the machine learning activity recognition used in data-driven approaches. The novel sensor selection method provides an iterative query mechanism to discover the best replacement sensor for an anomalous one by analyzing the on-body location of the available sensors and their proximity to the anomalous or nonrecoverable one. The intelligent selection method builds on an ontology defined to comprehensively and unequivocally describe wearable sensors and their main properties, including their exact placement on the human body. Future work includes the extension of the ontology towards the magnitude and sensor characteristics domains, as well as the application of ontological reasoning techniques to improve the sensor selection method and to reduce the increasing complexity of the queries.

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