Blending the Physical and the Digital through Conceptual Spaces

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Abstract. The rise of the Internet facilitates an ever increasing growth of virtual, i.e. digital spaces which co-exist with the physical environment, i.e. the physical space. In that, the question arises, how physical and digital space can interact synchronously. While sensors provide a means to continuously observe the physical space, several issues arise with respect to mapping sensor data streams to digital spaces, for instance, structured linked data, formally represented through symbolic Semantic Web (SW) standards such as OWL or RDF. The challenge is to bridge between symbolic knowledge representations and the measured data collected by sensors. In particular, one needs to map a given set of arbitrary sensor data to a particular set of symbolic knowledge representations, e.g. ontology instances. This task is particularly challenging due to the vast variety of possible sensor measurements. Conceptual Spaces (CS) provide a means to represent knowledge in geometrical vector spaces in order to enable computation of similarities between knowledge entities by means of distance metrics. We propose an approach which allows to refine symbolic concepts as CS and to ground ontology instances to so-called prototypical members which are vectors in the CS. By computing similarities in terms of spatial distances between a given set of sensor measurements and a finite set of CS members, the most similar instance can be identified. In that, we provide a means to bridge between the physical space, as observed by sensors, and the digital space made up of symbolic representations.

Keywords: Conceptual Spaces, Sensor Data, Virtual Space, Ontology.

1 Introduction

The rise of the Internet facilitates an ever increasing growth of virtual, i.e. *digital spaces* – distributed digital data which is loosely connected through cross-references, for instance hyperlinks, and which forms a set of distinct coherent information spaces which co-exist with the physical environment, i.e. the *physical space*. While the notion of digital space is often applied to virtual networking environments such as MySpace[1] or SecondLife[2], our definition of the term comprises any kind of structured

[1] http://www.myspace.com

knowledge or information space on the Web, whether it is made up of data stored via XML or relational database models, or structured linked data, formally represented through *Semantic Web (SW)* standards such as OWL [28] or RDF [29].

In that, the question arises, how physical and digital space can interact synchronously, what is particularly important when considering the fact that digital spaces in many cases represent physical ones, and hence, evolution of the physical space requires synchronous evolution of the digital one and vice versa.

Current and next generation wireless communication technologies encourage widespread use of well-connected *sensor-driven devices* which in fact produce *sensor data* by observing and measuring physical environments. This has already lead to standardization efforts, such as the ones by the Sensor Web Enablement Working Group[3] of the Open Geospatial Consortium (OGC)[4]. While sensors provide a means to continuously observe physical environments, several issues arise with respect to mapping sensor data to digital spaces, i.e. knowledge representations as described above.

Whereas sensor data usually relies on measurements of perceptual characteristics to describe real-world phenomena, knowledge representations represent real-world entities through *symbols*. The symbolic approach – i.e. describing symbols by using other symbols, without a grounding in perceptual dimensions of the real world – leads to the so-called *symbol grounding* problem [12] and does not entail meaningfulness, since meaning requires both the definition of a terminology in terms of a logical structure (using symbols) and grounding of symbols to a perceptual level [3][17].

In that, the challenge is to bridge between formal symbolic knowledge representations and the measured data collected by sensors by mapping a given set of arbitrary sensor data to a particular set of symbolic representations. This task is particularly challenging due to the vast variety of possible data sets.

Conceptual Spaces (CS) [10] follow a theory of describing knowledge in geometrical vector spaces which are described by so-called quality dimensions to bridge between the perceived and the symbolic world. Representing instances as vectors, i.e. *members* in a CS provides a means to compute similarities by means of spatial distance metrics.

We propose a two-fold knowledge representation approach which extends symbolic knowledge representations through a refinement based on CS. This is achieved based on an ontology which allows to refine symbolic concepts as CS and to ground instances to so-called *prototypical members*, i.e. prototypical vectors, in the CS. The resulting set of CS is formally represented as part of the ontology itself. By computing similarities in terms of spatial distances between a given set of sensor measurements and the finite set of prototypical members, the most similar instance can be identified. In that, our approach provides a means to bridge between the real-world - as observed and measured by sensor data - and symbolic representations within the digital space.

The remainder of the paper is organized as follows: Section 2 introduces the symbol grounding problem in the context of sensor data, while our representational

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[2] http://www/secondlife.com
[3] http://www.opengeospatial.org/projects/groups/sensorweb
[4] http://www.opengeospatial.org/

approach based on CS is proposed in Section 3. In Section 4, we introduce an application to a use case in the medical domain. Finally, we discuss and conclude our work in Section 5.

2 Sensor Data, Symbol Grounding and Spatial Representations

This section motivates our approach by introducing the so-called symbol grounding problem in the context of our work and introduces some background knowledge on metric-based spatial knowledge representation.

2.1. Sensor Data and the Symbol Grounding Problem

Sensor data usually consists of measurements which describe observations of phenomena in real-world environments. In order to ensure a certain degree of interoperability between heterogeneous sensor data, recent efforts, such as the OpenGIS Observations and Measurements Encoding Standard (O&M)[5], propose a standardized approach to represent observed measurements based on a common XML schema. However, in order to provide comprehensive applications capable of reasoning in real-time on observed phenomena in the physical space, i.e. the contextual knowledge produced by sensor-driven devices, one needs to bridge between the measurements provided by sensors and the formally specified knowledge as, for instance, exploited by the Semantic Web [24]. Figure 1 illustrates the desired progression from observed real-world phenomena, e.g. a certain color, to measurements provided by sensors, for instance, measurements of the hue, saturation and lightness (HSL) dimensions, to symbolic knowledge entities such as a particular OWL individual representing a specific color.

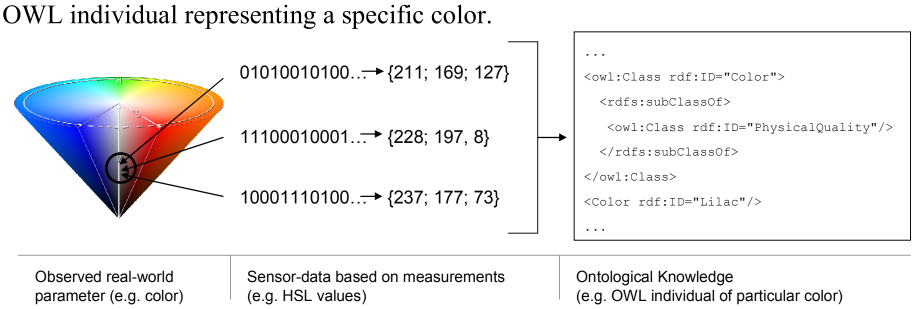


Fig. 1. Envisaged progression from observations in the physical space to ontological representations through sensor data.

However, whereas sensor data usually relies on measurements of perceptual characteristics to describe phenomena in the physical space, ontological knowledge presentations represent real-world entities through symbols what leads to a representational gap. Hence, several issues have to be taken into account. The

[5] http://www.opengeospatial.org/standards/om

symbolic approach – i.e. describing symbols by using other symbols, without a grounding in the real world or perceptual dimensions what is known as the *symbol grounding* problem [12] – of established SW representation standards, leads to ambiguity issues and does not entail meaningfulness, since meaning requires both the definition of a terminology in terms of a logical structure (using symbols) and grounding of symbols to a perceptual level [3][12]. Moreover, describing the complex notion of any specific real-world entity in all its facets through symbolic representation languages is a costly task and may never reach semantic meaningfulness.

Hence, in order to bridge between physical and digital space, the challenge is to map a given set of sensor observation data to semantic (symbolic) instances which most appropriately represent the observed physical entity within an ontology. In this respect, it is particularly obstructive that a vast amount of real-world phenomena, i.e. measurement data, needs to be mapped to a finite and much less comprehensive set of knowledge representations, e.g. ontological concepts or instances.

2.2. Exploiting Measurements through spatial Knowledge Representations

Sensor data usually consists of sets of measurements being observed from the surrounding environment in the physical space. In that, spatially oriented approaches to knowledge representation which exploit metrics to describe knowledge entities naturally appear to be an obvious choice when attempting to formally represent sensor data. *Conceptual Spaces (CS)* [10] follow a theory of describing entities in terms of their quality characteristics similar to natural human cognition in order to bridge between the perceived and the symbolic world. CS foresee the representation of concepts as multidimensional geometrical *Vector Spaces* which are defined through sets of quality dimensions. Instances are supposed to be represented as vectors, i.e. particular points in a CS. For instance, a particular color may be defined as point described by vectors measuring HSL or RGB dimensions. Describing instances as points within vector spaces where each vector follows a specific metric enables the automatic calculation of their semantic similarity by means of distance metrics such as the Euclidean, Taxicab or Manhattan distance [15] or the Minkowsky Metric [25]. Hence, semantic similarity is implicit information carried within a CS representation what is perceived as one of the major contribution of the CS theory. *Soft Ontologies (SO)* [14] follow a similar approach by representing a knowledge domain *D* through a multi-dimensional *ontospace A*, which is described by its so-called *ontodimensions.* An item *I*, i.e. an instance, is represented by scaling each dimension to express its impact, presence or probability in the case of *I*. In that, a SO can be perceived as a CS where dimensions are measured exclusively on a ratio-scale.

However, several issues have to be taken into account. For instance, CS as well as SO do not provide any notion to represent any arbitrary relations [23], such as *part-of* relations which usually are represented within symbolic knowledge models. Moreover, it can be argued, that representing an entire knowledge model through a coherent CS might not be feasible, particularly when attempting to maintain the meaningfulness of the spatial distance as a similarity measure. In this regard, it is even more obstructive that the scope of a dimension is not definable, i.e. a dimension always applies to the entire CS/SO [23].

3 Grounding Ontological Concepts in Conceptual Spaces

We propose the grounding of ontologies in multiple CS in order to bridge between the measurements provided by sensor-driven devices and symbolic representations of the SW.

We claim that CS represent a particularly promising model when being applied to individual concepts instead of representing an entire ontology in a single CS. By representing instances as so-called *prototypical members* in CS, arbitrary sensor-data can be associated with specific ontology instances in terms of the closest – i.e. the most similar – prototypical member representation.

We propose a two-fold representational approach – combining SW vocabularies with corresponding representations based on CS – to enable similarity-based matchmaking between a given set of sensor data and ontological representations. In that, we consider the representation of a set of *n* concepts *C* of an ontology *O* through a set of *n* Conceptual Spaces *CS*. Instances of concepts are represented as prototypical members in the respective CS. The following Figure 2 depicts this vision:

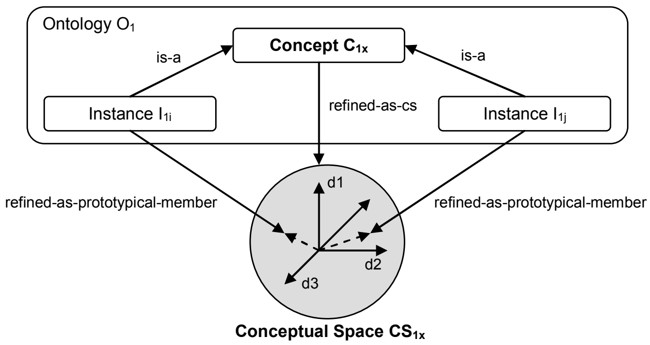


Fig. 2. Representing ontology instances through prototypical members in CS.

While benefiting from implicit similarity information within a CS, our hybrid approach allows overcoming CS-related issues by maintaining the advantages of ontology-based knowledge representations and provides a means to ground knowledge entities to cognitive dimensions based on measurements. To give a rather obvious example, a concept describing the notion of a geospatial location could be grounded to a CS described through quality dimensions such as its longitude and latitude. In previous work [4][5], we provided more comprehensive examples, even for rather qualitative notions, such as particular subjects or learning styles.

Provided our refinement of ontology concepts as CS and of instances as prototypical members, a given set of sensor data which measures the quality dimensions of a particular CS_i represents a vector *v* in CS_i which can be mapped to an appropriate ontology instance *I* in terms of the spatial distance of the prototypical member of *I* and *v*. Figure 3 illustrates the approach based on the color example introduced in Section 2.1. While measurements obtained from sensors are well-suited to be represented as vectors, i.e. members, in a CS, we facilitate similarity-based computation between a given set of sensor data and sets of prototypical members which represent ontological instances. For instance, the example in Figure 3 depicts the utilisation of a CS based on the HSL dimensions to map between color measurements obtained through sensors and prototypical members representing certain color instances. Based on the spatial distance between one measured color vector and different prototypical members, the closest vector, i.e. the most similar one is identified. In that, CS provide a means to bridge between observed sensor data and symbolic ontological representations.

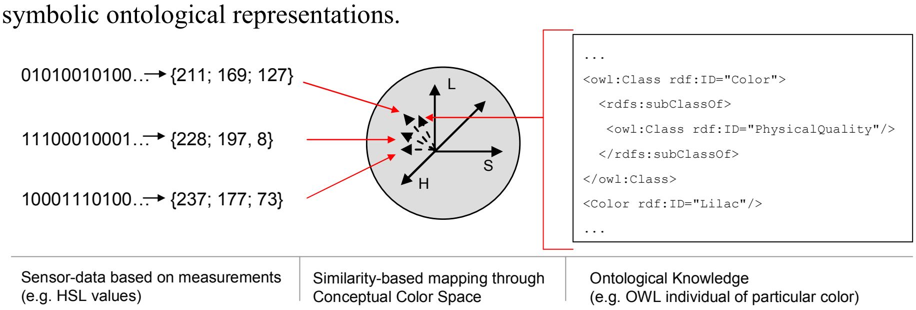


Fig. 3. Similarity-based mapping between distinct sets of sensor-based color measurements and ontological color instances based on a common CS using the HSL dimensions.

In order to be able to refine and represent ontological concepts through CS, we formalised the CS model into an ontology, currently being represented through OCML [16]. Hence, a CS can simply be instantiated in order to represent a particular concept.

Referring to [10][21], we formalise a CS as a vector space defined through quality dimensions d_i of CS. Each dimension is associated with a certain metric scale, e.g. ratio, interval or ordinal scale. To reflect the impact of a specific quality dimension on the entire CS, we consider a prominence value p for each dimension. Therefore, a CS is defined by

$$CS^n = \{(p_1 d_1, p_2 d_2, ..., p_n d_n) | d_i \in CS, p_i \in \Re\}$$

where $\Re$ is the set of real numbers. However, the usage context, purpose and domain of a particular CS strongly influence the ranking of its quality dimensions. This clearly supports our position of describing distinct CS explicitly for individual concepts. Please note that we do not distinguish between dimensions and domains [10] but enable dimensions to be detailed further in terms of subspaces. Hence, a dimension within one space may be defined through another CS by using further dimensions [21]. In this way, a CS may be composed of several subspaces and consequently, the description granularity can be refined gradually. Dimensions may be correlated. For instance, when describing an apple the quality dimension describing its sugar content may be correlated with the taste dimension. Information about correlation is expressed through axioms related to a specific quality dimension instance.

A particular (prototypical) member – representing a particular instance – is described through a vector $(v_1, v_2, ..., v_n)$ in the CS

$$M^n = \{(v_1, v_2, ..., v_n) | v_i \in M\}$$

where M is set of the valued dimensions v_i of the CS.

With respect to [21], we define the semantic similarity between two members of a space as a function of the Euclidean distance between the points representing each of the members. Hence, given a *CS* definition and two members v and u defined by vectors $v_0, v_1, ..., v_n$ and $u_1, u_2, ..., u_n$ of vector sets V and U, within *CS*, the distance between V and U can be calculated as:

$$|d(u,v)|^2 = \sum_{i=1}^{n} (z(u_i) - z(v_i))^2$$

where $z(u_i)$ is the so-called Z-transformation or standardization from u_i. Z-transformation facilitates the standardization of distinct measurement scales which are utilized by different quality dimensions in order to enable the calculation of distances in a multi-dimensional and multi-metric space. The z-score of a particular observation u_i in a dataset is calculated as follows:

$$z(u_i) = \frac{u_i - \bar{u}}{s_u}$$

where $\bar{u}$ is the mean of a dataset U and s_u is the standard deviation from U. Considering prominence values p_i for each quality dimension i, the Euclidean distance $d(u,v)$ indicating the semantic similarity between u and v can be calculated as follows:

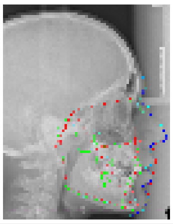
$$d(u,v) = \sqrt{\sum_{i=1}^{n} p_i ((\frac{u_i - \bar{u}}{s_u}) - (\frac{v_i - \bar{v}}{s_v}))^2}$$

For a detailed description of a formal procedure on how arbitrary ontologies can be represented through CS, please refer to [7].

4 Use Case: Bridging between Sensor Data and Ontologies in the Medical Domain

Within the medical domain, the traditional reasoning is based on (a) retrieving (diagnostic) measurements, then (b) classifying measurements along exemplary diagnostic values. The measurements can be directly mapped to prototypical members of a CS in order to map arbitrary measurements to classifications within a medical ontology *O*. Much effort is invested in building medical ontologies. For example, SNOMED CT [13] is a medical ontology that contains within its English version more than 300000 concepts, 900000 descriptions and 1300000 relations with increasing tendency. To reduce ambiguities in medicine it is essential to solve the symbol grounding problem. However, for most medical areas an adequate formal framework for this does not exist. Therefore we recommend that the development of formal descriptions is considerably intensified, so that more and more medical concepts are based on reproducible measurement results in order to improve the accurateness of medical diagnostics. In this Section, we refer to a use case of cephalometric diagnostics [1][22] in Orthodontics to illustrate how medical ontologies can be based on well defined CS in order to bridge between medical sensor measurements and symbolic medical data.

It is well established that the Cephalometric Analysis [1][22] provides useful guidelines in orthodontic diagnosis and treatment planning. Here, lateral skull radiographs are taken under standardised conditions and multiple measurements are retrieved from them, as depicted in Figure 4.



SNA:	79.00
SNB:	76.22
Ar-Go-Me:	116.75
NL-NSL:	3.93
ML-NSL:	29.49
IOK-IUK:	136.46
...	

```
...
<owl:Class rdf:ID="Cephalogram">
 <rdfs:subClassOf>
  <owl:Class rdf:ID="MedDiagnostics"/>
 </rdfs:subClassOf>
</owl:Class>
<Cephalogram rdf:ID="MaxRetrognathia"/>
...
```

Example for diagnostic measurements in medicine: Cephalometric Analysis | Some measurement results (cephalometric angles in degree) | Ontological Knowledge (e.g. classification "maxillary retrognathia" due to SNA < 80)

Fig. 4. From diagnostic measurements (here: results of Cephalometric Analysis) to ontological representations by orthodontic classifications.

We select 6 frequently performed cephalometric angle measurements as dimensions of a 6-dimensional CS which represents their possible combined measurement results:

$$CS = A^6 = \{(a_1, a_2, ..., a_6,) | a_i \in A\}$$

Here, A is a limited interval $A = \{x | -90 \le x \le 180\}$ for representation of angles. Table 1 shows for each dimension $a_i, i \in \{1,2,...,6\}$ the conventional name of the measurement and the proposed metric scale, data type and value range.

Table 1. CS A^6: Name, metric scale, range and data type of quality dimensions.

a_i	Name	Quality Dimension	Metric Scale	Data Type	Range
a_1	SNA	Angle: Maxilla position	Interval	Float	0..+180
a_2	SNB	Angle: Mandible position	Interval	Float	0..+180
a_3	Ar-Go-Me	Angle: Mandible growth	Interval	Float	0..+180
a_4	NL-NSL	Angle: Maxilla inclination	Interval	Float	-90..+90
a_5	ML-NSL	Angle: Mandible inclination	Interval	Float	-90..+90
a_6	IOK-IUK	Angle: Interincisal angle	Interval	Float	0..+180

For every dimension a_i there is an interval with SV_i being frequently used standard values. Depending on the measured angle (i.e. "below SV_i", "within SV_i" or "above SV_i") there are three possible diagnostic classifications for each dimension which were considered when representing prototypical members. Let B_i denote the medical ontology which contains the three diagnostic classifications of dimension i as concepts and let O denote the ontology which contains all possible combinations:

$$O := \{(b_1, b_2, ..., b_6,) | b_i \in B_i\}.$$

Now we can define for every instance $c \in O$ a prototypical member $u = (a_1, a_2, ..., a_6) \in A^6$ by defining its dimensions $a_1, a_2, ..., a_6$ as listed in Table 2. The table contains the interval with standard values in the form $SV_i = M_i \pm s_i$. We define prototypical members with $a_i = M_i - 2s_i$ for an angle below SV_i, $a_i = M_i$ for an angle within SV_i, $a_i = M_i + 2s_i$ for an angle above SV_i. Note that from these three possibilities the value $a_i = M_i$ is nearest to the angle if and only if the angle is within $SV_i = M_i \pm s_i$. In that, a close distance to $M_i - 2s_i$, M_i, or $M_i + 2s_i$ indicates either "below SV_i", "within SV_i" or "above SV_i". Because of these three possibilities (concepts), for each dimension there are $3^6=729$ prototypical members in CS A^6 to represent all 729 diagnostic combinations respectively instances $c \in O$.

Table 2. Values of dimensions a_i of prototypical members in case of certain diagnostic classifications from the ontology B_i . *SV* are frequently used standard values

a_i	SV_i	Angle below SV_i	Angle within SV_i	Angle above SV_i
a_1	82 ± 2	Maxillary retrognathy: a_1= 78	Normal finding of SNA: a_1= 82	Maxillary prognathy: a_1= 86
a_2	80 ± 2	Mandibular retrognathy: a_2= 76	Normal finding of SNB: a_2= 80	Mandibular prognathy: a_2= 84
a_3	126 ± 10	Horizontal growth: a_3=106	Normal finding of Ar-Go-Me: a_3=126	Vertical growth: a_3=146
a_4	8.5 ± 3	Anterior incl. of maxilla: a_4=2.5	Normal finding of NL-NSL: a_4=8.5	Posterior incl. of maxilla: a_4=14.5
a_5	32 ± 6	Anterior incl. of mandible: a_5=20	Normal finding of ML-NSL: a_5=32	Posterior incl. of mandible: a_5=44
a_6	131 ±6	Proclined incisors: a_6=119	Normal finding of IOK-IUK: a_6=131	Retroclined incisors: a_6=143

For example, in case of only normal findings (all angles are within SV_i) the prototypical member would be $u = (82, 80, 126, 8.5, 32, 131) \in CS$, in case of e.g. "Mandibular prognathy", "Vertical growth" (and else normal findings) it would be $u = (82, 84, 146, 8.5, 32, 131) \in CS$. Vice versa, based on the prototypical members described in Table 2, similarity computation in A indicates that the member $v = (79, 76.22, 116{,}75, 3.93, 29.49, 136.46) \in CS$ which represents measurements of the patient in Figure 4, is closest to the prototypical member $u = (78, 76, 126, 4.5, 32, 131) \in CS$ which represents the classification "Maxillary retrognathy", "Mandibular retrognathy", "Anterior incl. of maxilla" and else normal findings.

The example above illustrates the applicability of our proposed approach to bridge between sensor measurements and symbolic representations in the medical domain. However, the authors are aware that precise diagnostics in general require more complex CS descriptions to consider all parameters which are relevant for therapeutic decisions. Also the standard values (SV_i) of the example are averages which could be refined and adapted to the individual situation, e.g. by considering the ethnic ancestry and age of the patient. Nonetheless, with growing medical data sources, such as [18], medical diagnostics could be improved significantly by means of automated multidimensional similarity-computations which allow to bridge the gap between multiple medical sensor measurements and the medical knowledge captured in symbolic representations.

5 Discussion and Conclusions

In order to address the blending of physical and digital space we targeted the convergence of sensor data and formal knowledge representations as part of the Semantic Web. In that, we proposed a representational model which grounds ontological representations in CS to overcome the symbol grounding problem. While ontological instances are represented as prototypical members within a CS, arbitrary sensor data which measures the dimensions of the CS can be associated with the most appropriate instance by identifying the most similar, i.e. the closest, prototypical member to the vector which represents the sensor data. Our approach is facilitated through a dedicated CS Ontology which allows to refining any arbitrary concept (instance) as CS (prototypical member). In that, our representational model allows to bridge between sensor measurements and symbolic knowledge representations by means of similarity computation between vectors within CS and consequently, further facilitates the blending of physical and digital space.

In addition, we have shown an example from the medical domain to illustrate the application of our approach and its contribution to solve real-world problems. Here, current and future work aims at implementing an initial prototype which facilitates medical diagnostic processes based on similarity-computation in CS. The proposed approach has the potential to further support interoperability between heterogeneous sensor data and symbolic knowledge representations. While our approach supports automatic mapping between ontology instances and sensor-based measurements it still requires a common agreement on shared CS. In addition, incomplete similarities are computable between partially overlapping CS.

However, the authors are aware that our approach requires considerable effort to establish CS-based representations. Future work has to investigate on this effort in order to further evaluate the potential contribution of the proposed approach. Moreover, whereas defining instances, i.e. vectors, within a given CS appears to be a straightforward process of assigning specific quantitative values to quality dimensions, the definition of the CS itself is not trivial. Nevertheless, distance calculation relies on the fact that resources are described in equivalent geometrical spaces. However, particularly with respect to the latter, traditional ontology and schema matching methods could be applied to align heterogeneous spaces. In addition, we would like to point out that the increasing usage of upper level ontologies, such as DOLCE [11] or SUMO [20], and emergence of common schemas for sensor data such as the OpenGIS Observations and Measurements Encoding Standard, leads to an increased sharing of ontologies at the concept level. As a result, our proposed hybrid representational model becomes increasingly applicable by further contributing to continuous integration of physical and digital space.

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