Spatio-Temporal Normalization of Data from Heterogeneous Sensors

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Abstract: The growing use of sensors in smart environments applications like smart homes, hospitals, public transportation, emergency services, education, and workplaces not only generates constantly increasing of sensor data, but also rises the complexity of integration of heterogeneous data and hardware devices. In order to get more accurate and consistent information on real world events, heterogeneous sensor data should be normalized. The paper proposes a set of architectural abstractions aimed at representing sensors' measurements that are independent from the sensors' technology. Such a set can reduce the effort for data fusion and interpretation. The abstractions allow to represent raw sensor readings by means of spatio-temporal contextualized events.

1 INTRODUCTION

Smart environments are usually instrumented with various typologies of sensors. Sensors may have a fixed position, like a thermometer or a light sensor, or they may move inside the environment, like the sensors embedded in smartphones. Moreover, sensors are heterogeneous, thus producing measurements that are semantically linked to their sources. Applications that rely on sensors' measurements usually fall under the umbrella of Ambient Intelligence (AmI) that includes specific domains like smart homes, health monitoring and assistance, hospitals, transportation, emergency services, education, and workplaces (Cook et al., 2009). Such applications often are required to know the specific device that originated the measurement in order to understand and use the information provided. This leads to vertical systems, which feature low modularity and scarce openness.

When modeling sensors and related measurements, architectural solutions should face the challenge related to both heterogeneity and semantics. For example, authors in (Widyawan et al., 2012) propose a layered architecture that provides the low-level software, the middleware, and the upper-level services with detailed specifications of the involved sensors. This way sensors are well modeled, but their knowledge is distributed throughout all the system. Authors in (Dasgupta and Dey, 2013) focus on issues related to the management of large amount of data from sensors: the proposed approach consists in transforming sensor data in what authors call a *set of observations* that are meaningful for the applications. Lower levels embed semantics that is strictly related to the specific application. This lead to scarce reusability as the same abstraction rules for a specific sensor may not be applicable in different contexts. Finally, database approach is growing interest. Indeed, the database approach allows heterogeneous applications to access the same sensor data via declarative queries. This kind of solutions may resolve data heterogeneity at the application level, but there still persists the issue of sensor data management, since most of the existing solutions suppose homogeneous sensors generating data according to the same format (Gurgen et al., 2008).

The identification of a suitable set of architectural abstractions, able to represent sensor measurements independently from the hardware characteristics of the source, could improve reusability, openness, and modularity of software systems. These abstractions allow to remove the dependency from the sensor by contextualizing the measurements in a spatio-temporal frame. Measurements result in spatio-temporal events that can be stored inside a Data Base Management System (DBMS) or streamed inside a Data Stream Management System (DSMS) (Motwani et al., 2002), as proposed in (Gurgen et al., 2008). The main benefit is that applications no longer need to know the kind and the numbers of deployed sensors. Upon the occurrence of an event of interest, applications can decide to access all the other events that are related both spatially and temporally. In this paper neither the storage nor distribution of data is

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handled, but the focus is on the definition of such a set of architectural abstractions that could solve sensors heterogeneity issue, in order to be able to apply one of the mentioned approaches for data distribution, storage, and usage.

This paper will present the basic concepts along with the following simplified case of study. Consider a smart building composed by different rooms; in each room different sensors are located. In our example, we consider a room only (`room1`) that is instrumented as follow: in the top corner there is a camera (`cam1`) facing the centre of the room. Hanged on the wall there is also a thermometer (`therm1`). Moreover, a person in the room owns a smartphone with the accelerometer `acc1`. In this kind of contexts, smartphones are usually considered as extensions of the user, which means that their position is the same. Several applications can rely on the above listed sensors: a tracking application could try to follow the user (either a specific one or any user) and could make the position available to the system; an application could exploit the locations of the users to control the temperature in the rooms accordingly, based on their needs or preferences. These are just a few examples that can benefit from the proposed approach.

The rest of this paper is organized as follow: Section 2 introduces the basic concepts used to model spatial contextualization; Section 3 presents the proposed abstractions; finally Section 4 sketches some final remarks about the ongoing work and provides details about the future directions.

2 BACKGROUND CONCEPTS

Spatial contextualization has been derived from concepts defined in (Tisato et al., 2012; Micucci et al., 2014) and that will be summarized in the following.

A *space* is a set of potential locations, that are all the locations that could be theoretically considered in that space. For example, in a graph the potential locations are all the nodes. On the other hand, if a Cartesian space is used to localize entities within a room, then the potential locations are every point in $\mathbb{R}^2$ of the area delimited by the room perimeter. Applications explicitly manage effective locations, which are a subset of space's potential locations. For example, an application that calculates the trajectory of a mobile entity will only explicitly consider a finite number of locations in the Cartesian space, that is, the locations belonging to the trajectory.

A *zone* C_S is a subset of potential locations of a space S. It is defined by a set of effective locations termed characteristic locations in S and by a membership function that states if a given location of S belongs to the zone. Essentially, the membership function is a boolean function that is true when a location falls within the zone. According to the membership function used, different kinds of zones can been identified, such as: enumerative, premetric declarative, polygonal, and pure functional. We focus on the pure functional type. Figure 1 shows the concepts of space, zone, location and membership function.

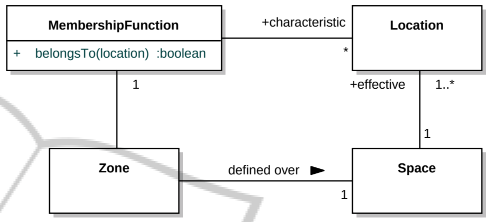


Figure 1: Space, Location, and Zone.

Given two different zones, a *mapping relation* is a generic function defined in $C_{S_1} -> C'_{S_2}$ (where S_1 and S_2 are spaces, and C_{S_1} and C'_{S_2} are zones defined on those spaces respectively). Thus it can be seen as a mapping between zones in different spaces.

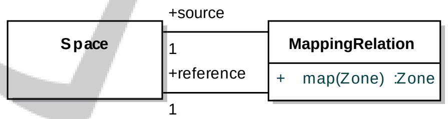


Figure 2: Mapping Relation.

Figure 2 pictures the concept of mapping relation with one of the spaces acting as *reference* space, so it can be seen in a hierarchical fashion with hierarchies of spaces mapped through mapping relations.

3 THE MODEL

Measurements from sensors can be modeled as data contextualized in a spatial-temporal context. Time contextualization is not detailed here for shortness. Concepts related to time and to clocks synchronization can be found in (Fiamberti et al., 2012). Before describing the model in detail, an overall presentation will be provided.

3.1 General Overview

The approach proposes an abstraction process able to produce spatio-temporal contextualized events, starting from low level measurements that are strictly sensor dependant.

Figure 3 provides a graphical representation of the identified abstractions: at the bottom level there are

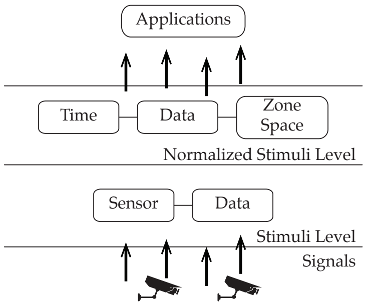


Figure 3: Abstractions.

physical *sensor*s, which are considered outside the system. Sensors produce *signal*s that are here intended as raw samplings. Raw sampling is then abstracted into *stimuli*, which are the lower level information the system receives and that is strictly related to its hardware source. In Figure 3, stimuli are depicted at the stimuli level and are represented by data associated to sensors. At the normalized stimuli level, stimuli are contextualized both spatially and temporally and are denoted *normalized stimuli*. For spatial contextualization we intend that the stimulus (data in Figure 3) has associated a zone in a space that models the physical environment. For temporal contextualization we intend that all the stimuli have associated a time value that is related to the same clock. This way, all the stimuli are contextualized in the same reference frames (time and space) and can be viewed by the applications as events occurred in specific places in the physical environment at specific time instants relieving them by low level and hardware dependent details.

3.2 Sensors

*Sensor*s are the meta representation of the physical sensors; they are in charge of acquiring *signal*s and providing *stimuli*. As shown in Figure 4, sensors are localized in a *physical space* (`PhysicalSpace`) through a *physical zone* (`PhysicalZone`). `PhysicalSpace` and `PhysicalZone` are specialization of `Space` and `Zone` respectively as defined in (Tisato et al., 2012; Micucci et al., 2014).

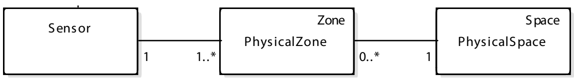


Figure 4: A sensor and its physical localization.

A physical space is a space that models the actual physical world; it is used to localize entities (and events also). A special class of entities are the sensors.

Localization means placing an entity in a well defined position inside the physical space. This can be achieved by using zones as defined in (Tisato et al., 2012; Micucci et al., 2014) and introduced in Section 2. This may suffice when the orientation of a sensor does not affect the interpretation of the acquired values. For example, the measurements of a temperature sensor are not affected by the orientation of the sensor itself. On the other hand, such a definition may be too poor. For example, consider a physical space as represented by a Cartesian 3D space with locations modeled as a triple (x, y, z). A camera may be localized through a zone that includes a characteristic location with values for x, y, and z equal to the real position in the world. Such localization is not sufficient to interpret the acquired frames as the orientation is also required. To fulfill this need, the concept of *oriented physical zone* has been introduced as a specialization of the physical zone, that also features the orientation, in order to give a more consistent representation of a position within a physical space.

Both physical space and corresponding locations are specialized in order to model specific spaces typologies (e.g., 3D Cartesian, 2D grid, and so on) and location typologies (e.g., a point in a 3D cartesian space, a cell in a 2D grid, and so on). Zones are not specialized because what characterizes a zone is its membership function that can model, for instance, cones, discretized spheres, and so on.

Considering the scenario introduced in Section 1, `room1` is represented by a 3D Cartesian space (a physical space). Suitable locations for this kind of space are 3D points. Several kind of physical zones can be defined over this space: single location zone, single location oriented zone, cone zone, sphere zone. Thermometer `therm1` is localized inside `room1` by means of a physical zone constituted by a single location that suffices to physically localize the acquired stimuli. Being sensor `therm1` in position (0.3, 0.4, 0.1), then, the characteristic location of its physical zone is a 3D point with values [0.3, 0.4, 0.1] (see Figure 5).

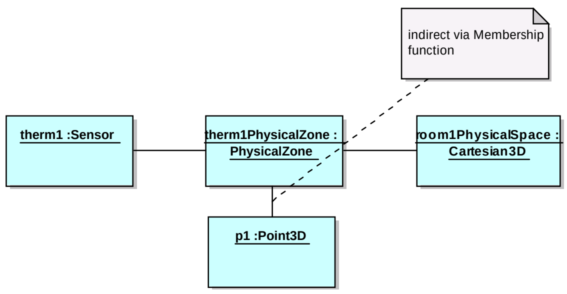


Figure 5: Therm1 physical localization.

Camera `cam1` has similar features: its position is an oriented physical zone that represents the corner of the room where it is fixed and the fact that is facing the center of the room. Finally, accelerometer `acc1` inside the smartphone is associated with the oriented physical zone occupied by the smartphone itself. In this case, the orientation represents how the smartphone is placed with respect to the room space, such information is fundamental in order to correctly interpret `acc1`'s data in most of domain applications (such as dead reckoning).

3.3 Stimuli

*Signal*s are raw data sensed (and usually sampled) by sensors. Physical sensors emit signals, which are usually in form of voltages values. These signals are then translated into *stimuli* through well-known conversion functions. As an example, a simple temperature probe is physically designed to output a voltage signal that is linearly proportional to the local temperature. In this example, the conversion function is the expression that maps such voltage readings into values that represent the temperature in degrees.

Stimuli are referred to the sensor that produced them and they are contextualized in zones (*data zone*s) of a specific space "owned" by the sensor: the *data space*. A data space represents the admitted values for the sensor's stimuli. For example, the data space of an accelerometer is a 3D Cartesian space, where the axes represent the ones of the acceleration data and are in m/s^2. It could have, as an example, a valid range of + or - 4g. Locations in that space are triples of values.

Data zones are simply zones defined in data spaces. For example, a stimulus from an accelerometer is located in a data zone whose characteristic location is a location whose values corresponds to the value read for each axis. If the stimulus is [x=0, y=1, z=1], then the characteristic location of the data zone is exactly [x=0, y=1, z=1].

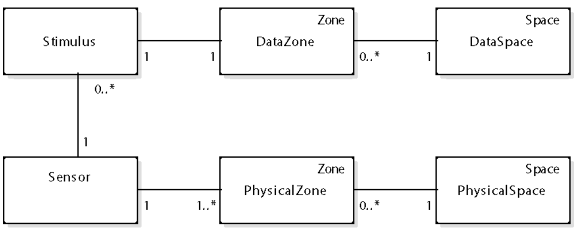


Figure 6: Stimulus.

Figure 6 depicts the stimulus. It is associated to the sensor that acquired its corresponding signal and it is spatially contextualized by means of a data zone (whose value equals the value of the sample) in the sensor data space. Being data space a specialization of space, it can be specialized like the physical zone to represent different kind of data space (e.g., Fahrenheit space, Celsius space, accelerometer space, and so on). The same holds for its locations.

It is worth noting that the distinction between physical space and data space and between physical zone and data zone is purely conceptual: they are all spaces and zones respectively as defined in (Tisato et al., 2012; Micucci et al., 2014).

In the example scenario previously introduced, there are three different types of stimuli. A sample from `therm1` is pictured in Figure 7. Sensor `therm1` generates stimuli in a Celsius format. Thus, the sensor data space is a Celsius temperature space that represents the space of the temperature readings by `therm1` and whose locations are simply values in the scale (-40 +40). A data zone for this kind of space includes a membership function with associated one characteristic location only. Suppose that `therm1` acquires a stimulus with value 23 Celsius Degree, then the `l1` value is 23. Moreover, the stimulus `temp1` is associated to `therm1` sensor so that the information related to the position of the sensor can be obtained.

A stimulus from `cam1`, instead, is localized via a data zone in a image data space that represents the space of the frames acquirable from `cam1`. The zone has associated a set of locations that corresponds to the matrix of the sensed image. Moreover, it is associated the sensor `cam1`. Finally, an acceleration stimulus from `acc1` is localized in a data zone whose associated location corresponds to the sensed acceleration. Such a zone is defined on a acceleration data space that is a three dimensional space. Moreover, it is associated to the sensor `acc1`.

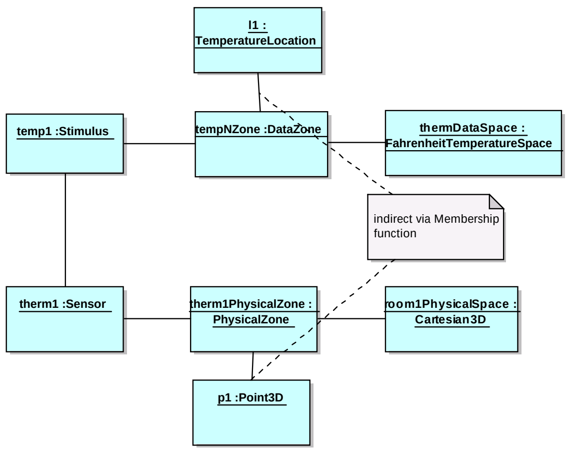


Figure 7: Stimulus Example.

3.4 Normalized Stimuli

A *normalized stimulus* is a further abstraction of a stimulus and is depicted in Figure 8. It represents the sensed value from a sensor that is spatially and temporally contextualized and that is unrelated from the sensor that produced it.

The normalization process takes into account the physical position of the sensor and its characteristics, in order to provide a physical zone in which the stimulus is located and that is referred to the same physical space in which the source sensor is immersed. Moreover, a normalized stimulus is located through a normalized data zone in normalized data space. For example, imagine that there are different temperature sensors: some of them acquires in Celsius and others in Fahrenheit. A normalized data space in this case can be a Celsius data space in which localizing all the temperatures.

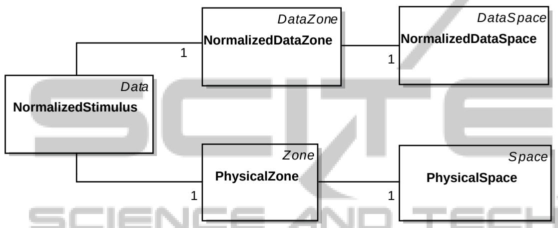
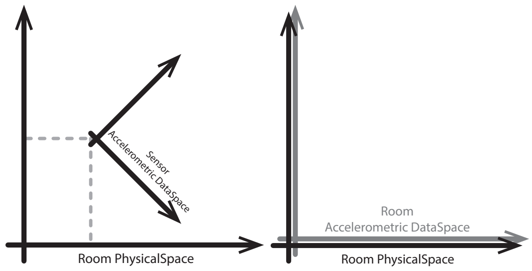


Figure 8: Normalized Stimulus.

More complicated situations may occur.



(a) (b)

Figure 9: Physical and Data Spaces relationships.

For example, Figure 9 shows the different relationships between a specific sensor's data space, and a normalized data space associated with a more broaden and generic sensor. The *room physical space* represents the physical space of the room in which the sensor is positioned (and oriented), while the *sensor accelerometric data space* represents the data space of the accelerometer values. As shown in Figure 9a, the two spaces are not *aligned*: in this example an oriented physical zone is required to consistently represent the position of the accelerometer inside the room physical space. The orientation of the sensor will be used as a parameter by the mapping relation function that will translate the starting data zone into its normalized counterpart, which will be related to the *room accelerometeric data space* shown in Figure 9b. For example, if the sensor is in the position showed in Figure 9a, the gravitational acceleration would be sensed among both the axes of the sensor, while the normalized value would only feature a $-1g$ on the y axis.

Considering the example scenario, the previously defined `temp1` stimulus depicted in Figure 7 was contextualized inside the `thermDataSpace` data space and was expressed in Celsius degrees. The corresponding normalized stimulus, as pictured in Figure 10 will be contextualized inside the `tempNormalizedDataSpace`, which, in this scenario contains temperature readings in Fahrenheit degrees, giving a good example of data zone normalization in order to be globally consistent with all the other homogeneous information source inside the room. Moreover the normalized stimulus is localized inside the physical space of room1 (`room1PhysicalSpace`). Since the sensor was not oriented and its data has no particular positioning, the position of the sensor and of the normalized stimulus are in this case equivalent.

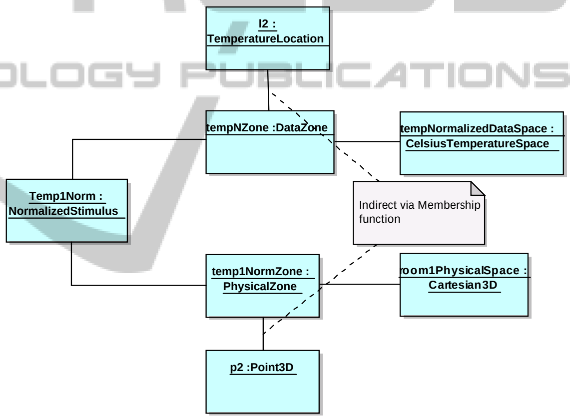


Figure 10: Normalization Example.

The stimulus from `cam1` needs a bit more of computation in normalizing the oriented physical zone of `cam1` into the non-oriented physical zone in which the normalized stimulus will be located. While the first represents the position of the camera (a single point, or a small well defined region of the physical space) and its orientation, the latter in order to be representative for the normalized stimulus must represent the physical cone viewed by `cam1`.

The normalization of the accelerations is similar to the temperatures: the acceleration data zone, referred to the acceleration data space is normalized and become a normalized acceleration zone in the `room1` accelerations data space (i.e., the data space in which all of the accelerations sensed in the room are contextualized). The acceleration is also enriched with its physical zone, which is a non-oriented physical zone derived from the oriented physical one of `acc1`.

3.5 Data Flow

In Section 3.3 and 3.4 stimuli and normalized stimuli have been defined. This subsection deals with how those normalization happens. In Section 2 the concept of mapping relation has been introduced: normalizing a physical zone into another physical zone can be trivial or quite complex depending on the nature of the data, but it should always be a repeatable and deterministic process, which means that it is possible to define a mapping function that relates any physical zone into a corresponding physical zone in the reference space. As already mentioned, the difference between *data* and *physical* is purely logical, so it is reasonable to say that data zones are normalized accordingly; it is nonetheless noteworthy that a mapping relation could easily need further information about the zones that need to be normalized.

Using mapping relations in order to remove any relationship between a sensor and the data it produces allows to obtain homogenous data, resolving one of the main issues of sensor heterogeneity.

Consider the acceleration previously defined and normalized in the reference scenario. The physical normalization is trivial and only consists in contextualizing the stimulus in the non-oriented part of the `acc1` physical zone. The data zone conversion instead, must use the orientation from the physical zone of `acc1` in order to normalize the acceleration from the accelerations data space of `acc1` to the `room1` accelerations data space that is jointly placed with the room1 physical space: this means that, apart from the usual conversions of scales and measurement unit, a roto-translation of the acceleration is needed. The information needed for this particular transformation is the orientation of the accelerations data space of `acc1`, which directly depends on the orientation of `acc1` itself. This is why `acc1` has an oriented physical zone and its normalized stimuli does not: the orientation has already been taken into consideration for normalizing the acceleration data.

Similarly, the cam1 stimuli are normalized into normalized stimuli that feature non-oriented physical zones. This time the orientation is not used to manipulate the data zone, but it is required, along with other intrinsic parameters of `cam1`, to determine the shape, size and displacement of the cone that represents the physical zone of each normalized stimulus.

4 CONCLUSIONS

The proposed model has been implemented in a preliminary proof-of-concept Java-based version in order to test the main ideas. The testing has been conducted exploiting simulated sensors, in particular accelerometers and thermometers.

While a solid and wider implementation is required, the approach has proven to be effective and, in the test case, efficient.

The main future directions include the management of other typologies of senors including cameras; an experimentation with real world sensors; and the realization of data-flow mechanisms that domain applications can exploit to access and query normalized stimuli.

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