ESTABLISHING MULTI-CRITERIA CONTEXTRELATIONSSUPPORTING UBIQUITOUS IMMERSIVEPARTICIPATION

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ABSTRACT

Immersive Participationentails massive participatory activities in the Internetengaging people, places and objects. This ispremised on the existence of an Internet of Things infrastructure supporting applications and services with the same richness of experience as the World Wide Web. This in turn presupposes the existence of models for establishing and maintaining context relations. Where these models do exist, they impose a limited interpretation of context relations in the presence of the inherent heterogeneous and dynamic characteristics of the supporting information. In this paper we introduce an approach towards establishing context relations through the use of an improved context relational model permitting a wider, more complete range of application specific scenarios. Additionally, wederive a measure of context proximity that considers the situation, attributes, relations, accuracy and heterogeneity of both the underlying information and the vast array of requirements for metrics supporting application problem domains.

KEYWORDS

Context-Awareness, Immersive Participation, Context, Context Models, Internet Of Things, Context Proximity, Sensor Information, P2p Context

1 INTRODUCTION

Ubiquitous and pervasive driven participatory environments advance the notion of immersion into a dynamic fusion of people, places and things. Rich context information drives the interactions among the underlying collection of connected things. The addition of context information enhances the experience of immersion in, e.g., online gaming and role-playing solutions, social media, virtual learning environments, and geo-caching, etc.

This is evidenced by the creation of massive immersive games such as Google Ingress[1] where global teams of users compete for world domination while simultaneously cataloguing real world artefacts. Theatre productions such Antigones Diary[2]and Maryam[3] produced by RATS Theatre[4]charts theatrical performances incorporating audiences in a massive immersion environment across multiple locations.

An Internet of Things (IoT) is central to enabling a ubiquitous and pervasive reality, which responds to and accommodates the establishing, optimization and exploiting of the dynamic relationships that exist between a user, his environment and services.Dey'scontribution to the definition of context and context awareness in [5]motivated context provisioning approaches such asSenseWeb[6], IP MultiMedia Subsystem (IMS) [7] , MediaSense [8] and SCOPE [9].

These approaches enabled the deployment of context centric applications and services withvarying degrees of availability, accuracy and reliability. However, with respects to

DOI : 10.5121/ijasuc.2013.4205

expressivity, they are limited to permitting a user to an understandingof his current state of being over his associated context information. An end user is able to understand that *"it is five degrees Celsius and I am walking 2km/h on the High Street"*.However, this alone lacks the expressivity required by Schilit and Adams who describedthree main aspects in context as *"Who you are, who you are with and what resources are nearby"*[10]. This expected level of expressivity is mandated by Dey in [5], expects that applications and services will be able to obtain answers to the question of *[which] entity is considered relevant to the interaction between a user and an application*.

Such entities have evolved over time to be regarded as presentities bearing both context and presence information and establishing relationships largely defined over semantic models such as that described by Dobslaw et al. in [11]. Adomavicius et al. in [12]suggested that semantic approaches are complemented by metric type approaches in answering the question of *"nearness"* as posed by Schilitet al. in [10] and Dey and [5] for the purposes of identifying and establishingcontext relations between entities.

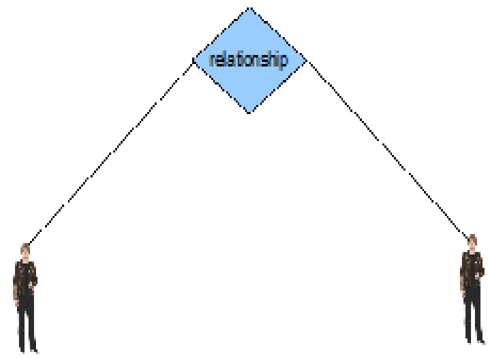

Figure 1 – The Presentity Triple

Solutions such as [11], [13] and [14] are deemed to provide adequate semantic based approaches. Therefore, establishing the types of relationships shown in Figure 1 is premised on our ability to definethe complementing metric-type similarity models which, according to Hong et al. in [15],is critical in realizing applications and services that can discover nearby sensors or points of information

We are therefore mandated to research models that can support the establishing of context relations over dynamic and heterogeneous context networks.These approaches must be dynamic, domain and activity aware while establishing stable relationship over intermittent and information with varying degrees of accuracy. Additionally such approaches must support the composite heterogeneous context information that underpins context networks. In this paper motivate the need for such a model through the contributions and shortfalls of existing models. We introduce a multi-criteria approach that supports both the dynamic behaviour of context as well as the heterogeneous nature of the wide array of applications and service requirements. In Chapter 2 we outline the background and motivation to our research. Chapter 3 describes the proposed solutions while Chapter 4 presents our analysis and results. Chapter 5 completes with a conclusion and discussion.

2 MOTIVATION & RELATED WORK

In Figure 2A,Pwhile connected to S,suggests a relation to Q.In an immersive scenario, if$S$ is a temperature sensor then the implication of this relation is would be that$P$and Q share, asimilar context and could be provisioned a common service. In the extended scenario in Figure 2B, where$P$is connected to S_1 and Q is connected to S_2, P shares a context similar to that of Q by a function of the similarity between the current values of S_1 and S_2. If the same application were using these values to adjust the environmental conditions of P and

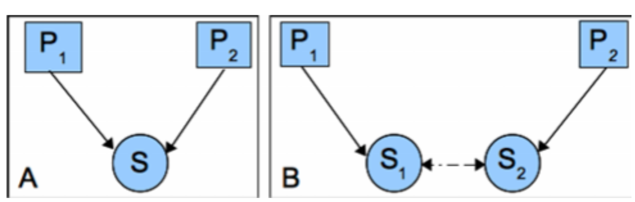

Figure 1 – Overview of Context Proximity

Q then the difference in the amount of energy required would be a factor of the difference between the values of S_1 and S_2, their proximity.

Consider the audience in our immersive play, *Maryam*, each equipped Body Nets of the types described by Tufail in [16] and Cook and Song in [17]. This generates a multitude of diverse context information, which can be used to make decisions concerning intelligent commuting scenarios as well as the discovery of social connections and services.However the deployment of applications and services using this context information presupposes the existence of models that support the definition, establishing and adjusting of context relations. These modelsas shown in Figure 3 are subsequently exploited to realise these context services.

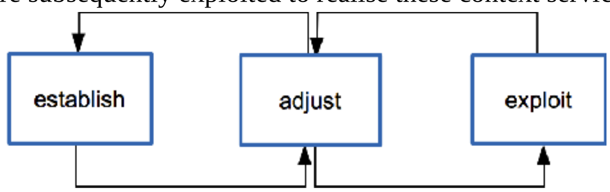

Figure 2 – Establishing Adjusting Exploiting Context Relations

Zimmermann et al. in [18]introduced such a model as a response to the generic nature of context as defined by Dey in [5]. This model on the *Operational Definition of Context*categorises context information into five groups: individual, time, location, relation and activity as shown in Figure 4.

Central to this model are time and location. Establishing context relations is possible when entities, within a time window, possess a spatial proximity below a specified threshold. The earliestapproaches to context proximity provided direct support for this model. This could enable users in our immersive environmentsto acquire a definition of proximity over spatial information,. Therefore realising early applications of the type implemented by Kanter et al. in[19].

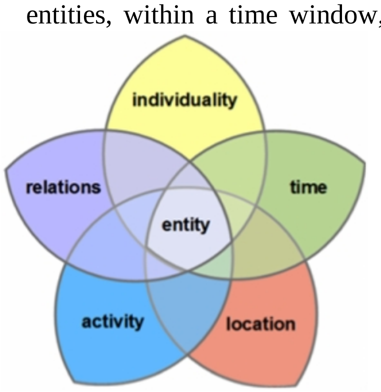

Figure 4 - Operation View of Context

Here, approaches sought to derive some knowledge of context similarity as a direct characterization of the observable entity proximities in the real world. This early class of proximity measures was therefore restricted to measurable distances of separation between entities.

The slow adoption of positioning systems resulted in approaches such as the AmbieSense Project[20], Smart-its Friends [21]Meme Tags [22]Activebadge[23]. These generally relied on the incorporation of physical artefacts such as radio tags and RFID in the real world. Proximity of context was a simply notion determined by the tag which is detected by an entity. Consequently, these faced limited adoption and deployment due to implementation and adoption costs as well as practicability.

With wider adoption of positioning systems such as the Global Positioning Systems (GPS), standard mobile devices were used in approaches such as WhozThat[24], PeopleTones[25] and Ulocate[23]to determineproximity with a high degree of accuracy. Geographical coordinates are modelled as vector points in $\ell_p - spaces$and distances derived as the$\ell_p - norm$ of any two entities $\{P, Q\}$ given as:

$$d(x, y) = \left(\sum_{k=1}^{n} |P_k - Q_k|^r \right)^{\frac{1}{r}} \qquad 1$$

where$r$ is usually 1 or 2.

Weagree with Zimmermann et al. in [18], that the process of managing context centric relations are realised over three distinct phases. However the reduction of context proximity to a single spatial problem limits the expressiveness of context aware applications. This as we disregard scenarios where spatiality has minimal significance to the delivery of a service.

In identifying the important aspects of context, Schilit in [10]suggests the significance of nearness or *proximity* as being the underpinning factor in identifying entities that ought to be considered related. We define *Context Affinity*as: *the perceived similarity between context entities as expressed over the characteristics of their relational context information.*Adomavicius et al. suggests in [26] that there are two approaches to context affinity, namely semantic and proximity based approaches; both of which are complementary in characterizing the relationship triples in a context network.

Measures of proximity enhance the ability to evaluate and respond to queries over the relationships among the constituent presentities in large and dynamic context networks.We define Context Proximity as: *the ease at which the context behaviour of one entity can be transformed into that of another entityover the characteristics of their current underlying context states.*Hong etal. suggests in [15] that the ability to derive measures of context proximity is a critical element of any infrastructural approach to context aware computing. Schmidt et al., in [27], Schilit in [10] and Dey in [5] agreed that we are required to establish relations over high dimensional context information thereby abstracting from spatiality and realising models that consider multi-dimensional proximity, Relational Proximity.

Relational proximity constitutes a more encompassing definition of context proximity as expected by Schmidt et al., in [27] while further subsuming spatial proximity with regards to expressiveness. This permits the creation of applications with a notion of proximity beyond that of spatiality. Additionally, relational proximity evolves the problem of establishing context relations by considering the inherent multidimensional characteristic of context when deriving measures of proximity. A model ϑ_{D}that derives the relational proximity of two entities $\delta_{(P,Q)}$ with respects to a problem domain $\mathcal{D}$ would consider a subset of relevant and available context information and derive a proximity such that:

$$\vartheta_{\mathcal{D}}\left(\overset{PQ}{\begin{Bmatrix} a_1 \\ a_2 \\ a_3 \\ \cdots \\ a_i \end{Bmatrix}, \begin{Bmatrix} a_1 \\ a_2 \\ a_3 \\ \cdots \\ a_j \end{Bmatrix}}\right) \longrightarrow \delta_{(P,Q)} \qquad 2$$

Adomavicius et al. in [28] supports the validity of such an approach suggesting that solutions could be realized as extensions of existing two-dimensional approaches. This, by using an n-dimensional distance metric such as derivatives of the $\ell_p - norm$ to derive a representation of proximity over multiple dimensions satisfying the requirements of Schmidt et al. in [29].Additionally, while the notion of temporality is central to context, the emphasis must be removed from actual time and expressed in a much broader sense encompassing scenarios where clock-time is superseded by state change graphs. In our scenario, substituting time with general state-change model creates a more flexible basis for establishing relations.

TheContextual Map proposed by Schmohl in [24] is one approach to using relational proximity as a means of establishing context relations. Each entity, Q, wishing to be provisioned a service based on a similarity of context is modelled as the centre of a hypersphere whose dimensions are the required context attributes. Each related entity, P, is a point in the hypersphere where context proximity $\delta_{(P,Q)}$ is derived using:

$$\delta_{(P,Q)} = \sqrt{\sum_{k=1}^{n} (a_i - a_j)^2} \qquad 3$$

In order to negate the effects of higher dimensionality[30], context attributes are classified into ranges based on their topological similarity. This approach also validated the use of relationalproximity as a suitable method for establishing context centric relationships.

The Contextual Map however, does not consider the context activity of the user, providing a general measure of proximity that in many cases would not be applicable. Two participants in our immersive scenario could possess very close context proximity with one driving while the other is sitting on the train. The definition of a range is static and does not reflect the current activity nor is adjusted to reflect the requirements of the deriving entity. Additionally, the importance of a range or attribute is not considered. This creates the paradox of a static definition of proximity between highly dynamic, heterogeneous context entities and thus cannot be reliably used as the basis for establishing context centric relationships.

An alternative approach, the scalar difference, is described by Padovitz et.al. in [31]. In contrast to the context map approach, this considers the situation of the entity when selecting the attributes contributing to this measure. The scalar difference measures each attribute with a separate sub-distance function and unlike the contextual map, considers both linear and nominal values as well as permitting weighting parameters for each attribute. The values are normalized with respect to the maximum values an entity could posses given its current situation or state and resulting in a value of between 0 and 1. The scalar difference is derived as:

$$\delta_{(P,Q)} = \sqrt{\sum_{k=1}^{n} d(a_i, a_j)_k^2} \qquad d(a_i, a_j) = \begin{cases} 1 \ if a_i \ or a_j \ is unknown \\ norm_{vdm}(a_i, a_j) \ if a is nominal \\ norm_{diff}(a_i, a_j) \ if a is linear \end{cases} \tag{4}$$

This is an extension of earlier work on the Heterogeneous Value Difference Metric in[32] which introduced composite distance metrics permitting a unified comparison of both nominal and linear valued attributes. These approaches are advantageous over pre-existing homogenous metrics by permitting comparisons on an individual attribute level and normalizing with respects to the data collection as opposed to being arbitrarily determined.

This approach however suffers from the curse of dimensionality [30] as the number of attributes describing a situation grows. This is particularly important in context centric scenarios where a multitude of dimensions could be used to characterize an entity's situation. Furthermore, the derivation of proximity across different situations is treated in the same way as within the same situation, disregarding the fact that some situations are more similar than others. Using this as the basis for establishing context relations in our scenario, the commuter sitting on the train could be given a closer proximity to a person driving on a parallel road than to another person sitting on the same train.

With respects to the drawbacks of previous and existing works in realising a suitable approach to context proximity, we identify the following desired properties of a good model for establishing reliable context centric relationships. Additionally, we include the desired properties of a supporting relational proximity approach more adequately reflecting the dynamic behaviours of the underlying context entities.

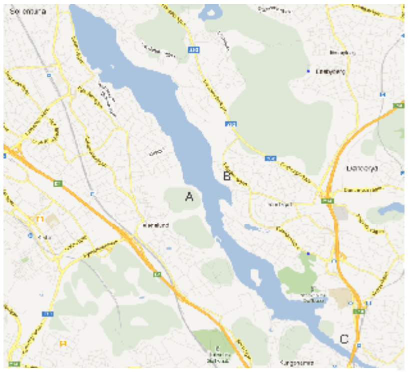

Figure 5 - Domain Aware Proximity

1. **Dynamic -** The dynamic nature of context networks must be reflected in any model seeking to derive a representation ofcontext proximity.
2. **Domain Aware -** Measures of proximity must consider the enclosing domain space thereby selecting and measuring attributes relevant to their contribution to the determination of proximity given the current problem space or

domain. This is in contrast to both Padovitz et al. in [31] and Schmohl and Baumgarten in [33] which suffer from generality by placing solely the user at the centre of the proximity measure at the expense of the application and activity. Consider Figure 5, and solving the problem of which entity is closer to A. The contextual map would suggest point B is closer disregarding the activity required to move from A to B or C. Further to this, Shahid et al. in [34] showed that proximity measures based entirely on the $lp - norm$ are not sufficient even for spatial proximity as they do not consider the domain nor the activity of the supported entities.

3. **Activity Aware** - Furthermore, the activity of the user must be a central factor, such that:$\left[P\left(\mathcal{A}_i^{\mathcal{D}}\right) \rightarrow Q\left(\mathcal{A}_j^{\mathcal{D}}\right) = 0\right] \equiv [\left(\mathcal{A}_i^{\mathcal{D}}\right) = \left(\mathcal{A}_j^{\mathcal{D}}\right)]$. While Padovitz et al. in [31]places an emphasis on activity, the suggested proximity approach effectively ignores the level of similarity between activities.
4. **Temporal-** A model for proximity therefore should substitute time as described in [18] for a more general approach to temporality. While Zimmerman et al. in [18] emphasized the centrality of time, the notion of temporal displacement should be considered as a general state change.
5. **Relational -**Models for establishing context relations must depart from spatiality as the overarching indicator of context proximity. We require relational approaches where an emphasis on location is only valid, where, like any other attribute, it is regarded as a significant or deciding factor.
6. **Accuracy -**Good models supporting context proximity must also consider the accuracy of the supporting information. This could either be achieved as done by Padovitz in [35]where the accuracy of the sensors are considered or as suggested by Walters and Österberg in [36]where heuristics involving sensor ranking may be used.
7. **Composite -** Measures of proximity as discussed by Wilson et. al in [32] benefit from heterogeneous and composite approaches metrics provided for more suitable approach to deriving metrics over multi-dimensional space. Measures of context proximity must therefore consider the heterogeneity of context information and be able to incorporate diverse types of context information that contribute to characterizing the situation of an entity.
8. **PsuedoMetric-**Measures of context proximity are not metrics by definition. However they are always positive and are symmetric within a very strict definition; where both entities have an identical situation and requirements. The domain problem and user requirements must consequently be identical with only the context values defining the current context state being different.
9. **Stable –** Models for establishing context relations must provide for stable relationships with a low churn rate, permitting a consistent experience. Relationships should be established and maintained against intermittently inaccurate context information or the intermittent lack of sensor information. Therefore approaches to evaluating context proximities must consider these factors.

3 PROBLEM

A connected things society is enriched by the development and deployment of context centric applications and services with support for the inherent dynamic interaction among the underlying entities. These interactions are, in turn supported by relational proximity models that are adaptable, adjustable and exploitable without suffering from innate generality.

Previous works in the area have largely been focused on the provisioning of the context information required to support context networks. Where applications and services have been deployed, they have either presupposed the existence of models for establishing and maintaining context relations or utilized context relational approaches that are inflexible in the presence of the inherent heterogeneous and dynamic characteristics of context networks.

In light of the challenges and the exposition of related work and weaknesses, we seek a method and support for establishing context relations through the use of an improved context relational model permitting a wider, more complete range of application specific scenarios. Additionally, we seeka measure of context proximity that considers the situation, attributes, relations, accuracy and heterogeneity of both the underlying information and the vast array of requirements for metrics supporting application problem domains.

4 MODEL FOR ESTABLISHING CONTEXT RELATIONS

In response to the above, we introduce a more dynamic heterogeneous approach towards establishing context relations through the use of an improved context relational model permitting a wider, more complete range of application specific scenarios. Additionally, we introduce a new approach to deriving context proximity that considers the situation, attributes, relations, accuracy and heterogeneity of both the underlying information and the vast array of requirements for metrics supporting application domains.

This creates a time invariant approach where the order of context observations do not affect the notion of proximity used for establishing relations, this is advantageous where general observations of entity behaviours over time provide sufficient grounds for establishing context relations. With this approach we further enable partial matching of context behaviours permitting complete context similarity where the behaviour of one entity P subsumes that of entity Q.

We add constraints for behaviour completeness, where sub-behaviours similarity is not sufficient to establish a relationship. Additionally we add constraints for time observations to consider the relative time in which context states are observed adding additional constraints where the order and time of observations are important. The accuracy of the supporting context information is also considered, reducing the likelihood of establishing context relations between entities where the accuracy of the context information is a factor. Finally, we consider the change observed context proximity over time as an additional constraint for eliminating entities which are either highly dynamic and therefore cannot establish relationships over a feasibly exploitable duration or static relationships that exists over an extended period.

4.1 Context Interactions

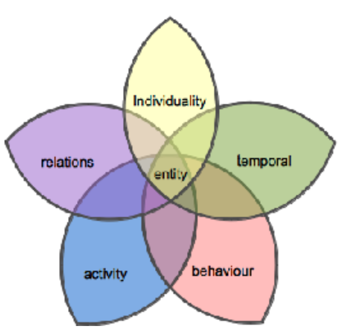

Figure 6 Context Interaction Model

Zimmerman et al. in [18] proposed an operational model for establishing and managing context centric relationships. However, citing the insufficiencies with respect to location and spatiality, we improve on this model to reflect our approach to establishing relationships.

Firstly, we subsume location with a more general context relational measure. This is then extended to establishing relationships over patterns of user behaviours as opposed to pairwise measures. Here, two entities establish a context relationship when their pattern of context behaviour lies within a specified threshold, maintaining this relationship providing the patterns of behaviours remain.

Location, rather than being the overarching indicator of proximity, is now incorporated as an attribute of *individuality* and subsequently an attribute used to estimate behaviour proximity when required by the problem domain. As described byZimmerman et al. in [18], relationships are time constrained and are established when a proximity threshold is met at the same time. Citing the need to establish relationships over patterns of behaviour that are not constrained by the time, we further subsume *time* with a *temporal*property, creating a more encompassing approach. This better reflects the notion of context progression over any measurable temporal displacementsuch as time or any other state change. We should be able to establish a context relationship between two entities having as similar behaviour regardless of the time in which they occur.

With our interaction model described, we define the general context model for organising and describing the behaviour of context bearing entities.

4.2 General Context Model

Having defined a model for identifying and establishing context relations, we are further required to define a general model for organising context entities and identify their current states and activities. To satisfy this, we adopt the general model of context spaces model as described by Padovitz in [31] and shown in Figure 7. Here, we confine the establishing of context relationships to a defined application or problem domain space. This space, universe of discourse of the application domain, is the subset of all global context information considered relevant to all interactions relative to problem domain or application and supports the delivery of any application or service relative to this domain.

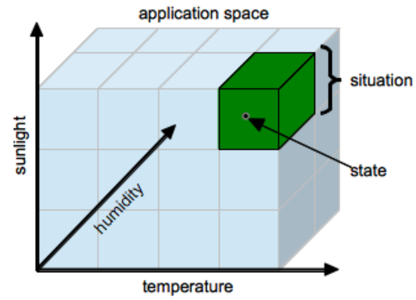

Figure 7 General Context Model

This is modelled as an n-dimensional hyperspace, where dimension corresponds to type, value subset and the domain for an element of context information. This domain is modelled as:

$$\square\mathcal{D} = \{(d_1^{min} < d_1 > d_1^{max}), (d_2^{min} < d_2 > d_2^{max}), \ldots, (d_i^{min} < d_i > d_i^{max})\} \qquad 5$$

In our immersive participation environment, such a domain could be the play "*Maryam*". A domain could be daily commuting. This domain universe is partitioned into situations or activities. Each sub-space represents an acceptable range of context information defining a real world situation or activity such that:

$$\square\mathcal{A}^{\mathcal{D}} = \{(a_1^{min} < a_1 > a_1^{max}, \omega_1), (a_2^{min} < a_2, > a_2^{max}, \omega_2), \ldots, (a_i^{min} < a_i > a_i^{max}, \omega_i)\} \qquad 6$$

$$\square\ (a_i^{min}, a_i, a_i^{max}\ \square\ d_i)$$

For the domain *Maryam*, activities could be *Scene 1*, *Scene 2*, *Scene 3*, etc.Activities definitions are not mutually exclusive and therefore several activities could overlap in their sub-space definition.

Finally, each situation contains context states; a combination of unique attribute values within a situation or activity space such that:

$$\square S^{\mathcal{A}} = \{s_1, s_2, \ldots\ s_i\}\ \square\ s_i\ \square\ \mathcal{A}_i \qquad 7$$

Each state corresponds to a context observation made on an entity. For the domain *Maryam*, a state would be the context information recorded from body sensors at *Scene 1*.A state may be occupied by one or more entities, each of which continually transits states within the context space. An entity within an application space is classified according to its current state information in order to determine the most likely situational space being occupied at a given point.

4.3 Activity Classification

With the problem defined, we are then required to identify activities of the underpinning context entities over their observable context information. Xu et al. in [37], Pärkkä and Ermes in [38] and Lee in [39]provide approaches for activity recognition and classification over sensor information. For our approach we selected the probabilistic approach described byPadovitz in [31].

Given an entity P bearing a context state $S^{\mathcal{A}} = \{s_1, s_2, \ldots s_i\}$ s_i $\mathcal{A}_i$ the activity $\mathcal{A}_i$ can be determined using a probabilistic heuristics approach, assigning the activity with the highest confidence calculated as:

$$q_1 \sum_{i=1}^{n} \widehat{w}_1 \,.\, \Pr\left(a_i^t \in A_i\right) + q_2 \prod_{k=1}^{m} Pr\left(a_k^t \; A_k\right) \quad 8$$

where $q1 + q2 = 1$. This is discussed in detail in [35]. With this approach, we consider state value membership, information accuracy and the importance of each context attribute to determining an activity. Here, we would observe states in Maryam and identify the current activity being experienced by the user.

The resulting value is the confidence of containment for the state in each known activity, assigning the activity with the highest confidence level. This approach satisfies primitive activity recognition as described in Section 4.2, however higher-level, more complex activities would require a combination of approaches and ultimately human intervention to correctly identify activities that are not readily discernible over raw context information. With the activities identified, we are then required to annotate similarities between pairs of sibling activities within the context domain.

4.4 Activity Similarity

Existing approaches to context proximity do not sufficiently consider the context activity when recommending entities for establishing relationships. For clarity, we consider that an activity is not simply confined to primitive movements and gestures such as *walking*, *running*, *sittinglaying*but rather encompasses higher level notions of activities such as *going to work*, *going home*, *shopping*, *watchingtelevision*, *washing*, *cooking*.

	stand	walk	sit	lay
stand	1	0.7	0.5	0.25
walk	0.7	1	0.4	0.05
sit	0.5	0.4	1	0.70
lay	0.25	0.05	0.70	1

Table 1 Activity Similarity

Such higher-level activities are not necessarily discernable from raw context information but can be derived by applying learning methods, human annotation and assumptions. The underlying context information could be very similar or even identical while the higher-level activities are not. Therefore, in order to consider the effect of the activity on the notion of context relationships, we introduce an activity similarity matrix between the states within an application or domain space.

The similarity matrix, $\mathcal{A}_{ij}^{sim}$,shown inTable 1 defines aMxN matrix of real values between 0.0 and 1.0 conveying the similarity between activities in a domain space. This similarity can be intuitively seen as the ease with which one activity can be transformed into another corresponding; the inverse of the amount of work required for transformationdisregarding of the actual context information observed. We therefore consider similarity between two activities within as a factor of overall entity similarity.

4.5 Relational Proximity

We define the relational proximity $\delta_{(P,Q)}$ between two entities as the similarity between both entities over their currently observable context behaviour. Intuitively, we calculate the ease at which it is possible to transform the behaviour of P to the behaviour of$Q$relative to a transformation window W in a given context domain D. In doing this, we create a point of departure from deriving proximity between pairwise observations, and instead consider the behaviours of the underpinning entities. This addresses issues with the dynamic nature of context entities, where isolated pairwise observations skew relationships due to errors, inconsistencies or unpredictable behaviours. This in turn reduces the churn rate in the establishing context relationships, which are otherwise lost at a higher rate with pairwise observations and thus more stable relationships.

For solving the problem of relational similarity, we adopted the Earth Movers Distance as described by Rubner et al. in [40]. The Earth Movers distance evaluates the similarity between two multi-dimensional distributions in some feature space, in our case the activity space. The EMD, given a ground distance, “lifts” the distance between these individual features into full distributions. It can be likened to moving mounds of earth to filling empty holes in the ground, calculating the minimum amount of work required to transpose the mounds into filled holes.

Computation of the EMD originates in the well-researched transportation problems where, given several suppliers and a corresponding set of consumers each with a limited capacity. The problem is then to determine the most cost efficient way to move good from the supplier to the consumer such that the demand is optimally met.

For relational proximity, the points of our distributions are represented as the observable context states for each window W with the resulted weighted graph modeling the similarity between any given pairs of entities(P, Q),with the weighted edges being the activity similarity between P and Q. With tis model, the EMD algorithm is then applied to derive the largest possible transformation between P and Q. As described by Rubner et al. in [40], the problem is therefore modelled as:

Given two entities P and Q with context observations such that:

$P = \{(s_1 \square\ \mathcal{A}_1^{\mathcal{D}}|c_1), (s_2 \square\ \mathcal{A}_2^{\mathcal{D}}|c_2), (s_3 \square\ \mathcal{A}_3^{\mathcal{D}}|c_3), \ldots (s_i \square\ \mathcal{A}_i^{\mathcal{D}}\,|c_i)\}$where P is the observed context behavior of entity P and s is each state observed for P under a window W, c is the confidence that $(s_1 \square\ \mathcal{A}_1^{\mathcal{D}})$

$Q = \{(s_1 \square\ \mathcal{A}_1^{\mathcal{D}}|c_1), (s_2 \square\ \mathcal{A}_2^{\mathcal{D}}|c_2), (s_3 \square\ \mathcal{A}_3^{\mathcal{D}}|c_3), \ldots (s_i \square\ \mathcal{A}_i^{\mathcal{D}}\,|c_i)\}$whereQ is the observed context behavior of entity P and s is each state observed for Q under a window W, c is the confidence that $(s_1 \square\ \mathcal{A}_1^{\mathcal{D}})$

D = d_{ij} is the ground distance between states across each observation. Here, each context attribute a , has a corresponding distance function $\mathcal{F}_a^{\mathcal{D}}$ is a function for deriving the distance or similarity between two attributes of type a. This measure is attribute specific or even attribute-domain specific and derives a value between the attributes that most suitably reflect the requirements of the distance. For the example shown in Figure 5, this distance could either be in line of sight or distance as measured by walking.

The ground distance d_{ij} is then taken as the distance between pairs of s_i, s_j calculated as:

$$d_{ij}(s_i, s_j) = \frac{\left(\sum_{k=1}^{n}\left[w_a * \left|\mathcal{F}_a^{\mathcal{D}}(a_i, a_j)\right|^r\right]_k\right)^{\frac{1}{r}}}{\left(\sum_{k=1}^{n}\left[w_a * \left|\mathcal{F}_a^{\mathcal{D}}(a_i, a_j)_{max}\right|^r\right]_k\right)^{\frac{1}{r}}} \text{ where } a_i \square \mathcal{A}_i^{\mathcal{D}}, a_j \square \mathcal{A}_j^{\mathcal{D}} \qquad 9$$

Where w is the weighting for each attribute.The value of r can be adjusted to reflect the perceived distance between P and Q as shown by Shahid et al. in [34]. The distance is normalized with respects to the maximum distance between states in both activities. Our measure of proximity therefore logically subsumes the existing$Lp - norm$ approaches. For ease of calculation we take $d_{ij} = (1 - d_{ij})$.

Having selected PQ and D, we construct the weighted graph, Gthat models the flow of context between P and Q positioning the context states of P and Q as *consumer–supplier* pairs with the *ground distance* being the distance between each state.

Our goal is then to determine the maximum possible flow of context**F** = $\lfloor f_{ij} \rfloor$, between s_i, s_j of P and Q that minimizes the overall context transformation cost, where:

$$WORK(P \rightarrow Q, \boldsymbol{F}) = \sum^{m} \sum^{n} f_{ij} d_{ij} \quad (10)$$

The following additional constraints are considered:

1. $f_{ij} \geq 0 \qquad 1 \leq i \leq m, \; 1 \leq j \leq n$
2. $\sum_{i=1}^{m} f_{ij} \leq P \quad 1 \leq i \leq m$ (11)
3. $\sum_{j=1}^{n} f_{ij} \leq Q \quad 1 \leq j \leq n$
4. $\sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij} = min\left(\sum_{i=1}^{m} P, \sum_{j=1}^{n} Q\right)$

The first constraint permits the transformation and hence the proximity from $P \rightarrow Q$ and not the opposite. The second and third constraints limit the transformation $P \rightarrow Q$ to the maximum number of context observations made for P and Q respectively. The final constraint forces the maximum transformation possible between both entities. This is called the total flow. For our algorithm, the flow is the activity similarity between pairs of P and Q. This is then solved as an instance of the transportation problem. The EMD as described in by Rubner et al. in [40] finds the minimum during the transportation problem, however for simplicity we inverted the distance and found the maximum transformation the co-efficient of the minimum cost-flow.

The Context Proximity

After solving the transformation problem and deriving the optimal context flow $\boldsymbol{F}$, the context proximity, $\delta_{(P,Q)}$, is the earthmover's distance defined as the work done between both entities normalized by their total flow.

$$\delta_{(P,Q)} = \left(\sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij} d_{ij} \right) * \left(\sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij} \right)^{-1} \quad (12)$$

We normalize the distance using the maximum possible flow between P and Q. Since sampling of context entities is done over a window W, the normalization factor avoids scenarios where more active entities with larger sample sizes are less favoured to less active, more stable context entities. It is important to note, that $\delta_{(P,Q)}$ is indifferent to the size of both sets of observations and permits partial similarity where the behaviour of P is subsumed by the behaviour of Q.Therefore $\delta_{(P,Q)} \mid w = \delta_{(P,Q)} \mid \frac{1}{2} w$.This is a distinct advantage of our approach and excess observations are inherently discarded.

The Completeness Constraint

We acknowledge the existence of domains where the indifference to partial matching is not desirable and the completeness of containment is important for relations such that $P \cap Q = P$ □ Q. For these scenarios, earlier work such as we extend the proximity measure to be normalized relative to the maximum potential transformation of either P or Q, such that

$$\delta_{(P,Q)} = \left|\left(\sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij} d_{ij} \right) * \left(\sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij} \right)^{-1} \right| \left| \sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij} = max\left(\sum_{i=1}^{m} P, \sum_{j=1}^{n} Q \right) \qquad 13$$

The Confidence Constraint

Citing the inherent inaccuracies context information, we further add a confidence constraint to adjust the perceived proximity. This allows us to consider scenarios over unreliable context information. To accomplish this, we adjust the distanced_{ij} to reflect the potential errors in the underlying context information such that:

$$d_{ij} = d_{ij} \square \left| c_{ij} + \left((1 - c_{ij}) * (1 - k) \right) \right| \; where \; c_i = \sum_{i=1}^{n} \widehat{w}_1 \, . \, \Pr\left(a_i^t \in A_i \right) \qquad 14$$

This confidence measure is described by Padovitz et al.and considers the accuracy of the sensors using several factors described in [35]. However for scenarios where the confidence is a trade off, we, we add the confidence factor k, which allows us to adjust this trade-off. We then proceed to find the transformation after assigning the new values for d_{ij}.

TheTemporal Constraint

Scenarios involving context-bearing entities may require the time displacement between states as a factor for establishing context relationships. For calculating proximity considering the temporal constraint, we adjust the size of the observation window W. We note that when W is at its minimum, then $Lp\,(P, Q) = EMD\,(P, Q)$. By adjusting we permit wider variations in the temporal differences between state observations reducing the time constraints. Increasing Wincreases the constraint on the nearness of observations with respects to their temporal attribute.

The Continuity Constraints

Finally, we derive the measure of proximity stability between two entities as a means of filtering entities with unstable relationships. Two participants in our play*Maryam* that maintain a stable proximity over time are considered to be better candidates for establishing a relationship. Equally, we could be interested in those participants that occasionally have closer relationships, e.g., we might be interested in filtering out friends. The first constraint finds the standard deviation of $\delta_{(P,Q)}$ as the window W progresses. We call this the co-relational constraint defined as:

$$R_{(P,Q)} = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} \left(\delta_{(P,Q)_i} - \mu \right)^2} \; and \; \mu = \frac{1}{N} \sum_{i}^{N} \delta_{(P,Q)_i} \qquad 15$$

Where the greater the deviation, the unstable the relationship between is. Secondly, we derive the convergence factor between two entities; the rate at which their context proximity is converging defined as:

$$Cf_{(P,Q)} = \frac{\Delta \delta_{(P,Q)}}{\Delta W} \qquad 16$$

With this factor we can consider entities that are diverging or moving apart or entities that are continually getting closer. In our play *Maryam*, we can consider people that are moving towards the same scene or adopting the same pattern of visiting successive scenes.

4.6 Algorithm

```
foreachentity P,do:
for each domain D to which P belongs, do
initialize M, the activity similarity matrix forD
foreach attribute a in Ddo
select FD, the attribute distance function for each attributea
Assign weightw_a for each attribute a
       formulate distance functiond
select the set of state observations, s  within window W
deploy distance function according to aggregation strategy
distributed/centralized
foreach aggregation point, do:
       for eachfounded entity Q in D, do
       select the set of state observations, S within window W
for each state s in S, do
              calculate confidence of containment, c
              assign to activity A with confidence c
              for each attribute a in state s, do
              calculate FD(a-a) and FD(a-a)max
           calculate the distance between Ps and Qs
find the optimal flow ∑_{i=1}^{m} ∑_{j=1}^{n} f_ij d_ij as a transportation problem
calculate the EMD(P → Q)
        adjust for each required constraint
       calculate change rate and deviation
return Q and P --> Q
```

5 EVALUATION

We implemented our algorithm as described in Section 4.6 for evaluation and comparison to other simpler approaches described in Section 2. We chose to evaluate this against the Lp type metrics suggested by earlier research and highlight the advantages of our approach. However, evaluating context based similarity measures lack the existence of both a standard data set for evaluation as well as a standard evaluation methodology. For our simulation we chose the Opportunity Activity Recognition Challenge dataset [41] that contains sensor information from body nets and associated activities tagged for each context observation made.

Firstly, we defined an application domain space, as described in Section 4.2, dividing this space into the situational sub-spaces defining each activity within the domain. Additionally, we created an activity similarity matrix for the domain space, defining the similarities among all constituting activities. Secondly, a context entity was created as the requestor for context relationships and a set of competing entities created with corresponding data points and random context observations. For each simulation, each observed state is classified as an activity and the most relevant result, entities that are most similar in context behaviours, are selected and annotated. Our establishing algorithm is then applied across the collection of entities and states returning the top 10 entities from the corpus. The alternative solutions are applied to each simulation. Here, we used the Euclidean distance as the chosen $Lp - norm$ pairwise evaluation method.

The evaluation method chosen was the precision method, more specifically, P@ top N, more commonly associated with document and web content similarity evaluation. Here, we evaluate the performance or our algorithm by the number of relevant results with the total results returned within a cut of point such that:

$$P@N = \frac{|relevantresultsinN \cap resultsinN|}{|totalresultsinN|}$$

Comparison of $\boldsymbol{Lp - Pairwise}$and $\boldsymbol{\delta_{(P,Q)}}$

Figure 8 shows the P@10 comparison for both approaches. Here, our algorithm outperforms the Lp metric as a measure of context similarity over time. This is as a result of the cross-bin property of the earthmover's distance, selecting more similar context observations over the chosen window as opposed to the bin-bin matching behaviour of the Lp norm approaches. This is more reflective of the natural dynamic behaviour of context and context bearing entities, which are not fixed but are continually changing and evolving.

This more natural approach suggests the establishing of context relationships over dynamic context behaviour, observed and compared over time and can more readily handle brief inaccuracies in context information, sporadic context behaviours that are in comparison to the general trendrelatively insignificant. The Lp norm underperforms as it is influenced by minor deviations through forced bin-bin comparisons. Here, the proximity $\delta_{(P,Q)}$ can be intuitively seen as the ease at which one set of context observations$P$ can be transformed into another set of context observations Q, and subsequently the context similarity between P and Q.

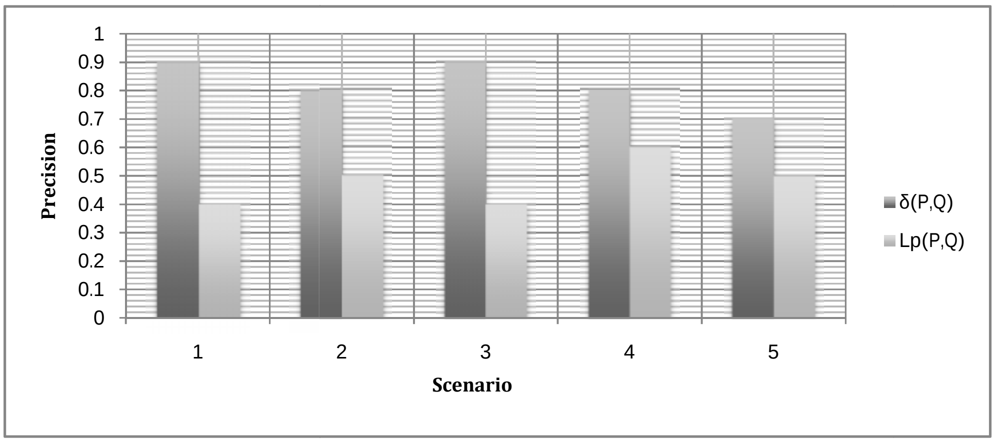

Figure 8 Precision

Effect of Measuring Behaviour and Activity

We evaluated the significance of considering the current activity on the precision of our context proximity measure. For each of the five scenarios we compared the precision of each of the following methods: Lp –based pairwise state observations, $\boldsymbol{\delta_{(P,Q)}}$ without considering activity and $\boldsymbol{\delta_{(P,Q)}}$.This is show in in Figure 9.Measuring proximity over behaviour generally performed better when compared to the Lp-norm distance measures even where the activity is not considered as a factor. This approach more naturally extends the notion of context proximity as is perceivable from a human perspective as similarities over patterns of behaviour.

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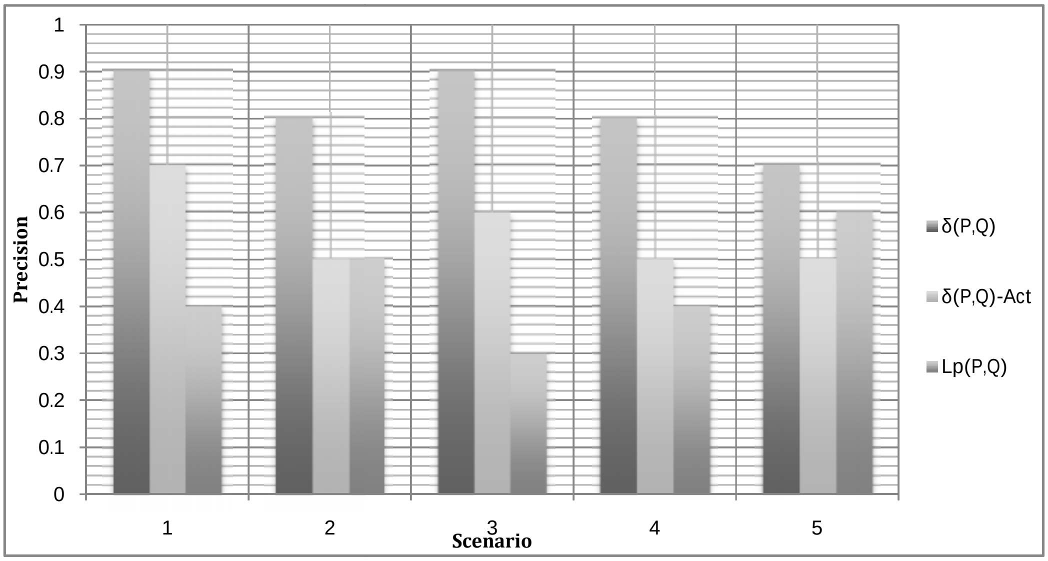

Figure 9 Effect of Activity

following methods: Lp –based pairwise state observations, $\boldsymbol{\delta}_{(P,Q)}$ without considering activity and $\boldsymbol{\delta}_{(P,Q)}$. Measuring proximity over behaviour performed better when compared to the Lp-norm distance measures even where the activity is not considered as a factor. By achieving higher precision with the activity being considered, it shows that our approach more naturally extends the notion of context proximity as is perceivable from a human perspective as similarities over patterns of behaviour. The difference between the Lp-based measure and the $\boldsymbol{\delta}_{(P,Q)}$ without considering activity is relatively less significant than the approach considering both factors. Observing the behaviour without giving consideration to the activities being undertaken by each entity therefore reduces the precision.

Modifying the Observation Window *W*

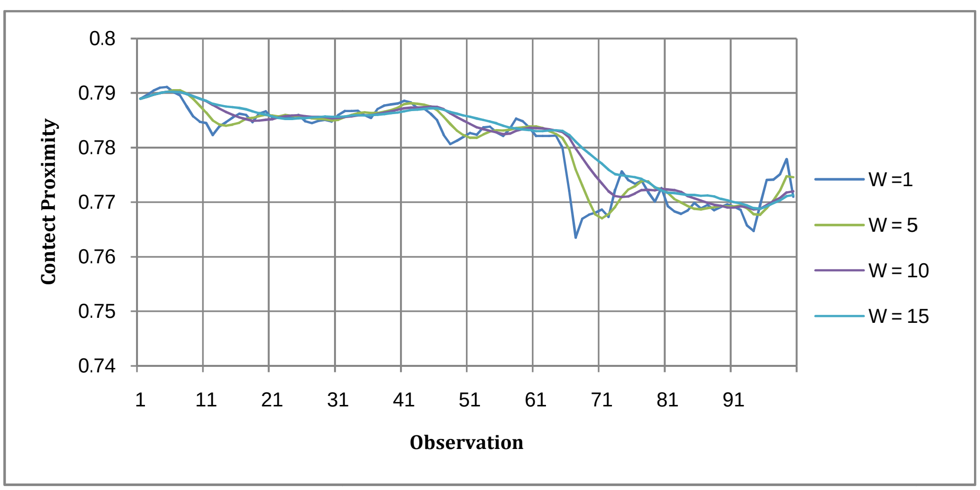

Figure 10 Adjusting *W*

We adjusted W, the observation window and evaluated its effect on the derived proximity. Where W=1, the effect is the same as pairwise observations using the underlying distance function adjusted for activity similarity. As can be seen on Figure 10, we lift a more generalized behaviour from the underlying dynamiccontext behaviour, reducing the impact on localized changes such as information errors or loss on establishing and maintaining context relationships. The behaviour is less affected by localized changes in proximity, i.e. the curve was smoother. The net effect being that we are able to maintain context more stable relations over behaviours while still reflecting the general underlying pairwise associations between entities.

Completeness Constraint

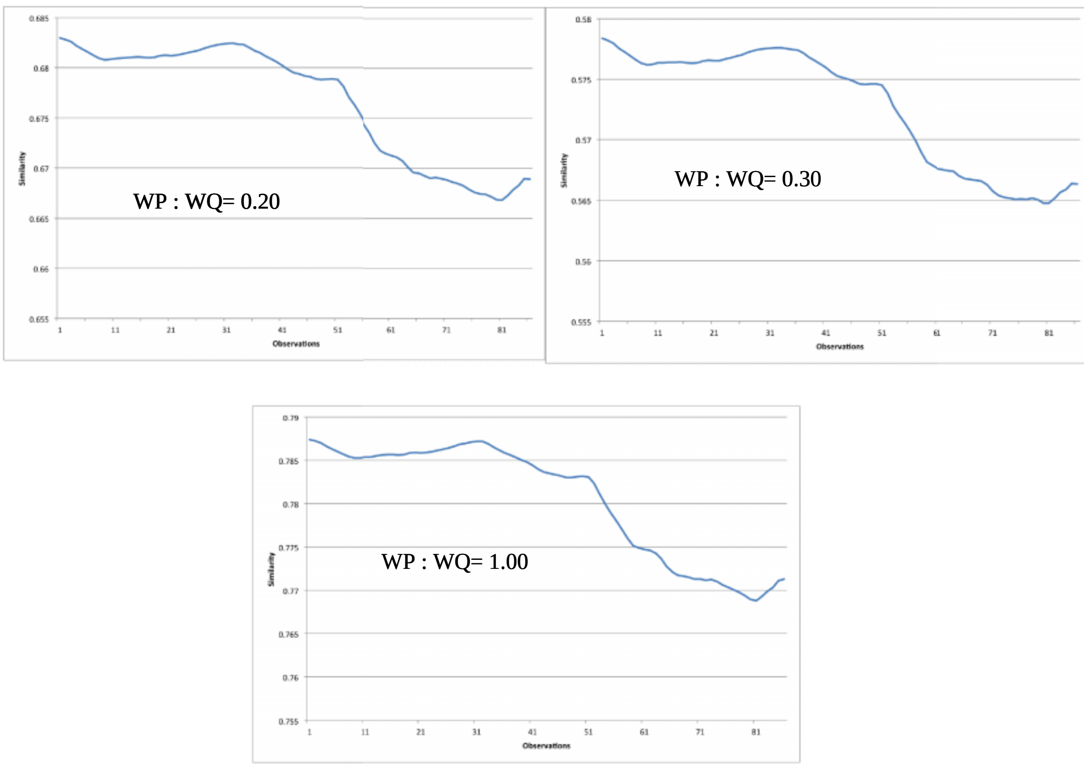

Figure 11Completeness Constraints

We adjusted the window size independently for each entity and compared the resulting proximity measures shown in Figure 11. We show the ratio of the observation window W for each evaluation. As shown, the general behaviour lifted from the underlying context information remained, however the real proximity values are adjusted to reflect the incompleteness in context information being compared as would be experienced in highly dynamic scenarios. We are however still able to compute partial similarities over the missing information, still reflecting the general context behaviour between the two entities.

Relationship Churn Rate

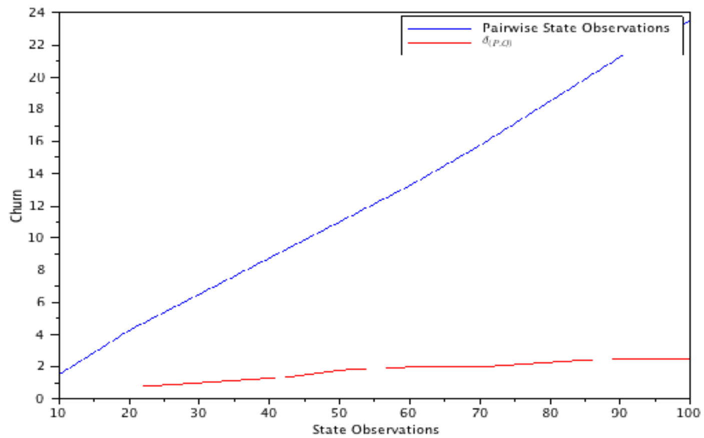

Figure 12 Relationship Churn Rate

Establishing context relationships over highly dynamic data can result in a high churn rate with respects to the creation and destroying of relationships as context continually changes and evolves. We establish context relationships between the most similar entities and evaluated the effect of our approach on the churn rate context relationships when compared to existing pairwise relational approaches.

These results are shown in Figure 12. The churn rate over pairwise relationships grows exponentially as the number of context states observed grows. This is as a result of the dynamic behaviour of context entities, along with inaccuracies in the underpinning sensor informationresult in high rate of removal of context relationships that are perceived to be no longer valid. By establishing relationships over behaviour, we add tolerance for these changes and therefore improve uponthe previous approaches reducing the need to remove and re-establish context relationships at a faster rate. This is seen more clearly in Figure 10, where we lift the context relationships into a behaviour creating a smoother interaction between entities.

The Continuity Constraints

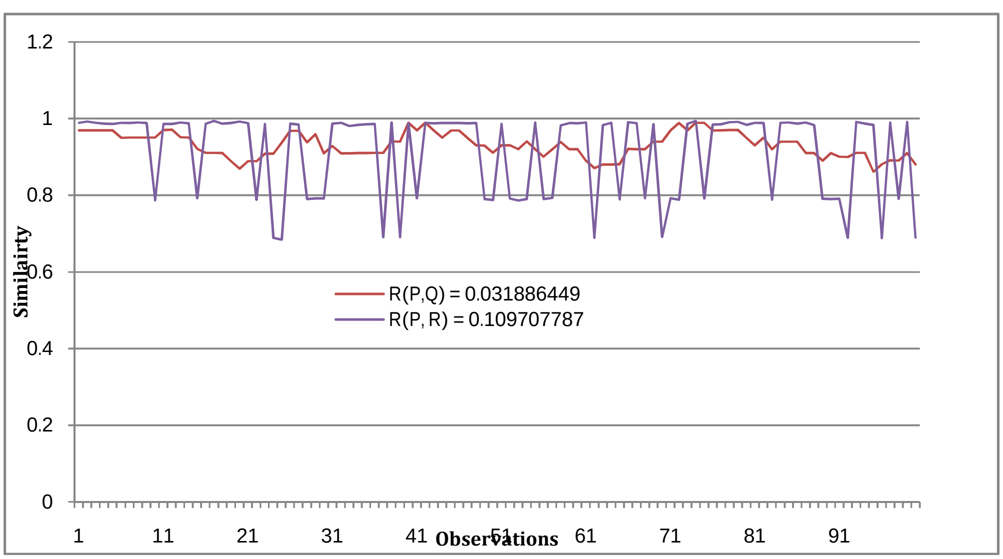

Figure 13 Continuity Constraints

We further derived the continuity constraints according to Section 4.5 and illustrate this in Figure 13. The graph shows the change in context similarity as observations progress. Here we show how this can be used to identify more stable relationships between entities identified as having a lower overall value for $R_{(P,Q)}$. This in turn identifies better candidates for establishing context relationships over time. However, an entity might be interested in more sporadic entities in which a higher value for $R_{(P,Q)}$suggests a better candidate, such as scenarios where we want to exclude entities within our personal network in favour of discovering newer entities.

6 CONCLUSION

In this paper, we presented an approach to establishing context centric relationships between entities on an Internet of Things. This satisfies the requirements of a context relational model supporting the establishing, adjusting and exploiting of context-based relationships in massive immersive environments. With this approach, we are capable of identifying candidate entities that can be fused to realise new user experiences and deliver more immersive applications and services.

We proposed an improved context interaction model that abstracts from location as the overarching indicator of context and proposed a context relational measure to determining related context entities. Our measure consists of aVDM-based distance function, which considers the significance of each attribute in determining context proximity. Secondly, the proposed interaction model establishes relationships over the dynamic behaviours of interacting entities, which continually evolve with respect to their engagement in immersive environments..

With a pairwise distance and Activity-Activity similarity, we then subsumed our distance measure in a more general EMD-based proximity. Here, sets of behaviours are modelled as consumer-supplier pairs in a transport problem where the EMD then lifts the distance between the constituting states into a distance between the context behaviours of both entities. Thisis the ease at which one set of behaviour can be transformed into the other. We added optional constraints for confidence in the context information, a completeness constraint for situations where a full behavioural match is desired.

Our algorithm outperformed other approaches for deriving context proximity when compared using Top@10 analysis method.We showed that our model functions over partial observations, successfully lifting the general context behaviour while optionally penalising for incompleteness. This gives support for missing context observations, comparing entities over the information that is available. We demonstrated that as we increase w, we lift more general behaviours patterns between two entities over the underlying context behaviours allowing us to create the same types of relationships with less sporadic interference. Finally, we showed that our algorithm outperformed previous approaches with respects to the churn rate of context relationships or the rate at which relationships are established and destroyed.

With such a model, we can now examine approaches for adjusting the derivable context relationships and exploiting these relationships to create enhanced immersive environments. Futurework includes identifying additional parameters that can improve the detection and stability of context relationships, identifying optimal parameters for scenarios.

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