Representing and Reasoning about Cultural Contexts in Intelligent Learning Environments

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Abstract

There is a growing interest within educational research to produce culturally-aware intelligent learning environments (ILEs) that capitalize on the affective benefits of positive cultural resonance and avoid the counter-productive effects of culturally ignorant designs. Several challenges arise when attempting to produce culturally-appropriate content for ILEs. These stem from the need for semantic representations of cultural conceptualisations that go beyond folk approaches, have sufficient details for intracultural reasoning, and which can be matched with the cultural backgrounds of students who use these ILEs. This paper tackles these challenges firstly through the formalism of a lower-level ontology for describing the cultural semantics commonly used in educational content and secondly with a software component for reasoning about this ontological knowledge in relation to student cultural backgrounds. An application was developed to test the practicality of the approach and assess its utility in locating culturally-appropriate educational resources for students. The evaluation results revealed that the majority of content selections made by the system were rated as highly appropriate by 90% of the participants on average and confirmed the viability of the approach.

Introduction

Cultural contexts for the purposes of this paper refer to the conceptualisations and meanings associated with the conditions and environments within which human existence and perception occurs. This definition stems from the various viewpoints expressed in the literature which suggest that culture has a dynamic nature governed by rules, and is attributable to natural and artifactual entities (Jost and Hamilton 2005; Sharifian 2003). Individuals typically attach a cognitive load or meaning to the conditions and environments within which their perceptions occur. The recognition that takes place when something familiar is observed by an individual results in cultural resonance within that person especially when cultural beliefs and perceptions manifest in a tangible way. This means that individuals react to their immediate environment depending on their cultural interpretation, which can be positive or negative, of what they see, hear and feel.

The need within educational research to capitalize on the emotive benefits of positive cultural resonance and avoid the counter-productive effects of negative cultural resonance has been steadily increasing due to globalization. As such approaches are emerging in the literature for integrating cultural contexts into Intelligent Learning Environments (ILEs). One challenge that arises when attempting to produce culturally-aware content for ILEs is differentiating between folk approaches and legitimate cultural conceptualisations. Folk approaches stem from subjective, personal descriptions and perceptions of cultural semantics. Henrich and McElreath (2007) explain that cultural contexts are cumulatively built up over time and are associated with individuals who belong to groups that observe and adopt specific beliefs, behaviour, customs and language references. True cultural conceptualisations therefore cannot be defined using individual perspectives because they are created by group-level perceptions (Sharifian 2003). Furthermore, these conceptualisations require language neutral representations that separate cultural details from high level abstractions (Agnesund 1997) in order to go beyond cosmetic, tokenistic use of cultural contexts.

In order to avoid the pitfalls of folk approaches, culturally-aware ILEs require computational frameworks that are grounded in formal cultural models and theories (Blanchard and Mizoguchi 2014) and have been empirically evaluated using intercultural and intracultural evaluation (Mohammed and Mohan 2013b). With these requirements in mind, this paper describes an approach that aims to formalize the cultural semantics commonly used in educational content at an appropriate level of granularity for capturing subtle but critical differences across student cultural backgrounds. Firstly, by building on existing research, an

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ontological annotation scheme was developed for describing conceptual categories of cultural semantics relevant for use in ILEs. Next, a software unit is described that uses a combination of techniques from faceted semantic search and relational instance-based search to reason and return a ranked list of resources that are considered to be culturally appropriate for a given student. The implementation details and tools used to create the ontology and an application for testing the approach in this paper are discussed. The procedure and the results of an experimental study conducted using the application are outlined. An analysis of the findings and empirical evidence reported in the study is done together with a discussion of the significance of the results and the approach taken. The paper concludes with a summary of the research contributions made and the future plans for advancing the research ideas expressed.

Representing Cultural Semantics

Observable manifestations of culture have been referred to as cultural elements or more specifically contextual elements (Blanchard and Mizoguchi 2008; Mohammed and Mohan 2013a). An analysis of various frameworks, experience reports, methods and techniques described in the literature for representing and using culture in educational systems led to the identification of the high-level categories in Table 1 which represent language-independent abstractions of real world phenomena

High-Level	Description of High-	Example(s)
Concept	Level Concept	
Tangible	Physical entity that is or	Plants, Insects,
Animated	has been alive	Animals
Entity		
Tangible	Physical inanimate enti-	Artefacts,
Inanimate	ty that can be seen and	Objects, Food
Entity	felt	
Abstract	Things and representa-	Music, Smell
Inanimate	tions that cannot be	
Entity	seen or felt	
Tangible	Physical space, loca-	Town, City,
Locale	tion, area or place	River
Observable	Feeling of an entity,	Feeling,
State	state of affair of an en-	Situation
	tity	
Observable	Occurrence or happen-	Festival,
Event	ing involving one or	Accident, Trans-
	more entities	action
Observable Ac-	Step(s) taken by an en-	Verbs
tion	tity or involving an en-	
	tity	
Observable	Quality or trait of an	Adjectives
Characteristic	entity, locale, event, or	
	action	

Table 1 Conceptual Categories of Contextual Elements

Using these abstractions, the Contextual Element Resource Annotation (CERA) ontology was designed to meet the need for a language-neutral markup scheme. Figure 1 shows a portion of the ontological signature of CERA. The More Advanced Upper Ontology of Culture (MAUOC) (Blanchard and Mizoguchi 2014) and SUMO¹ (Suggested Upper Merged Ontology) were used to build the semantic backbone of CERA. SUMO provided a comprehensive hierarchy of spoken human languages used by members of a contextual group and helped to define the language origin of linguistic concepts that are used to describe one or more contextual elements. The MAUOC on the other hand, provided high-level classifications of entity abstractions namely Physical Entity, Continuant Entity, Abstract Entity, and Semi-Abstract Entity concepts which were subsumed by the Entity concept in CERA. These were used to classify the eight types of high-level concepts from Table 1.

A contextual element is represented in CERA partly by its lower-level lexical value(s) and partly by its abstract upper-level concept(s) using the *is_known_as* relationship. This abstraction is in keeping with the conceptuallinguistic approach recommended by Agnesund (1997) and follows a single-ontology approach for representing localised natural language as in the DOSE platform (Bonino et al. 2004). The *Resource* concept connects an educational resource to its instantiation of the CERA ontology and identifies all of the *Entity* concepts depicted in the educational material.



Figure 1 Subset of CERA Ontology Signature

Sharifian (2003) explains that over time subsets of cultural conceptualisations become mainstream within cultural groups in society such that an individual's proximity to and participation in these groups reflects his/her degree of

¹ http://www.ontologyportal.org/

cognition of such beliefs. Mohammed and Mohan (2013a) describe an approach for modeling an individual's membership to cultural groups that is based on this theory using several categories of cultural context. Their contextual student model was used as the basis for the Setting, Economic Activity, Environment Type, Geographic Region, Religious Group and Ethnic Group concepts in CERA. These concepts are thus crucial for defining the relationship between an individual's cultural background and the cultural semantics surrounding contextual elements. Figure 1 therefore illustrates in particular how the Entity concept derived from the MAUOC relates to these aspects of cultural context. The Contextual Group concept ties together conceptualisations at a country level. This is important because many models use country-level categorizations as a starting point for drilling down to deeper classifications of cultural semantics. Finally, directed relationships connect the concepts in a meaningful way and set up patterns that can be used for reasoning about the entities represented.

Design of the CER

A contextual element repository (CER) was designed to provide the underlying functionality for making use of the CERA ontology when representing and reasoning about cultural contexts. The CER is part of a larger system called ICON (Instructional Content Contextualiser) for generating dynamic cultural contextualisations in ILEs and relies on a cultural contextual student model described in (Mohammed and Mohan 2013a). The model defines intracultural estimates of student membership to various contextual groups and was integrated into the CER for cultural filtering of contextual elements based on appropriateness. As mentioned earlier, some of the CERA concepts were motivated by these group level categories and now provide points of semantic overlap for reasoning in the CER. Figure 2 shows the components of two core units of the CER: a Resource Annotation Unit and a Resource Retrieval Unit.



Figure 2 Components of the CER Core Units

The Resource Annotation Unit consists of three components which work together to generate instantiations of content-descriptive ontological metadata that capture the cultural semantics of the contextual elements depicted in/by a learning resource. The Annotation Core provides an API and a GUI for interacting with this unit. The CERA Metadata Structure stores the CERA ontology and is used by the Metadata Generator for creating, modifying and saving the instances and relationships in instance ontologies. These annotations apply to entire resources and map low level visual features in images and parts-of-speech in text to corresponding high level conceptual representations. Resources are therefore described using both localised natural language and abstract conceptual categories.

The Resource Retrieval Unit conducts query expansion and metadata-based resource retrieval using the five components shown in Figure 2. This unit allows the CER to select resources, ranked by cultural appropriateness for a student that can be used in ILEs. Queries processed by the Query Handler are based on lexical search terms, student cultural backgrounds or a combination of both. Instance ontologies for each resource are loaded using the Metadata Parser into the Retrieval Core. The Weight Estimator analyses the ontological signature of each instance ontology using an instance-based method (Wang et al. 2012) that checks for matches between the student's cultural student model data and specific relationship-instance patterns in the signature of the CERA instance ontologies shown in Figure 1. The semantic context of an element is therefore mapped from geographical, religious, ethnic, and terrain/setting perspectives to the demographic and cultural background of the student. Hollink, Schreiber, and Wielinga (2007) show that as more semantic relationships are used to expand a query, optimally up to four nodes long, the higher the recall of the query. Also the type of relationships (subsumption and relational) between the instances makes a difference and this was accounted for in this approach through the use of specific patterns.

Weights are assigned based on how closely a resource's contextual group categories (instance values) align and map to those in the student's cultural background using the following algorithm.

```
WEIGHT-ALGORITHM
for resource R in CER{
   for each contextualEstimate CE in CSM{
      Calculate and assign weight W<sub>CE</sub> to R for
      estimate CE.
   }
   Score S = sum of all weights for R.
   If S > score of the lowest rated resource in
   the list then insert R into list of selected
   resources
  }
```

The approach is similar to the cultural interest score generated by Blanchard (2009) but can be applied to textual resources in addition to multimedia resources. For each contextual group estimate in the student's cultural student model, the Retrieval Core analyses the values of the estimates for matches with the metadata values for a particular resource. For example, if a contextual element is commonly found in the North-West region of a country and if the student's dominant geographic region is North-West then the element is a potential match and is scored based on the strength of the student's association to the North-West region of his/her country. The element will then be checked for matches with the remaining contextual estimate categories. Resources are scored based on the overall weights assigned and the CER then returns a list of resources ranked by cultural appropriateness for the student.

Implementation

A contextual element selection (CES) application was built to evaluate the design described in the previous section. The application was implemented using Java which facilitated seamless integration of the annotation and retrieval units with existing Java-enabled ontological tools and technology namely Protégé (Protégé 2013) and the OWL2 API (Hitzler, Krötzsch, and Rudolph 2009).

In order to reduce developer bias for particular contextual elements, sixty pictures featuring cultural conceptualisations were selected from the national library website of the target country, Trinidad and Tobago. The semantic conceptualizations depicted in the pictures were then annotated using instantiations of the CERA ontology. Instances of conceptual classes in CERA were created using the OWL2 API to reflect the entities depicted in the image resources and their contextual background associations. For example, Figure 3 shows an example of one of these pictures followed by a snippet of its accompanying CERA ontological metadata. It shows a picture of a type of fruit (Carambola) commonly knows as a *Five Finger* throughout Trinidad and Tobago.



Figure 3 Example of an Image Resource in the CER for the Cultural Context of Trinidad and Tobago

```
<owl:NamedIndividual>
 <rdf:about="../cera.owl#5_finger.png">
  <rdf:type rdf:resource="../cera.owl#Resource"/>
 <contains
    rdf:resource="../cera.owl#Five-finger"/>
</owl:NamedIndividual>
<owl:NamedIndividual
 <rdf:about="../cera.owl#Five-finger">
 <rdf:type
    rdf:resource="../cera.owl#Food"/>
  <is relevant for
    rdf:resource="../cera.owl#Agricultural"/>
  <is common to
    rdf:resource="../cera.owl#South"/>
  <has setting rdf:resource="../cera.owl#Rural"/>
 <is known as
    rdf:resource="../cera.owl#Carambola"/>
  <is known as
    rdf:resource="../cera.owl#Star-Fruit"/>
 </owl:NamedIndividual>
```

The URIs in the code snippet were shortened for easier reading. The code snippet specifies that the image file named 5_finger.png is an instance of the Resource conceptual class and it contains one or more entities referred to as a Five-finger. The Five-finger entity is a type of Food and has specific cultural contexts associated with it (common in agricultural situations, rural settings, and can be found in the Southern part of the country). Other cultural references for a Five-finger are Star Fruit in Trinidad and Tobago and Carambola outside of Trinidad and Tobago. These references were included in the metadata using the is_known_as relationship between the Entity instances referring to the Five-finger entity.

Using a cultural student model as a basis, the CES application selects ten textual elements and eight image resources that depict localised contexts and presents these to the students who then evaluate the selections and enter feedback data. So, the *Five-finger* resource would be matched with students whose cultural backgrounds feature strong overlaps with rural, agricultural settings common to the southern parts of Trinidad and Tobago. This was done by mapping the alignment of CERA instances in a resource's metadata to equivalent instances in the student's cultural model described in (Mohammed and Mohan 2013a) and then reasoning about the strength of any overlaps found using weights determined by the contextual group estimates described earlier.

Experiments and Results

A study was conducted using the CES application to find out whether contextual elements (text and images) selected using the approach described in this paper were appropriately matched with a student's cultural background.

Participants

Fifty-six (56) undergraduate students, 28 males and 28 females, from the University of the West Indies in Trinidad and Tobago voluntarily participated in the study. The students were enrolled in Computer Science and Information Technology undergraduate degree programmes and were aged between 18 and 25 years (mean=19.55, s.d. = 1.48). 35.7 % were of East Indian descent, 28.6% were of African descent, and 35.7% were of mixed ethnicities. The religious breakdown was as follows: Christian (66.1%), Hindu (19.6%), Muslim (8.9%), and None (5.4%).

Procedure

Participants in the study were first asked to enter their personal demographic information into the system which was used to create their cultural student models. Next, the participants logged into the CES application which loaded the student models and initiated the selection of contextual elements using the approach described in the paper. Each participant was presented with a set of 18 contextual elements (10 text-based and 8 image-based) and was asked to rate the selections for appropriateness. Element appropriateness in the study referred to how fitting the participant considered the element to be for use in educational content such as exercises or problem descriptions, how offensive or inoffensive the element was to the participant, and how suitable the element was for the participant given his/her cultural background. In addition, participants were required to describe their impressions of the elements together with any other feedback they wished to give about the appropriateness of the elements presented. Usage logs were uploaded to a server by the participants upon completion of their evaluation. These were then retrieved from the server for analysis.

Results

The participants rated the contextual elements for appropriateness using a 4-Point Likert scale and the results are shown in Table 2 below.

	Text	Image
Very Appropriate	83.2%	96.8%
Mostly Appropriate	8.2%	2.2%
Inappropriate	6.8%	0.5%
Very Inappropriate	1.8%	0.5%

Table 2 Percentage of Appropriateness Ratings for Contextual Element Selections

The majority of ratings were in the 'Very Appropriate' and 'Mostly Appropriate' categories. A chi-square test performed on this data resulted in $\chi^2 = 50.19$ for 3 degrees of freedom, p < 0.001 and Cramér's V (φ_c) = 0.2231. Since the value of χ^2 is greater than $\chi^2_{0.005}$ =12.838 the null hy-

pothesis of independence is rejected which means that there is a dependency between the content type of the contextual elements and the appropriateness ratings given by the students. The strength of this relationship is indicated by the value for φ_c which implies a moderate and significant association.

Analysis and Discussion of Results

The results showed that the majority of the participants rated the selections as 'Very Appropriate' (90%). There were significant associations between the content type (text or image) and the appropriateness ratings given by the participants for the contextual elements referenced or depicted. Text-based content received a lower score for appropriateness (83.2%) compared to images (96.8%). A study conducted by Peesapati, Wang, and Cosley (2010) gives insight into a possible explanation for this result. They reported that people felt more closely associated to photographs that depicted aspects of their own cultural backgrounds. The participants probably had a similar reaction and felt closer to the cultural references in the images than to those in the text-based content.

In addition, the descriptive feedback given revealed that in many cases the participants did not know or could not recall the localised terms for entities depicted in the images but yet they were aware of cultural semantics associated with the images. This observation could also account for the higher incidence of the lower appropriateness scores for text-based content since if a participant is unfamiliar with the localised term used for a contextual element then he/she would be more likely to rate it lower for appropriateness. This is seen in the larger number of inappropriateness. This is seen in the larger number of inappropriateness (0.5%). Furthermore multiple interpretations of a localised textual term led to possible misconceptions and consequently lower appropriateness ratings.

These results confirm two points related to the goals of the research in this paper. Firstly, the results confirm that the CERA ontological metadata structure was appropriate for representing the cultural contexts expressed in educational materials since the element selection was based on this metadata scheme. Secondly, the results show that the weighting algorithm and semantic search technique used in the selection process worked well since the selections were highly rated for appropriateness. The results also highlight the importance of using culturally-appropriate content especially for text-based materials which have more room for multiple interpretations and consequently different outcomes with respect to cultural resonance.

Several assumptions were made when carrying out this research and there were limitations to the approach used. Images were sourced from the national library of Trinidad and Tobago and these were presumed to have covered a sufficient variety of the cultural range in the country. The CERA ontology was devised as means of structuring and reasoning about the cultural contexts expressed in these images however the extent of the conceptualisations facilitated by CERA was limited to only the tangible category described in (Blanchard and Mizoguchi 2008). Extension of the ontology is necessary in order to handle other aspects of culture such as behaviours, beliefs, norms and gestures. Another constraint was the partial handling of automated conceptual disambiguation. Only a controlled set of conceptual abstractions were used in the CER and this meant that certain conceptualisations were excluded since tools were not readily available for carrying out the kind of semantic disambiguation required. However research is emerging in this area such as in (Karanasios et al. 2014) which can be used to extend the CER functionality. Alternatively, an extension can be added using a lexical database such as WordNet.

Conclusion and Future Work

The paper described an approach for using a semantic annotation scheme and weighting mechanism for structuring and reasoning about the semantics of cultural conceptualisations expressed in educational content in ILEs. The approach was realized using the contextual element resource annotation (CERA) ontology and the contextual element resposity (CER) which are both part of a larger system for dynamic cultural contextualisation of ILEs. The evaluation results revealed that the CERA ontology was successfully used to structure and reason about the cultural semantics of images such that appropriate selections were made in relation to student cultural backgrounds. Furthermore, the data supported the notion put forth in the paper that positive cultural resonance can be produced using culturally appropriate content.

The upsurge in educational videos presents a challenge for culturally-aware technology enhanced learning. Although this paper does not directly tackle video and audio content, the techniques and approaches that were developed are extensible to these forms of content. Future work therefore includes improvement of the CERA ontology and modifications of the querying mechanism for handling multimedia content.

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