Exploring Computational Mechanism for Contexts

Leiguang Gong[1]

Abstract--- **Human problem solving is done within a context, which constrains the solution space. There have been growing interests in computational modeling of contextual knowledge representation and context-based problem solving. There are different approaches to exploring the concept of context and corresponding computational mechanism for representing and utilizing the contextual model, both formal and empirical based on different interpretations of the notion. This paper explores and discusses some aspects of the computational mechanism for contexts, and proposes a goal-directed framework for context-based problem solving. In this model, a context is defined in terms of an object and its relationships with other objects. Every context is centered at such an object, and cannot exist without it. A problem-solving task (e.g. find an object) with this framework can thus be defined as a process of determining a context or a sequence of contexts in which a solution path (e.g. steps for finding the object) can be decided. A set of operations is specified for context manipulation. The questions the author tries to answer are: what is context, how can contexts be formed and manipulated, and how can contexts be used in reasoning and problem solving.**

I. INTRODUCTION

Strictly speaking, all human problem solving is done within a context, which constrains the solution space. Even universally applicable solutions are conditioned by the only universe we know of. Philosophers and psychologists have studied the concept of context for quite sometime [1,6,10,14,19]. However, serious interest and research effort in the scientific community of machine intelligence have only been demonstrated in the last ten to fifteen years. Most research in machine intelligence still assumes context is defined a-priori by the investigator and is external to the computational problem solving systems, though the importance of representing and using contextual knowledge or information in a explicit and systematic way has been recognized by more and more researchers and demonstrated by increasing number of theoretical works and application systems [3,5]. In the area of computational intelligence, there are many different approaches to exploring the concept of context and the corresponding computational mechanism for representing and utilizing the contextual model. Like any other subjects in the field of artificial intelligence, there are both formal and empirical approaches. Research on formalizing contexts [4,13,17,18] has been primarily concerned with the locality of knowledge, i.e. relativity of trueness in knowledge bases, and its applications in knowledge representation and integration. The most well known example of such application is the Cyc system [15]. The empirical approaches, that are often more closely associated with real-world applications, focus on domain-specific architectures and techniques for representing and using contextual knowledge and information [5,7,11,16,20]. Many industrial applications of contexts such as context-aware computing and CRM systems [9] are based on empirical approaches. Research emphases for those applications are acquisition and representation of (user/customer) contextual information and the design of inference rules that encode the context-based inference steps. Various model, design architectures, and techniques have been proposed and developed [5,11,20].

The functional nature of contexts is its filtering, constraining power. It is no surprise that many personalization-based applications such as CRM, information delivery, HCI and etc. are built based on the concept and related techniques. Cyc and others use the concept to structure knowledge bases to maintain the consistency and trueness. However, contexts in the context of problem solving, particularly in real world physical contexts related applications such as navigations, HCI, robots, etc. are the subject's perception of its environment and surroundings. The task to the subject is to achieve the intended (e.g. find an object) or unintended goal (e.g. get out of the unexpected dangerous situation). The challenge is to find the right solutions and find them quickly. From a computational point of view, such problem solving process can be formulated as a process of context transformation. For a given context and a goal, the subject constructs an initial solution space from the knowledge memory, and then transforms the given context stepwise into a context in which the final goal is directly reachable. The criteria for guiding or controlling the transformation are goal-directed and domain-specific. Additional knowledge and

1. T. J. Watson Research Center, IBM, Hawthorne, NY 10532, USA, leiguang@us.ibm.com

information may be acquired either from memory or from other subjects or external environment as the transformation proceeds.

This article will focus on the discussion of some basic issues and concepts for goal-directed context-based problem solving. Specific examples (both realistic and hypothetic) will be used in the discussion. We propose a generic computational framework for contexts. The proposed model is not intended to explore and interpret the full semantics and the mechanism of contexts in human cognition and problem solving, rather to try to model some important aspects of computational mechanism of contexts. The questions we try to answer are: what is context, how can contexts be formed and manipulated, and how can contexts be used in reasoning and problem solving.

II. WHAT IS CONTEXT

Context is one of most frequently used word [3]. In modern language, the word context is defined in dictionaries (www.dictionary.com) bearing two basic meanings: (1) “To knit or bind together; to unite closely” and (2) “That which surrounds, and gives meaning to, something else.” Although there are many other interpretations, the basic meanings are same. But in computational modeling of contexts, the understanding and interpretation of the notion has become increasingly diverse and various. All kinds of definitions and treatments of the notion can be found from the research literature in the field [2,3,7,20]. However, no matter how different these definitions are most of them fall into either (1) or (2). From a computing point of view, these two definitions specify two different computational mechanisms. If we looked at closely how the notion of context is actually used in both human communication and computational systems, two patterns of usage stand out: “in the context of X” (CO) and “the context for X” (CF), where X stands for any physical or conceptual entity and event (e.g. a game, the human history, AI research, etc.). For instance, by saying “in the context of yesterday’s baseball game”, we generally mean a space of all things and events within the ball game. By saying the context for yesterday’s baseball game, we generally mean a collection of things and events externally related to the ball game. These two patterns of using contexts represent two different, though complimentary, views and treatments of the notion. Most (if not all) works in contextual modeling either intentionally or unintentionally reflect one of the two views. The pattern of CO views a context as a space of everything grouped or contained by a thing X (e.g. a game). Computational systems with this view try to answer the general question, “what can be said and done given the X”. On the other hand, the pattern of CF views context as a space of things externally related to and referenced by X. Computational systems with this view try to answer a question of “what is the contextual space for X, and how can this space be used to help understand X”. In computational terms, a common semantic element of the two different views and treatments of context is the notion of space, i.e. a space of information structured from either external sources, or from internal sources, or from both. In CO, such spaces are formed (knitted) through partitioning of larger information or knowledge spaces. In CF, such spaces are the results of growing about reference objects. CO models the mechanism defined in (1) and CF models the mechanism defined in (2). CO and CF represent the two general approaches to contextual modeling in machine intelligence. Because of our interest in CF modeling, we will only give a computational definition based on (2).

We assume that a meaningful context does not exist without a reference object. In other words, a context is always defined in reference to an object, i.e. centered at an object. The object can be anything from a physical entity to an abstract concept such as a person, a house, a word or sentence, an idea, a feeling, an event and so on. A context can be in general defined as a space of objects or entities, and relationships/associations among them centered at a reference object. we adopted a simpler and more quantifiable definition.

A *context* is the collection of an object and its relationships with other objects including these objects. The object is called target object o or reference object. To formulate this more concisely, $c = (o, R, B)$, where R is the set of all the relationships the target object has with all the objects in B. An *object* is a physical or conceptual entity with a unique identity. An object with more than one subcomponents or parts is called compound object. An object is atomic if it does not have subcomponents. A table leg can be treated as an atomic object, whereas tables as a compound object. A *relationship* is a mutually connected bond between two objects (e.g. *is-a, contained-in, married-to*, etc.).

III. APPROACHES TO CONTEXT

3.1 General Approaches

As we indicated in the previous section that there are two general approaches to contextual modeling: CO and CF.

- The CO approach can be expressed as following: Given a context C (a set of unspecified or partially specified assumptions), what then can be inferred within C? C may be recursively defined by one or more smaller contexts or sub-contexts.
- The CF approach can be specified as:

Given an object of interest O, what context or a sequence of contexts can be formed, such that a task about object O can be accomplished?

Most formal approaches are CO approaches, since they treat the notion of context as a mechanism of structuring (knitting) knowledge in terms of logical partitions, or simply described as ist(c,p) (asserting that the proposition p is true in the context of c). The significance of research in contextual knowledge representation using CO has been demonstrated in building very large-scale knowledge bases [15]. In CF approach, context is modeled as a space of objects and their interrelationships in the vicinity of an (or a group of) object (or called target object or reference object). The basis of this model is the referential relationship or association between the target object and its surroundings. Such mechanism specifies a neighborhood of things and relationships anchored by a or a group of target or reference objects either recorded from the world external to the problem solver or internally in its memory [14]. This object of reference plays a central role in both human and machine context-based problem solving. It in general refers to the goal of the problem solving. For instance when we talk about the context for an English word, usually understanding the meaning of the word is the goal of a human or machine reader. In medical imaging diagnoses the determination of abnormal findings is usually made in the context of specific human body parts (e.g. brain) or biological subsystems (e.g. digestive system). Furthermore, in a complex problem solving, to reach a final goal may require the fulfillments of some intermediate goals. The realization of each intermediate goal may in turn depend on its own context. For instance, to understand the word in the above example may require a clear understanding of another word in a statement as part of the context for the first word. The context for understanding the second word is usually different from the context for the first word. Generally speaking, the CO approach is rather static in nature, for it must serve the purpose of logical partition of a knowledge base, though the partitions can be gradually expended and revised by various means of learning. But contexts may not be formed or changed during a particular session of problem solving. On the other hand, CF approach is a rather dynamic mechanism, since it has to be formed, by the human or machine problem solver, during the process of a particular problem solving cycle. As a matter of fact, the two seemly very different treatments to contexts represent two closely interrelated aspects of context-based problem solving. For instance, the task of a goal-directed intelligent agent upon entering a situation/environment is to timely form an internal representation of the situation (i.e. context) in such a way that irrelevant information can be quickly filtered out, and useful information preserved. In the process of context formation and other related operations, the agent may recall the similar experience it had before along with the contextually structured knowledge for dealing with the situation if such knowledge is available internally. The experience learned from this encounter will be remembered and processed with other collected lessons internally by the agent's learning mechanism, one of key learning results will be the expansion or revision of the contextual partitions of the internal knowledge base.

In context-based problem solving, frequently a goal or a task is directly related to an object. This is particularly true for image understanding and robot navigation, where the main goal is to localize a target object. In CRM and many online customer service systems [20], the goal is to understand the customer's needs. Applications of this kind require the recognition and understanding of the target objects in terms of their contexts. The question then is what is the context for a target object? How can such a context be formed, represented and used? If the localization or understanding of the target object cannot be accomplished directly, what context manipulations can be done to help go through necessary intermediate steps?

We propose an object-centered computational model of contexts for machine intelligent problem solving. In this model, a context is defined in terms of an object and its relationships with other objects. This object is called the reference object or the target object. Every context is centered at such an object, and cannot exist without it. A problem-solving task (e.g. find an object) can thus be defined as a process of determining a context or a sequence of contexts in which a solution path (e.g. steps of finding the object) can be decided. A set of operations or operators is specified in this framework. The actual rules (criteria) for deciding specific contexts are problem-specific. The proposed framework is intended to explore some aspects of the very elusive and complex concept of context in the context of machine intelligent problem solving, and to facilitate systematic design of context-based modeling and problem solving systems.

3.2 A Framework for Goal-Directed Context-based Problem Solving

Generally speaking, the usage of contexts by intelligent systems is supported by the assumption that a context or a set of contexts may either contain the solution to a problem or may provide sufficient supporting data or information. This assumption is quite valid for most context-based problem-solving tasks. A general computational framework of context for machine intelligent problem solving is illustrated in Figure 1. The context engine (the middle block) works with and supports a problem solving or planning system by forming or representing an initial context, revising or changing (shifting, growing, and shrinking) the context according to the current goal. The initial context may be acquired through various types of sensors such as cameras and microphone, and/or from other interaction channels.

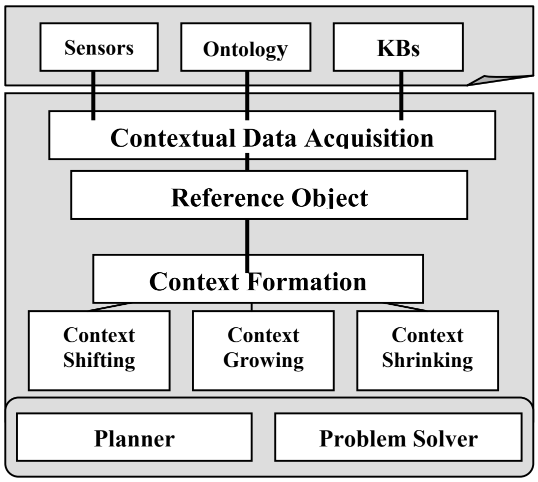

Fig. 1. A framework for context-based problem solving

In this framework, once a reference or goal object is determined, the formation of a context or a set (sequence) of contexts can be carried out either interactively with the external environment (e.g. continuous sensor data or a human user), or internally as a planning process [12] if the task is fixed at the beginning (e.g. analyze a CT scan for brain abnormalities) and prior knowledge about the domain is available (e.g. a semantic net model of the human brain in knowledge bases (KBs)). The question is for a given specific task, what contextual information is needed and how such desired context(s) can be determined and formed. We will explore these issues in the next section followed by some application examples.

3.3 Context Manipulations

An initial context for a specific problem-solving task can be characterized as being either too broad, too narrow, irrelevant, or just right. If the initial context is too broad, the problem solver may have difficulties focusing on most relevant and valuable information. If it is too narrow, then most relevant and valuable information may be missing. If the initial context presented to the problem solver has nothing to do with the given task, the context is irrelevant or wrong. However, in some situations to achieve the final goal may require a strategy of achieving some intermediate goals using different contexts, though the initial context is relevant to the task. So it is fundamentally important for a context-based intelligent system to be able to correctly evaluate the initial context. Context evaluation is still an open research problem, and will not be further discussed here.

The following context operations are specified: context shifting, context growing, and context shrinking, defined as following:

3.3.1 Context Formation

Given a world of objects and relationships $w\{O, R)$, a context c_i can be formed by a formation function f, i.e. context $c_i = f(w) = (o_i, R_i, B_i)$ where o_i is the reference or target object, R_i is the set of relationships o_i has with the set of objects B_i. For instance, in image understanding, a vision system requested to detect a specified object such as a boat from a satellite picture, may first form an initial contextual model about the boat and its relationship with other possible background objects. In this case, w is all the objects and their relationships recorded from the entire visual field in the photo, o_i is boat, B_i is the entire background, and R_i is the relationship *in*. In CRM applications, an intelligent system must be able to form, from all available customer data w, an initial representation of a customer o_i profile (i.e. contextual model of the customer), such that valuable information about the customer (such as the customer's financial interest) can be retained and used for inferring the system's recommendations or suggestions for product or service purchasing. B_i in this case may contain things like family members, properties, education background, etc. R_i may include relations like *has, owns, interested-in*, etc. In highly controlled and constrained applications, such contextual formation can be done in an optimal way, i.e. no irrelevant or redundant information will be collected and represented. In less controlled real world environments, application systems like robot navigation and active vision systems may not, at the beginning, have a clear idea about the boundary of the required context. The initial context formation most likely is an approximation. The degree of relevancy of the approximation is determined by both the perception power and the prior knowledge about the environments of the systems.

3.3.2 Context Shrinking/Pruning

For a given context $c_i = (o_i, R_i, B_i)$, a *context-shrinking* operator is defined as: $hop(c_i) = c_j$ where $c_j = (o_i, R_j, B_j)$, and $R_j \subset R_i$ and $B_j \subseteq B_i$. The new context is pruned in that it at least has fewer relationships. Please note that the operator implies that when an object has no relationship with the reference object, the object is automatically removed from the context. There may be multiple relationships between the object and the reference object. Pruning one relationship may not necessarily result in the object being removed from the context. In the previous vision system example, the initial context background may be too big to focus on. The vision system may need to reduce the context to the point (e.g. river) that the target object can be quickly and uniquely identified. In the above CRM example, the initial context formation may contain too much information about the customer. Some kind of filtering is needed to prune the space. Context shrinking or pruning is a filtering and focusing mechanism. A fundamental aspect of human intelligence is the ability to filter away irrelevant or relatively unimportant contextual information, and to concentrate on the contextual space within which the solutions or the goals can be found or achieved efficiently. The question of what and how much should be pruned is an open and challenging one, and can only be answered in the context of a specific system and the context of the problems the system is asked to solve.

3.3.3 Context Growing

For a given context $c_i = (o_i, R_i, B_i)$, a *context-growing* operator *gop* when applied to a context creates a revised context with more relationships. It is defined as: $gop(c_i) = c_j$, where $c_j = (o_i, R_j, B_j)$, and $R_i \subset R_j$ and $B_i \subseteq B_j$. This operator is the inverse of the shrinking operator. Sometimes, for whatever reason, an initial context may not be broad enough to cover needed information, or too much prune is done to the previous context. The context thus needs to be expanded to the point that sufficient information is available for the system to reach the goal. For instance, the vision system in the above example may fail to localize the target object with the initial contextual information. It may be due to its initial contextual model of the perceived world is too narrow and does not contain the target object. Or it may because the initial field of view is too small to cover the target object. In either case, the initial context has to grow until the necessary information is present. The same question asked for context shrinking can be raised here too.

3.3.4 Context Shifting

For a given context $c_i = (o_i, R_i, B_i)$, *a context-shifting* operator *sop* when applied to a context creates a new context that at least has a new target object. It is defined as: $sop(c_i) = c_j$, where $c_j = (o_j, R_j, B_j)$ and $o_i \neq o_j$. Context shifting is signified by the change of focus, i.e. reference object. Many real world applications involve complex problems, where a goal can only be achieved stepwise through the realization of some intermediate sub-goals. To achieve these sub-goals, the initial context has to be transformed (shift) into a sequence of different contexts within which the solution paths to the sub-goals can be found. In vision example, if the detection of the target object boat requires the detection of another object *river*, the context for localizing *river* has to be formed. In situations (e.g. robot navigation) where unexpected events occur, the system is forced to change its priorities and shift of context must be made.

4 EXAMPLES

In image understanding, the goal usually involves detection or recognition of some object(s) or interpretation of some relationship(s) between objects in spatial contexts. This class of problems is particularly difficult to solve, when the initial visual context is very large and there are many objects similar to the target object to be recognized in the scene. For instance, it would be very difficult and time-consuming to look for a particular highway from a large satellite image of the earth without a spatial context small enough to constrain the analysis and recognition process.

A spatial context consists of a set of objects and the relationships between them. In imaging terms, a spatial context is the whole or part of an image space, i.e. an array of pixels or voxels within which a target objects is likely to be detected. Thus, the earth in a satellite image defines a spatial context as an approximately round-shaped region within which major landmarks such as oceans and mountains can be located. These landmarks can be used to further localize other less significant geographical objects, such as rivers, forests or deserts. Such landmarks, including the earth itself are reference objects, which provide anchor points for defining specific contexts. To establish the presence of a reference object frequently requires the presence of yet another reference object. Such a sequence of reference objects represents an abstract plan for detecting the target object from the given scene or image. The order in which contexts are established specifies a sequence of focal regions from which the chain of reference objects can be localized. We [11] report the experiments with MR scans of human brain. The task is to detect multiple sclerosis (MS) lesions from the image. In this problem, the initial context for the task is the entire image space with both the brain structure and the background. Our image analysis system determines in order to localize the MS lesions more accurately the initial spatial context needs to be reduced in a series steps. The system, according to its priori knowledge about the brain anatomy, generates a processing and analysis plan specifying a sequence of target or reference objects and their relationships (i.e. contexts). The nested containment of different anatomical and pathological (MS lesion) structures is a simple *contained-in* relationship and is used in the formation of a sequence of contexts (plan) for recognition. According to the analysis plan (detect brain first, then white matter, and finally MS lesion) generated by the planner [12], the system shift from the initial context (specified by the MS lesion and its *contained-in* relationship with the entire image) to a new context (specified by the new target object brain and its *contained-in* relationship with the image). Once the brain structure is segmented, the context shrinking operation is performed to eliminate the background region and the region of skull. Next, the context specified by the white matter and its relationship of *contained-in* the brain become present. The process continues until a smallest context (i.e. lesion is *contained-in* the white matter) is obtained.

Some more complex tasks require the problem solver not only to locate objects, but also to understand and interpret the relationships between the objects of interest. Assume we have a digital secretary for handling the incoming telephone calls for a company executive. The decision to any incoming call the secretary has to make are assumed to be either "put call through" or "take the message". Apparently such decision-making very much depends on the secretary's understanding and interpretation of the relationship between the caller and the called i.e. the executive. However, the importance of the relationship is all relative and context-based. The initial contextual information our digital secretary has is the caller and the executive. They are related at the moment by a caller-called relationship. Apparently such a context (centered-at the executive) does not provide enough information for it to make a appropriate decision. The context needs to be expanded (by *gop* operation). So the information that the caller married to the executive (relationship) is added to the initial context. At this moment, the decision of "put through" seems to be the right one, but still the secretary is not sure. It then adds the fact that executive is currently *in* a (important) *meeting*. Now it looks like that the secretary should just take a message from the caller, but it recognizes that not enough is known about the caller's present context. The secretary then shifts the context from executive-centered to the caller-centered, and collects that the caller (the executive's spouse) is in a medical emergence room. The secretary put the call through immediately to the executive.

V. DISCUSSIONS AND FUTURE WORK

Context is a very elusive concept. While research on contextual modeling and problem solving has been intensified in recent years, a coherent computational theory about context has yet to be developed. This article proposes a computational framework for context-based reasoning and problem solving. The framework is based on the definition of context as a space of objects and their relationships centered at a reference or target object. The work reported here is still limited in several ways. More studies are needed to understand the extent of generality of this model and its potential and limitation in broad range of application domains. Some important issues such as the evaluation of the goodness of a context and the comparison of contexts are yet to be investigated.

REFERENCES

[1] D. Annis, "A Contextual theory of epistemic justification", Amaerican philosophical Quarterly, 15: 213-29, 1978.

[2] M. Benerecetti, P. Bouquest, and C. Ghidini, "On the dimensions of context dependence: partiality, approaximation, and perspective", Proceedings of CONTEXT 2001, pp. 59-72, 2001.

[3] P. Brezillon, "Context in problem solving: a survey", The Knowledge Engineering Review, 14(1):1-34, 1999.

[4] S. Buvac, "Quantificational logic of context". In Proceedings of the Eleventh National Conference on Artificial Intelligence, AAAI, Menlo Park, Ca. (AAAI-93), Washington, DC, 1993:412 -419.

[5] G. Chen and D. Kotz, "*A Survey of context-aware mobile computing research*". Technical Report TR2000-381, Dept. of Computer Science, Dartmouth College.

[6] S. Cohen, "Knowledge, context, and social standards", Synthese, 73: 3-26, 1973.

[7] A. Dey and G. Abowd, "Toward a better understanding of context and context-awareness", *Proceedings of the CHI 2000 Workshop on The What, Who, Where, When, and How of Context-Awareness*, The Hague, Netherlands, April 2000.

[8] IV. Ezhkova, "Knowledge formation through context formalization", Journal of Computers and Artificial Intelligence, 8(4): 305-22.

[9] J. Fink and A. Kosba, "A review and analysis of commercial user modeling servers for personalization and world wide web", Journal of User Modeling and User-Adapted Interaction, Kluwer Academic Publishers, 10: 209-48, 2000.

[10] A. Goldman, "Psychology and philosophical analysis", Proceedings of the Aristotelian Society, pp. 195-209, 1989.

[11] L. Gong, and CA. Kulikowski, "Defining spatial contexts for focused image analysis", in Proc. of IEEE SYSTEMS, MAN, AND CYBERNETICS 2001. Arizona, pp. 1184-87.

[12] L. Gong, and C. Kulikowski, "Composition of image analysis processes through object-centered hierarchical planning", IEEE Transaction on PAMI, Vol. 17, No.10, pp. 997-1009, 1995.

[13] R. Guha, "Contexts: a formalization and some applications", PhD thesis, Stanford Univ. 1995.

[14] F. Heylighen, "Advantages and limitations of formal expression", Foundations of Science 4(1), 1999.

[15] D.B. Lenat, "Cyc: a large-scale investment in knowledge infrastructure." Communications of the ACM 38, No.11, 1995.

[16] C.L Lin, P. Burlina and R. Chellappa. "Global activity detection: contextual recognition of regular object configurations". Technical Report, CAR-TR-748, Center for Automation Research, Univ. of Maryland, Dec. 1994.

[17] J. McCarthy, "Notes on formalizing contexts", Proceedings of 13th IJCAI, Vol. 1, pp. 555-60.

[18] J. Sowa, "Representing and reasoning about contexts", Proceedings of AAAI-92 workshop on prepositional knowledge representation, Stanford, pp. 133-42. 1992.

[19] N. Vassallo, "Contexts and philosophical problems of knowledge", Proceedings of CONTEXT 2001, pp. 353-66, 2001.

[20] T. Winograd, "Architectures for context", *Human-Computer Interaction*, 16:2-3, 2001.