A Context Model for Ubiquitous Computing Applications

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Abstract. Now these days, much research has been carried out on context-aware computing that is an important field in the area of ubiquitous computing, which offers a pervasive vision to implement a smart system by connecting computers, sensors and other peripherals in wired or unwired fashion. The main focus of this paper is on context modeling to design a real-time face recognition system for ubiquitous computing. In this research, a real-time framework with the combining concepts of context-awareness and genetic algorithm referred as real-time genetic algorithm (RGA) is proposed that meets the characteristics of context model and developments of a ubiquitous application. This framework is implemented on a real-time environment and a recognizable success is notified.

1 Introduction

Ubiquitous Computing [1][2][3], Unicom in the shortest form integrates computation into the environment, rather than having computers which are distinct objects. Pervasive computing is the another term for ubiquitous computing.Computer Scientists hope that embedding computation into the environment would enable people to move around and interact with computers more naturally than they currently do. This system dynamically adapts to the needs of the user and to the current operational context. Thus, ubiquitous system would exhibit a high level of adaptive behavior in order to respond to a wide range of contexts and stimuli that may be difficult to define a priori in a comprehensive manner.In addition, the context and input stimuli experienced by adaptive software applications and the effectiveness of the adaptive behavior they exhibit are highly dependent on the user's involved and the environmental context. One of the goals of ubiquitous computing is to enable devices to sense changes in their environment and to automatically adapt and act on these changes based on user needs and preferences.

Context [9] is information that can be used to characterize the situation of a real world entity, basically location and identity. Due to the rapid development of sensors, it is easy to capture an entity to sense and use context. Context-awareness [6, 9] is the system that takes the advantages of context. To make understandable about a context-awarness system, it is important to make a context model [9]. In this research, a context model is proposed and related experiments establish the developed concepts.

2 A Context Model

A context model represents a designer's understandings and feelings on context that is the organization of the physical world's data into logical structure, the key idea to

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implement in an artificial way, and a foundation for the implementation of context-awarness function. Objects are the basic elements of a model and these objects are described with logical or physical entities and relations between them. The proposed comprehensive model (shown in Fig.1) is composed with four layers i,e, sensor layer, core layer ,context layer, and application layer. Each layer uses its own data of different type from its previous level.

(a) Sensor layer: These data are produced from the environment through a set of sensors. The output set of sensor layer is denoted by

$$Sd = (S_{t,1}, S_{t,2}, \ldots\ldots S_{t,n}) \,,\; Sd_{\,t,n} = (\,Sen_n,\, t,\, h_n)$$

Where, $Sd_{\,t,n}$ denotes the sensor data of sensor i in time t, Sen_n denotes the value of nth sensor and h_n, the hidden parameter, is a value between 0 to 1 to model uncertain characteristic of context. The hidden value is assigned to each kind of sensors.

(b) Core layer: As this is the basic part of this system because the performance of the entire system depends on this, it is referred as core layer. Data from Sensor layer are treated as input to this core layer. The output of core dataset is defined as

$$\mathrm{Cd} = (\mathrm{Cd}_{\,t,1}, \mathrm{Cd}_{\,t,2}, \ldots\ldots, \mathrm{Cd}_{\,t,m}), \mathrm{Cd}_{\,t,i} = (\tau_{i,t}, t, h_{\,i}).$$

Where, $\mathrm{Cd}_{\,t,i}$ denotes a semantic piece called core data at time t. Each sensor corresponds to a core data. τ denotes an assertion that is to retrieve a fact from the sensor data and the fact cannot be divided to more trivial parts, such as Person (Kim) and Element (Spectacles). Sometimes AND, OR and NOT operations are performed to construct more complicated facts.

(c) Context Layer: In this layer, context situation is identified based on core data. It makes cluster for recognition and makes sense to the software system. Context situation is defined as

$$\mathrm{S} = (\mathrm{S}_1, \mathrm{S}_2, \ldots.., \mathrm{S}_p), \mathrm{S}_i = (\mathrm{Cd}_i, \mathrm{Ser}_{\,i}, p_i).$$

Where, $\mathrm{Cd}_{\,i}$ denotes the core data, which constitutes the situation, Ser_i denotes the services for the $\mathrm{Cd}_{\,i}$, and p_i stands for priority for each context situation that is predefined.

(d) Application Layer: This layer determines the action to be performed on the basis of context situation and services. The application to be executed is determined as

$$\mathrm{A} = (\mathrm{A1}, \mathrm{A2}, \ldots\ldots \mathrm{An}), \mathrm{Ai} = (\mathrm{S}_i, \mathrm{Mod}_i, \mathrm{trig}_{\,i})$$

Where S_i is the context situation, Mod_i is the program module to take action, and trig_i is the triggering for the application.

The design of the comprehensive context model is shown in Figure 2, where three databases are used for element collections, context ontology and actions. Element collection is proposed because of the system's real-time application, as if there new element is detected, it is added to the database.

Context ontology deposits the context category for a new incoming context and keeps the track of context. As a result, every context is at least one entry in this table. It is used for real-time adaptations while the sensor detects system changes with time, contexts are classified and make a entry into the table.

Action database, an off-line database, stores the probable actions that are specified by this system. A look-up table implements this to reduce the execution time.

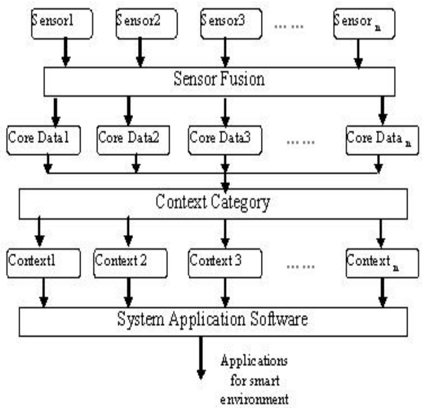


Fig. 1. A context model

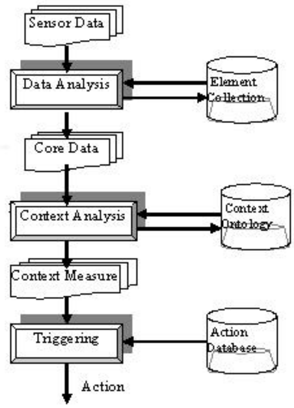


Fig. 2. Design paradigm of the conceptual context model

3 Proposed Experimental Environment

The proposed real-time framework of the genetic algorithm is suitable for adaptive, ubiquitous and pervasive applications with the capability of real time adaptation called real-time genetic algorithm (RGA). The designed real-time genetic algorithm operates in two modes: the evolutionary mode and the action mode. In the evolutionary mode, it accumulates its knowledge by exploring its application environments, while in the action mode; it performs its designated task using the accumulated knowledge from the evolutionary mode. The evolutionary mode is either online or offline adaptation. For offline adaptation, environmental context is categorized according to some predefined characteristics (here, illumination) and genetic algorithm is used for learning. For online adaptation, when a new context is encountered, it directly interacts with the action mode. Whenever an application environment changes, the system accumulates and stores environmental context knowledge in terms of context category and its corresponding action.

3.1 Environmental Context-Awareness

Environmental context-awareness is carried out using environmental context data that is defined as any observable and relevant attributes and its interaction with other entities and/or surrounding environment at an instance of time [6].

For identifying and categorize environmental context data, Fuzzy Adaptive Resonance Theory (FART), a variation of first generation ART [6,7] algorithm is adopted. First ART, named ART1, works with binary inputs, while FART is a synthesis of the ART algorithm and Fuzzy operators that (FART) allows both binary and continuous input patterns [6]. The image space of object instance with varying illuminations must be clustered properly so that the location error can be minimized. However, the classification of images under varying illumination is very subjective and ambiguous. Thus, FART method, which shows robustness in subjective and ambiguous applications in order to achieve optimal illumination context clustering, is preferred for adaptation.

The performance of clustering is improved by observing previously clustered data repeatedly [6].

3.2 Proposed Real-Time Genetic Algorithm (RGA)

FART has its capability for incremental learning that introduces clustering for real-time system in a dynamic environment. For real-time learning, As with the usual work for separating environmental context, FART looks for an unknown type of cluster, if it finds, it makes a new cluster as shown in Fig.3.

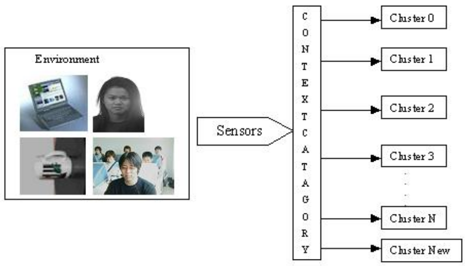


Fig. 3. On-line learning using FART

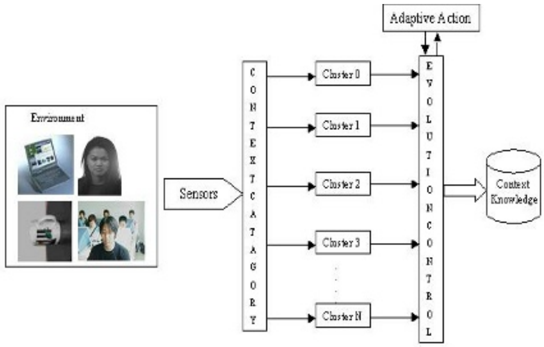
RGA consists Context-Category Module (CCM), Evolution Control Module (ECM), Adaptive Action Module (AAM), and Context Knowledge Base (CKB) as shown in Fig 4.CCM identifies a current context using environmental context data. AAM consists of one or more action primitives, which can be heterogeneous, homogeneous, or hybrid operational entities. For example, the action primitives of a pattern classifier are divided into preprocessing, feature representation, class decision, and post processing primitives. ECM searches for the best combining structure of action primitives for an identified context. The structures of optimal actions are stored in the CKB with the corresponding context expression.

Initially, the system accumulates the knowledge through off-line evolution (Fig 4. a) to the CKB that guarantees optimal performance for individual identified context. The CKB stores the expressions of identifiable contexts and their matched actions that will be performed by the ECM. The matched action can be decided by either experimental trial-and-error or some automating procedures. In the operation time, the context expression is determined from the derived context representation, where the derived context is decided from the context data.

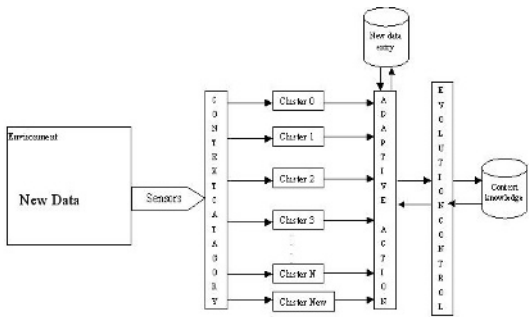
The adaptive task is carried out using the knowledge of the CKB evolved in the evolutionary mode and then action mode is performed. For on-line evolution, when a new context data is found, it generates a new category and updates the CKB as shown in Fig 4.b. The detail process for RGA is as follows:

Step1. Environmental contexts are clustered by CCM using FART.
Step2. The action configuration structure of the AAM is encoded as the chromosome and the fitness of GA is decided.

Step3. GA decided the most effective subset of action configurations using the associated training action data.
Step4. The chromosome with their associated contexts (either trained or new context) is stored at CKB.



(a)



(b)

Fig. 4. Block diagram of proposed RGA (a) off-line evolution, and (b) on-line evolution

4 Design Example

The proposed framework is applied in the field of visual information processing i,e face recognition. Face images with different illumination are preferred for this experiment due to its spatial boundaries so that it is easy to distinguish among the environmental contexts. In this research, FART constructs clusters according to variation of illumination as shown in Fig5. The AAM of RGA consists of three stages: preprocessing, feature extraction and classification [8]. The action primitives in the preprocessing steps are histogram equalization, contrast stretching and retinex [8]. The action primitives in the feature extraction stage are PCA and Gabor representation [8] and finally cosine distance measurement is concerned for classification.

Fig. 5. Example of face images clustered by FART on different illumination

5 Experimental Results

In this experiment, FERET face image dataset with its normal illumination fafb and bad illumination fafc are used for making artificial environmental contexts. Both real-time and non real-time GA based face recognition experiments are carried out. FART has constructed 9 types of cluster for non-RGA and 13 types for RGA and hybrid vectorization method is applied for clustering. Fig.6 shows the result for non-RGA technique.

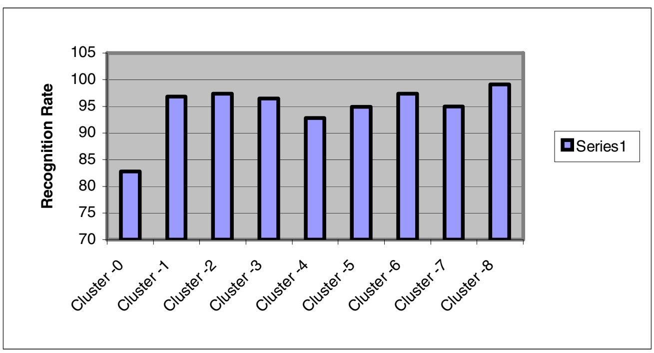


Fig. 6. Performance of face recognition with non-RGA

Fig. 7 describes the recognition rate as well as recognition ratio between Real-time and non real-time GA. Initially the system has accumulated knowledge from the environmental context through offline evolution and it produces more than 96% accuracy, however, when a lot of context categories are present, it takes comparatively more time for evolution, as a result the recognition rate decreases. Gathering knowledge from offline evolution, the on-line evolution starts and for some times it achieves better performance than previous offline system. After some times, as the number of contexts increases, the recognition rate decreases, while the evolution is finished, it receives the highest recognition rate. In this figure, off-line evolution is shown up to position A (0-6 cluster), on-line evolution starts from cluster 6 and it produces upward recognition rate up to cluster 9. From cluster 9, it decreases its accuracy up to cluster 12. And finally, at the finishing point of the evolution, it produces maximum recognition rate due to less number of context.

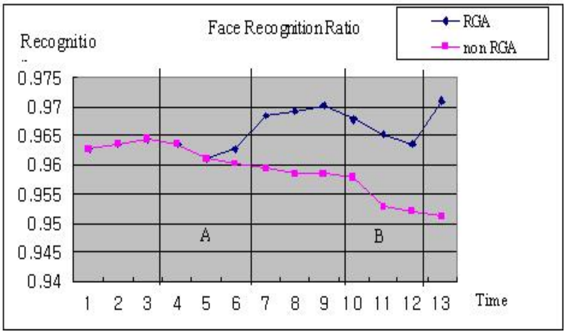


Fig. 7. Face recognition rate for RGA with respect to time

6 Conclusion

This paper proposes a comprehensive model for context-awareness to make a ubiquitous environment. In this research, a four-layered context aware model is introduced and this concept is applied to a robust face recognition scheme using real-time genetic algorithm. The important feature of the proposed model is the context data i,e to make categorize the environmental data and illustrated experiments bring out this categorization very successfully. Although multiple sensors are proposed, experiments are carried out on a single sensor and our future experiments will contribute on multiple sensors and sensor fusion. The developed system produces highly robust and real-time face recognition system on different illumination categorized images with the technique of adaptation by real-time genetic algorithm. This research also establishes a new concept for adaptive real-time genetic algorithm that reduces the execution time of traditional genetic algorithm with higher performance and this makes a notable contribution for ubiquitous computing.

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