상황 인지 시스템에서 개선된 역전파 알고리즘을 사용하는 진보된 학습 메커니즘을 위한 프레임워크

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요 약

본 논문에서는 상황 인지 시스템의 작업 부하를 줄이고 추론 성능을 향상시키기 위하여 개선된 역전파 알고리즘을 사용하는 진보된 학습 메커니즘을 위한 새로운 프레임워크를 제안한다. 학습 메커니즘은 상황 인지 시스템의 전체 성능을 좌우하는 매우 중요한 부분이지만 현재까지 사용자들의 상황 정보를 대상으로 학습 메커니즘의 개선을 통한 상황 인지 시스템의 성능을 향상하려는 연구는 많이 진행되지 않았다. 역전파 알고리즘은 상황 인식 시스템의 학습 메커니즘을 위한 가장 적합한 알고리즘 중에 하나로서 제안된 프레임워크는 기존의 역전파 알고리즘을 개선하고, 시스템 캐싱을 이용하여 작업 부하를 효율적으로 관리함으로써 추론 성능을 향상시켜 상황 인지 시스템의 전체 성능을 향상시킨다. 성능평가를 통하여 제안된 프레임워크가 상황 인지 시스템의 전체 성능을 향상시키는 것을 보인다.

키워드 : 유비쿼터스 컴퓨팅, 상황 인지, 학습 메커니즘, 역전파

A Framework for an Advanced Learning Mechanism in Context-aware Systems using Improved Back-Propagation Algorithm

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ABSTRACT

In seeking to improve the workload efficiency and inference capability of context-aware systems, we propose a new framework for an advanced learning mechanism that uses improved back propagation (BP) algorithm. Even though a learning mechanism is one of the most important parts in a context-aware system, the existing algorithms focused on facilitating systems by elaborating the learning mechanism with user's context information are rare. BP is the most adaptable algorithm for learning mechanism of context-aware systems. By using the improved BP algorithm, the framework we proposed drastically improves the inference capability so that the overall performance is far better than other systems. Also, using the special system cache, the framework manages the workload efficiently. Experiments show that there is an obvious improvement in overall performance of the context-awareness systems using the proposed framework.

Key Words : Ubiquitous computing, Context-aware, Learning mechanism, Back propagation

1. Introduction

Although theory of ubiquitous computing started to prevail since 19th century, but until recently, the ubiquitous computing has drawn attention from researchers. Under this circumstance, more aspects of factors are needed to concern with, in terms of mobile users, distribute devices and changing environment. Users of the ubiquitous environment, provide sufficient information which describes their current situation. We call this information as context. According to the definition in [1], "*Context is any information that can be used to characterize the situation of an entity.*" If a system uses context to provide the relevant information and/or services to its clients, it is context-aware. However, the relevancy depends on the user's task[1]. Context-awareness system collects and utilizes context. It is necessary for system to be context-awareness in ubiquitous environment[2].

As the price of mobile devices(e.g. cell-phone, PDA, and etc.) decreases, mobility has become the main data source of context-aware environment. To provide better service to mobile users and avoid information flood, the

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context-awareness systems should be proactive according to the changing environment[3]. This requires context-aware systems to have the ability to learn users' environment and to predict users' behavior pattern. Most of the current computing systems are capable to process the users' explicit input and output the result. But they are not aware of users' status[4], for example, where is the user, what the user is doing, when the user does it, who is beside the user, and etc. Some of them focus on providing a uniform model to context, and some of them focus on providing an interface for different applications and distribute context, and some of them focus on how to manage context. But none of these systems can satisfy the requirement of ubiquitous computing environment completely, especially for the mobile user.

In this paper, we propose a new framework for an advanced learning mechanism of context-aware systems. We chose the Back Propagation(BP) algorithm[10] as the basic learning mechanism due to its ability of learning relationships in complex data sets. The standard BP algorithm has limitations that it is too slow to provide the output in a short time. We introduced a dynamic momentum parameter added on the original BP algorithm with the view to make the BP algorithm avoid oscillations and respond instantly. The parameter value is calculated with reference to the LMS(Least Mean Square) between the obtained output and the desired output. By experiment, we prove that by using the improved BP algorithm in the proposed framework, the system can precisely be proactive according to the users' changing environment.

This paper is organized as follows: in section 2, we review the previous context-awareness systems and the original BP algorithm. In section 3, we propose an advanced learning mechanism and improved BP algorithm for it. In section 4, we make a comparison for the proposed framework. And the conclusion and future work are given in section 5.

2. Related work

Most of the existing contxt-awareness systems have a common deficiency, that is, limitations in proactive and adaptation to the changing environment for the lack of learning mechanism. In [5], Dey et al. introduced their context toolkit system. The system aims to provide balanced touch to different kinds of applications through the distributed context and gives the idea how context can be used. But it does not consider proactive and learning mechanisms. Roman et al. developed theGaia context-awareness system to manage context[6]. This system throws light on assisting mobile applications to be developed and implemented in active spaces and supports mobile applications in a limited area. But it still lacks the ability of learning and proactive through the users' environment. A. shehzad et al. emphasized on interactivity among applications[7]. They proposed a context model in the purpose of having a common understanding of the contextual information but no proactive functionswas mentioned. S.S.Yau et al. proposed the adaptive and object-based middleware RCSM in 2004[8]. This context-awareness system is designed for the mobile networks. So, it supports the mobile users and adapts to users'changing environment. In addition, this system supports using some specific contextual information to trigger corresponding actions. However, this system also lacks the ability of learning to proactive. H. Park et al. included context inference, learning, event triggering module of theirframework for the purpose of deal with various context[9]. In learning module, they listed some possible algorithms for learning but no material solutions.

For the robust context-awareness system, we chose BP algorithm as one of the most appropriate solution. From [10], a basic BP algorithm contains 3 layers: input layer, hidden layer and output layer. Input sample is processed step by step in terms of hidden units through input layer. Then it is transmitted to output layer after passing through all the hidden units. During this process, the state of units of each layer influences the next layer. After comparison of present output to expected output, the results are transferred to BP module if they are not matched. During the BP process, error signals are transmittedthrough original forward path but in converse direction, and weight value is modifiedby each unit in each hidden layer on the expectation of the minimized error signals.

3. Proposing architecture

To achieve better performance, it is crucial for context-awareness systems to adopt proactive behaviors and the key point lies in finding user patterns. However, due to distinct characteristics of individual user behavior, user patterns are diversely different. Therefore, learning is considered as an efficient way to get the pattern.

In this chapter, our learning mechanism and improved BP algorithm for robust context-awareness systems are introduced.

3.1 Learning framework

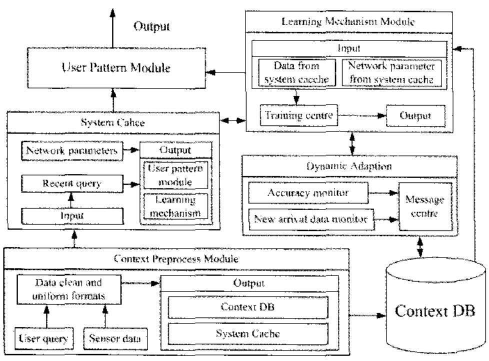
We propose a new framework that uses improved BP algorithm as the learning mechanism in context-awareness system. As shown in fig.1 shows, user and sensors can be the context sources(i.e. context can either come from user input or detected by the sensors).

Context Pre-process Module deals with the original context from usersand sensors. Since the raw data are in variety of forms and expressions. It is necessary to convert the context into normalized forms which are easy for the system to process. Some context is aggregated to a higher level. For instance, 9:00 am, 10:20 am all areaggregated to morning. After that, useless data are abandoned here and essential context is sent to System Cache and stored in the context DB. The context DB stores the historical context including input context and the context predicted by the system.

Dynamic Adaptive Module between BP and context DB keeps the BP network[1] up-to-date. The trigger event of update is controlled here, when new arrival context accounts for certain percent of the total context, the old BP network can not predict accurately. We need to go on training our network to improve the accuracy. The Dynamic Adaptive module will continue training network with the new context in DB when the trigger event happened, until the error rate is within the default value.

System Cache makes context awareness system possible to response faster. Users would not change their habits suddenly, the maintaining of the latestinput context and their options will dramatically improve the response time. These recorded options can be provided rapidly without computing when users repeat their queries. Also, the cache stores the parameters of BP network for different users (users use BP networks respectively, because each user is different individual), which makes it possible to support multiple users and response in a short time. BP, a background process that mines users' patterns, needs to be trained before using.

Context DB is the database of our framework. It maintains and provides the data for training and update.



(Fig. 1) Framework for learning mechanism

1) http://www.neural-networks-at-your-fingertips.com/bpn.html

Preprocessed data are sent here to store, when the trigger event happened, Dynamic Adaption Model will send message to ask Context DB provide the corresponding data to Learning Mechanism for training. After training, it is possible to categorize the new coming context to the already knownclassification and conclude the user pattern. By adjusting the default error rate, the accuracy can be controlled in an acceptable range. The structure of network such as number of hidden layers and nodes of each layer depends on applications specifically.

User Pattern Module stores the most recently query result. When the recently query is matched in System Cache, the corresponding answer can be provided directly from here.

Learning Mechanism is the algorithm chosen for learning. In our research, an improved BP algorithm is introduced and will be discussed in next section.

3.2 Imprvement of BP

The motivation of using BP algorithm is its ability of learning relationships in complex data sets which can not be easily perceived by humans. It has the ability to modify the output according to the changing of user context. It doesn't requirethe whole network rebuild when new context comes.

Standard BP algorithm has two drawbacks. First, learning speed is slow. Second, there are oscillations during learning. These problems cause its low efficiency. We modify the original BP algorithm so that it becomes suitable for the proposing framework. From [10], the formula for update weight in BP is

$$\Delta\omega_{ij}(t+1) = -\eta\partial E(t+1)/\partial\omega_{ij}(t) + \alpha\omega_{ij}(t)$$

Where α is momentum, and E is

$$E = \sum_{k-1}^{m} E_k = \sum_{k}^{m} \sum_{t}^{q} (y_t^k - c_t^k)^2 / 2$$

The momentum is the factor which drastically affects the learning speed. Large values of momentum can accelerate the learning process but the drawback result is oscillations during learning. On reverse, smaller values of momentum decelerate the learning process. Normally, the momentum α is fixed before training. Here, we propose a strategy for dynamic adjusting momentum α. This strategy makesthe BP network faster and avoids oscillations. The basic idea is, check $E(t+1)$ every time. If $E(t+1) > E(t)$, which means learning is too slow, we should accelerate the learning process by increasing α. If $E(t+1) > E(t)$, which means learning is too fast, oscillations may occur, we should reduce the learning process by decreasing α. The improved BP algorithm is illustrated in table 1.

When $E(t+1)>E(t)$, which means learning is too fast, it is necessary to slow down the learning process. Due to $\frac{E(t+1)}{E(t)}<1$, then $\alpha(t+1)<\alpha(t)$. The learning process is decelerated.

When $E(t+1)>E(t)$, that means learning is too slow. It is necessary to increase the learning speed. Due to $\frac{E(t+1)}{E(t)}>1$, then $\alpha(t+1)>\alpha(t)$ learning process is accelerated.

By dynamically adjusting momentum every time, BP avoids oscillations during learning and also accelerates the learning process.

3.3 Learning steps

Because of the variety of raw data, some preparatory work needs to be done before learning, which are collection and cleaning of each user context, and storing them in context DB to train BP network. The raw data are first sent to Context Preprocess model which will clean the data and generate them to suitable format or higher level to make them available for proposed Learning Mechanism. Preprocessed data will be sent to Context DB which maintains all the necessary data for training and updating our network. According to different situation, diverseBP network (difference in number of hidden layers and nodes of each layer) will be constructed. The training of BP network for each user should continue until the desired error rate is reached. Meanwhile the parameters of BP network for each user are stored in system cache respectively.

When user inputs query or sensors detect changing of environment, the context is sent to context pro-process module where contexts are converted into normalized forms and some context is aggregated to a higher level. The essential contexts are selected to be stored in the context DB and sent to the system cache. If the context information already exists in system cache, the output can be provided directly by system cache as it stores the recently queries and answers. Otherwise, the cache selects parameters of BP network according to the specific user and sends to BP network Learning Mechanism Model.In Learning

〈Table 1〉 Improved BP algorithm

1. Initial $\alpha(0)$, $\omega(0)$, and the expect error ε
2. Calculate and store the latest two Mean Square $E(t+1)$ and $E(t)$
3. Adjust momentum as $\alpha(t+1)=\alpha\cdot\frac{E(t+1)}{E(t)}$
4. repeat step 2 and 3 until get the output match the expect error ε

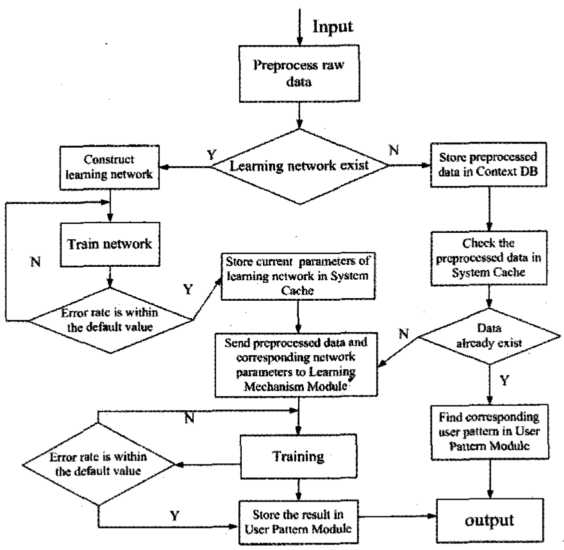
Mechanism Model, BP network learnsthese contexts, categorize them to already known classification to fetch the user pattern and sends the results to both output and system cache for repeated queries. Fig 2 shows the learning steps.

The dynamic adaptation module is in charge of the update of BP network. When the accuracy of BP network decreases or new context takes up certain percent of the total context, this module sends messages to both Context DB and Learning Mechanism Model to manage them goes on training BP network until it matches the expected error rate. Thus, the accuracy isguaranteed.

4.Implementtation

We choose GPS system as the symbol of context-awareness system to implement our learning framework. A basic BP network is generated by the Neural Network Toolbox for MATLAB for the learning processwhich contains three layers: input layer, hidden layer, and output layer). A user environment context DB which contains three months' context information is provided for training.

We made a scenario using learning process to predict the usual destination of GPS user. Each GPS user has own pattern. We split the users into two halves depending on their behavior, one half of users with fixed routes, whose positions can be inferred accurately by their starting position and the other group of users with ahigh probability changing their routes frequently. For the first groupsof users, we can make some explicit rule for inferring the destination. For the second group of users, it is difficult for human to explicit their rules. But if we can learn from these users'history DB, it is possible to get the user pattern to find the most likely destination in a high



(Fig. 2) Learning steps of proposed framework accuracy.

In our scenario, the following context information is chosen: User ID, which distinguish different user; event date which illustrate the date when the event happens; event time, similar to the event date, illustrating the exact time when the event happens; transportation mode which gives the way how user behaves, say, where is the user from and where to go is illustrated by start position and destination. Table2 shows the training sample.

We train the BP network with context DB until we get the output within the desired error rate. Then, the network has the ability to give the most likely output.

In our case, according to the input context we create five nodes for input layer, six nodes for hidden layer, and three nodes in output layer for giving the most possible result. The testing result is shown in table 3.

5. Performance evaluation

After building the learning network for context-awareness system, it is possible for the GPS system to predict the future location of a GPS user. Benefit from this ability, more information can be provided to the users without any query, such as weather, traffic jam, the shortest path. At the same time, workload isobviously reduced. Fig 3 shows the comparison of workload among systems.

〈Table 2〉 Sample of training data set. Since the raw data is in variety of forms, we clean and normalize them to following forms

Input					Desired Output
User ID	Date	Time	Mode	From	To
User1	Monday	Morining	Bus	S1	C3,C4,C1
User2	Monday	Afternoon	Car	S1	C2,C1,C5
User1	Tuesday	Evening	Car	S3	C2,C3,C4
User3	Friday	Afternoon	Walk	S5	C6,C1,C2
User3	Wednesday	Morining	Car	S4	C5,C4,C5

〈Table 3〉 Testing result. By using test data of table 2, our learning network output the most likely three destinations and their probability respectively.

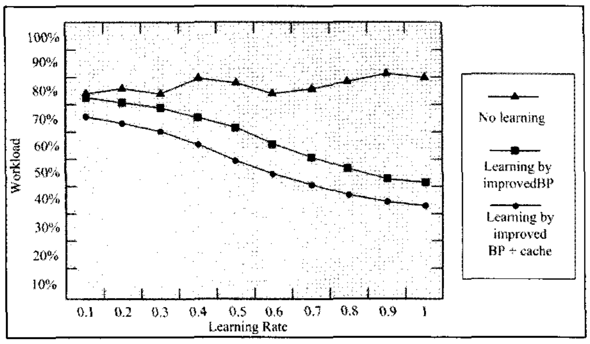
Input					Output	
User ID	Date	Time	Mode	From	To	Probability
User 1	Monday	Morning	Car	S1	C1	60%
					C3	87%
					C4	74%
User 3	Friday	Afternoon	Walk	S1	C1	85%
					C2	64%
					C5	84%
User 1	Tuesday	Evening	Car	S3	C2	77%
					C3	80%
					C6	88%
User 4	Monday	Morning	Bus	S5	C2	91%
					C5	65%
					C6	46%
User 2	Thursday	Evening	Car	S4	C1	87%
					C3	69%
					C5	77%

Besides BP, other algorithms such as Baye's theorem are widely used. For GPS systems, Bayes could also be adopted as a satisfying learning mechanism. But BP is superior to Bayes on the control of prediction accuracy. Furthermore, when the new context accounts for some percent of the total context, Bayes network requires rebuilding rather than improvement on the current network. Fig 4 shows the accuracy comparison between Bayes and BP with different learning rates.

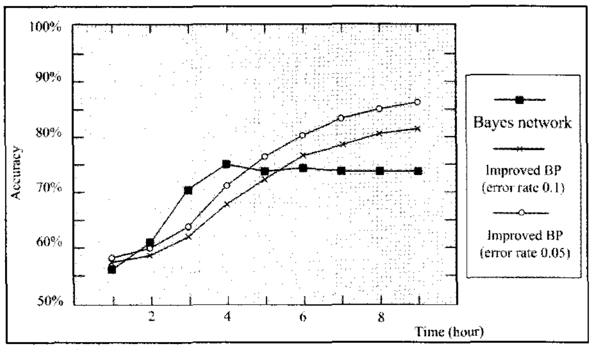
6. Conclusion and future works

In this paper, we proposed a learning framework of context-awareness systems using BP algorithm as learning mechanism for ubiquitous computing environment. Different from standard BP, we improved it to become suitable for the proposedframework regardless of its slowness. Using this framework, context-awareness systems evidently reduce the workload and provide better service. Through the tests, we proved that our framework performs far beyond just acceptable.

Future work in this are includes how to select the



(Fig. 3) The workload comparison between the system using learning and without learning



(Fig. 4) The accuracy comparison between using Bayes and Backpropagation essential context for learning. Training a BP network is CPU-cost computing. Schedule management for training and user service is also important. In addition, the proposed BP is not yet completely optimized. More effective algorithm should be discovered for better performance.

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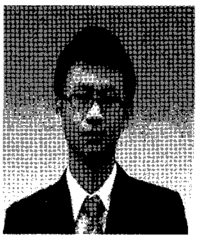

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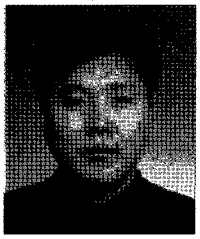

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