Usage of Neural Networks in Ubiquitous Computing Systems

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***Abstract*—One of most perspective techniques for sensing in ubiquitous computing systems is neural networks. In this paper we describe features of usage of neural networks in ubiquitous computing and its implementation for solving of some tasks in middleware ubiquitous computing system for smart environment.**

I. Introduction

Ubiquitous computing is a set of technologies which provide support of human environment where various computers are melted in and connected to humans, objects and surroundings to allow solving of different real time tasks anytime, anywhere. Ubiquitous computing systems (UCS) provide more comfortable everyday life in particular for elderly or handicapped [1].

Now ubiquitous computing and smart cooperative object are viewed as a major paradigms shift from conventional desktop application development. This view is enabled through the use of diverse hardware (sensors, user devices, computing infrastructure etc.) and software, anticipating user needs and acting on their behalf in a proactive manner [2], [3]. This diversity of hardware and software information increases the degree of heterogeneity.

Ubiquitous computing (just as intelligent robotics) is a field of AI in which all problems of AI are concentrated and not only AI.

In order to realize such ubiquitous computing environment, three technology areas are required:
1) sensing technology where information on user and surrounding environment are perceived and collected,
2) context aware computing [4], [5] technology where such information are processed and properly presented to users as different services,
3) network technologies where information are collected from sensors and distributed to customers – services and users.

One of most perspective technologies for sensing is neural networks. In this paper we describe features of usage of neural network in ubiquitous computing and its implementation for solving of some tasks in middleware ubiquitous computing system for smart environment [6].
We may pick out following main features of ubiquitous computing systems (UCS):

1) distribution of obtaining and processing of sensor information,
2) variety of information needed processing,
3) necessity of learning during interaction with environment, in particular, in respect to existing of unexpected events and objects needed for including into processing,
4) essential role of different kinds of human-machine interaction,
5) high requirements to security,
6) data processing in real time,
7) wide usage of embedded processing units.

There are following tasks for neural networks in development of ubiquitous computing systems:

1) perception, i.e. recognition of objects and changes in environment, in particular, invariant recognition of moving objects, e.g. recognition of gesture, position and emotions of human beings,
2) clustering and recognition of events and scenarios (sequence of events in time),
3) prediction of future events and situations,
4) indoor localization of mobile devices.

From above we can formulate following requirements to neural networks for UCS:

1) Relatively fast processing of information in both learning and recalling,
2) Incremental learning, i.e. availability to perceive new information without loss of old knowledge,
3) Availability of easy extraction of structure from learned neural network for building of symbolic knowledge for usage in machine-human interaction.

In this paper we describe some neural based applications developed in Ubiquitous Computing Laboratory of Kyung Hee University (South Korea) by author himself and under supervising of author.

II. Indoor location estimation of mobile devices

Location information is an integral and crucial component of ubiquitous computing applications. In building localization usage of Wireless LAN received signal strength (RSS) is both feasible and economical. Battiti *et al* [7] have employed neural networks for this problem. They used feed forward back propagation network that takes RSS of 3 Wireless Access Points (AP) to cover 624 square meter area. 200 samples were used to train neural network for each target location. They reported median estimation distance error of 1.75 meter. This was a best result in comparison with obtained before that with usage of Bayesian classification and filtering [8], Statistical learning theory [9] and *K*-Nearest Neighbors

[10][11][12]. But this model assumes that all the inputs are available at every location all the time. Practically, this approach has limited applicability because in real life scenario some AP may not be visible (not in range) at all the locations for all the time. In [13] [14], [15] a modular approach was proposed and developed that perfectly cater for this situation.

Basic concept behind WiFi RSS based location awareness is that Received Signal Strengths from different Access Points (APs) follow certain patterns, so called fingerprints, at a particular location. These patterns are captured at each location and stored in a database namely ‘Radio Map’. Process of capturing signal strength patterns at particular locations is called 'site calibration'. In Radio Map every pattern of RSS corresponds to point of location. This is data for learning of neural network and during location estimation learned neural network is used for recognition of location.

In our modular neural network we use some multi-layer perceptrons (MLP) for different subsets of visible access points, stored in so-called matrix of visibility obtained during site calibration. The structure of such modular neural network is shown in fig. 1. Here are shown three modules 123, 13 and 12 for visible AP 1) 1, 2, 3, 2) 1, 3 and 3) 1, 2 respectively.

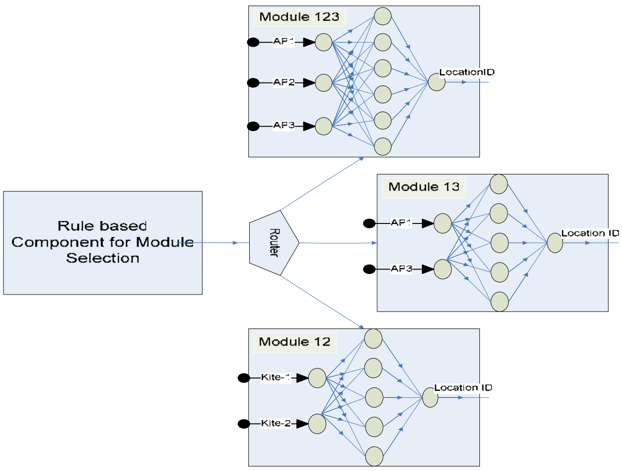

Fig. 1. Structure of modular neural network for location estimation.

Experimental prototype was implemented for three corridors of Engineering Building 3rd floor (Fig. 2). Here the access points and location points are having red and green colors respectively. We evaluate our location estimation system performance with both overall and location specific measures. Results show superior performance to previous approaches.

In [16], [17], [18] we suggested another neural network model for location estimation based on Fuzzy ARTMAP [19]. This model has same accuracy as modular MLP based system but one is easier and demands less time for development of system. Instead of training a separate pattern recognition module for each visibility cluster we incorporate this contextual information into one classifier thus making it context-aware (fig. 3). Here is Fuzzy ARTMAP with vector of RSS and context-visibility (left part) and vector of identification of place (right part). And also may be one

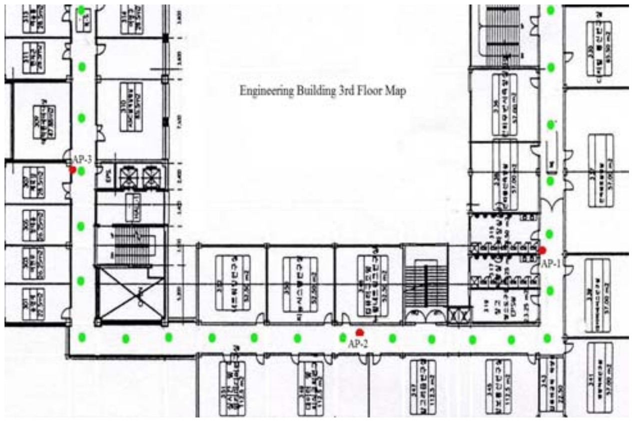

Fig. 2. Location Map, Target Locations and location of Wireless Access Points

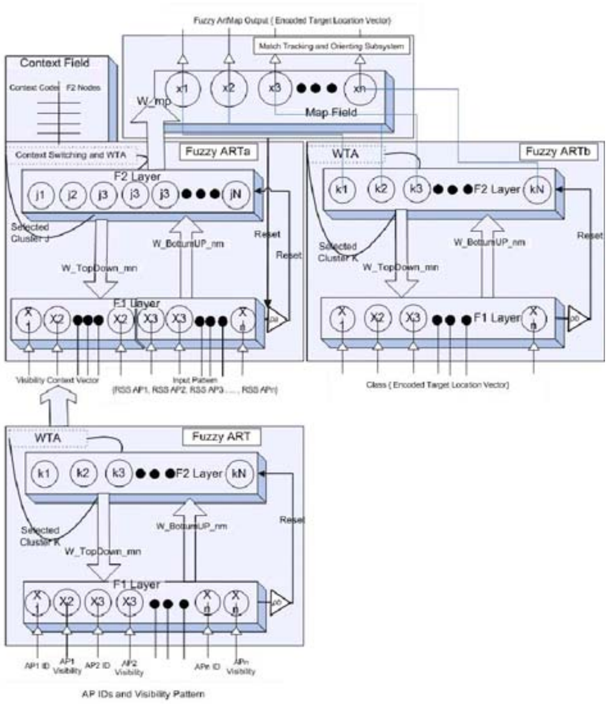

Fig. 3. Structure of neural network for location estimation based on Fuzzy ARTMAP.

Fuzzy ART for preprocessing of vector of visibility (down part).

III. USAGE OF HYBRID NEURAL NETWORK FOR INVARIANT RECOGNITION AND NOVELTY DETECTION IN DYNAMICAL ENVIRONMENT

One of most important of ubiquitous system (e.g., smart home or healthcare system) is ability to observe an environment, i.e. to detect any changed essential for tasks being solved by system, to recognize known or unknown human beings and its faces, gestures and emotions. This capabilities demand from corresponding tools on the one hand flexibility (ability to involve in processing new unexpected images) and on the other hand stability and invariant recognition, i.e. recognition of transformed same images.

We suggest and investigate [20-24] one hybrid model of neural network based on ART-2 [25] and multi layer perceptron (MLP) with error back propagation (EBP) training algorithm (Fig. 5). In this model we keep the advantages (flexibility, i.e. combination of stability and plasticity) of unsupervised learning by Adaptive Resonance Theory (ART) and reduce major disadvantage of ART – the sensitivity to transformations of input patterns. Multi layer perceptron provides preprocessing of patterns for invariant recognition because its hidden layers form secondary features during learning. It could be said that in MLP each hidden layer provides conversion of any feature space to another one.

There are many other approaches to achieve invariant recognition by neural networks, for example proposed in [26-29]. But each of them is either too complex or specialized for determined any kind of images and transformations.

We suggested potentially universal approach for invariant recognition which can be implemented in real time systems, because it not requires long time processing as in usual applications of EBP.

In our model the first several layers of neurons are organized as MLP. Its outputs are the inputs of model ART-2. MLP provides conversion of primary feature space to secondary feature space with lower dimension. Neural network ART-2 classifies images and uses secondary features to do it. Training of MLP by EBP (with limited small number of iterations) provides any movement of an output vector of MLP to centre of recognized cluster of ART-2 in feature space. In this case the weight vector (center) of recognized cluster is desired output vector of MLP. It could be said that the recognized class is a context in which system try to recognize other images as previous, and in some limits the system “is ready to recognize” its by this manner. In other words neural network “try to keep recognized pattern inside corresponding cluster which is recognizing now”.

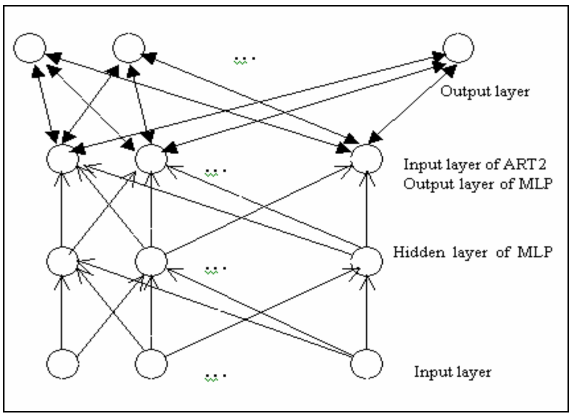

Fig. 5. Structure of hybrid neural network MLP-ART2.

Action of the suggested model is described by the following unsupervised learning algorithm:

1. In MLP let the weights of connections equal to $1/n$, where n is quantity of neurons in the previous layer (number of features for first hidden layer). The quantity of output neurons N_{out} of ART-2 is considered equal zero.

2. The next example from training set is presented to inputs of MLP. Outputs of MLP are calculating.

3. If N_{out}=0, then the output neuron is formed with the weights of connections equal to values of inputs of model ART-2 (the outputs of MLP).

4. If N_{out}> 0, in ART-2 the algorithm of calculation of distances between its input vector and centers of existing clusters (the weight vectors of output neurons) is executing using Euclidian distance:

$$d_j = \sqrt{\sum_i (y_i - w_{ij})^2}$$

Where: y_i – i^{th} feature of input vector of ART-2, w_{ij} – i^{th} feature of weight vector of j^{th} output neuron (the center of cluster). After that the algorithm selects the output neuron-winner with minimal distance. If the distance for the neuron-winner is more than defined a vigilance threshold or radius of cluster R, the new cluster is created as in step 3.

5. If the distance for the neuron-winner is less than R, then in model ART-2 weights of connections for the neuron-winner are recalculated by:

$$w_{im} = w_{im} + (y_i - w_{im})/(1 + N_m)$$

Where: N_m – a number of recognized input vectors of m^{th} cluster before. In addition, for MLP a recalculation of weights by algorithm EBP is executing. In this case a new weight vector of output neuron-winner in model ART-2 is employed as desirable output vector for EBP, and the quantity of iterations may be small enough (e.g., there may be only one iteration).

6. The algorithm repeats from step 2 while there are learning examples in training set.

Note that in this algorithm EBP aims at absolutely another goal different from that in usual MLP-based systems. In those systems EBP reduces error-function to very small value. But in our algorithm EBP is needed only for some decreasing distance between actual and desirable output vectors of MLP. So in our case the long time learning of MLP is not required.

Note that EBP and forming of secondary features are executed only when image “is captured” by known cluster. So selection of value for vigilance threshold is very important. Intuitively obvious that one must be depending on transformation speed of input images and may be changed during action of system.

In our experiments we used three variants for calculation of vigilance threshold:

1) it is fixed value selected empirically,

2) it is calculated for every image by formulas $S/(N_a^2)$, where S – average input signal, N_a – number of output neurons of MLP (input neurons of ART-2),

3) it is calculated as kD_{min}, where D_{min} – minimal distance between input vector of ART2 and weight vector in previous image, $k>1$ – coefficient.

Last method shows best results.

Experiments were conducted with different series of visual images: 1) simple pictures drawn by graphic editor [20], [21], 2) frames extracted from video [21], [22], 3) series of faces with different pose and illumination [22], 4) data from sensors of simulated mobile robot [23], [24].

Typical behavior of this model in experiments is shown in fig. 6. There is change of recognized cluster at sufficient changes of visual image (i.e. going away of object from field of vision)

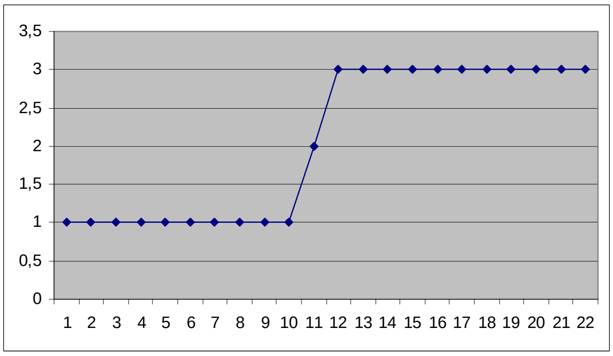

Fig. 6. The recognized clusters at moving of simple image across field of vision.

In experiments with simulated mobile robot in unknown environment for searching of path to target among obstacles we got dramatically reduce of situations when robot asks user "What to do?" when it can not recognize any situation (fig. 7).

In [30] we generalized this approach and suggested Unsupervised Hybrid Learning Model (UHLM) based on unsupervised learning (and reinforcement learning) and supervised learning (MLP). In this model the unsupervised learning model is used as teacher for supervised model.

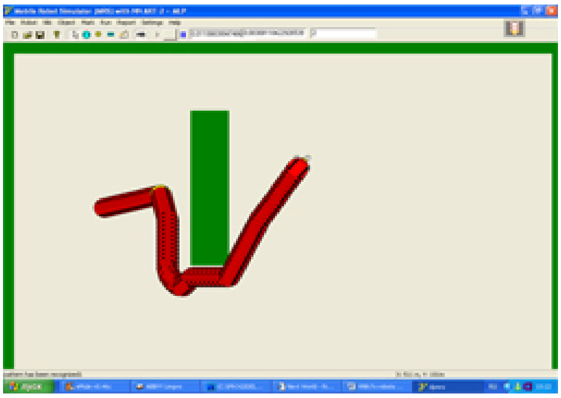

Fig. 7. Screenshot of simulation of moving of robot from start (left) to target (right) with usage of model MLP-ART2.

For this hybrid model using reinforcement learning, i.e. positive and negative awards, we proposed modified error back propagation algorithm providing adaptation of weights based positive and negative instances [30].

For this case it is needed MLP with 2 modes of EBP – positive or negative respecting for attraction and repulsion of target output vector. Let call this kind of EBP as Error Back Propagation with Punishment (EBPP). Positive mode of this model is classic EBP. The negative mode provides update of weights with opposite sign. Thus updates of weights in EBPP are described by following formula:

$$\Delta w_{ij} = ar\varphi_j x'_i ,$$

where:
w_{ij} is weight of connection between ith neuron and jth neurons;
a is value of award, 1 or -1;
r is a rate of learning;
φ_j is error propagation for jth neuron;
x'_i is derivative of active function of ith neuron.

Function φ_j for calculation of error propagation for output layer differs from same function in usual EBP algorithm. For case $a=1$ it is same as in EBP classic algorithm:

$$\varphi_j = y_j(1-y_j)(d_j - y_j) ,$$

where y_j and d_j are actual and desirable output of neuron respectively.
For case $a=-1$ the function φ_j is determined as

$$\varphi_j = ky_j(1-y_j)\exp[-\frac{1}{2\sigma^2}(d_j - y_j)^2]$$

The expression $y_j(1-y_j)$ of this formula represents the derivative of neuron's state like in usual error back propagation. The exponential function in this formula provides maximal value of φ_j at equality of actual and desirable states of jth neuron. Value σ represents the sensitivity in neighborhood of danger vector. Coefficient k may be interpreted as a level of timidity and may be connected with simulation of emotions.

Another variant of calculation of φ_j is possible. For example, for $d_j \neq y_j$ function φ_j may be represented as

$$\varphi_j = \frac{ky_j(1-y_j)}{d_j - y_j} .$$

For $d_j = y_j$ function φ_j may be determined as constant value k.

Unlike classical EBP with positive award the punishment in EBPP provides adaptation of weights to repulsion of target output vector (danger vector). Particular case is learning to predict of events in time. In this case MLP may be replaced by recurrent neural network (model RNN-RL) dealing with sequences of patterns, e.g. Elman model [31] with EBP through time.

IV. Conclusions

In this paper we formulate requirements to neural networks for applications in ubiquitous computing environment and shortly describe some neural networks based research and applications developed in Ubiquitous Computing Laboratory of Kyung Hee University by author himself and under supervising of him. In particular, we propose our perspective hybrid neural network model based on MLP and ART-2 for development of such applications oriented on invariant recognition of visual and other images and suggested effective models based on neural networks MLP and ARTMAP for indoor location estimation of mobile devices. Experiments with these models show its high potential capabilities for usage in development of ubiquitous computing systems, in particular, smart house and health care systems. Because limited size of this paper it was impossible to describe some other our researches about neural networks in ubiquitous computing systems, e.g. usage of neural networks in information security [32], semi-supervised learning for classifiers [33] and so on.

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