An ANFIS-based Model for Mobile Learning System

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Abstract- **Mobile learning (m-learning) is a kind of learning model allowing learners to obtain learning materials anywhere and anytime using mobile technologies and the internet. Personalisation is becoming more important in the area of mobile learning. Learner model is partitioned into smaller elements in the form of learner profiles, which collectively represent the entire learning process. Machine learning techniques have the ability to detect patterns from complicated data and learn how to perform activities based on learner profiles. This paper discusses a systematic approach in reasoning the learner contexts to deliver adaptive learning content. This paper adopts the Adaptive Neuro-Fuzzy Inference System (ANFIS) approach for delivering adapted learning content to mobile learners. ANFIS uses the hybrid (least-squares method and the back propagation gradient descent method) as learning mechanism for the Neural Network to determine the incompleteness in the decision made by human experts. The MATLAB simulation results indicate that the performance of the ANFIS approach is valuable and easy to implement. These results are based on analysis of different model settings; they confirm that the m-learning application is functional. But, an increase in the number of inputs being considered by the model will increase the system response time and hence the delay for the mobile learner.**

Keywords- Mobile learning, ANFIS, learner modeling, adaptation.

I. INTRODUCTION

Mobile-learning (M-learning) is seen as either an extension of e-learning which traditionally meant learning that takes place at a computer or a completely new paradigm that lets someone learn anywhere and at any time. Constable et al. (2008) define m-learning as “the combination of e-learning and mobile computing”. Yordanova (2007) defines m-learning as “learning that is wireless and ubiquitous”. Wains and Mahmood (2008) define m-learning as “a type of e-learning which blends wireless and mobile technology for learning experience”. Deegan and Rothwell (2010) give a definition of m-learning as “Learning with the aid of a mobile device”. Deegan and Rothwell (2010) have classified m-learning into five categories in terms of usability aspects and these classifications include-Learning Management, Supportive, Content-based, Context-based and Collaborative. Using the mobile device in order to register for courses, view grades, retrieve homework, submit assignments and annotate common artefacts fall under the Learning Management category of M-learning. Using the mobile devices for supporting traditional learning (in classroom or lecture hall),e-learning or distance learning like direct communication between lecture and student falls under the supportive category of e-learning. Wains and Mahmood (2008) describe the use of SMS system to supplement real-time TV learning which comes under this category. The same paper notes the use of SMS in English lesson in Japan and in distance education in Philippines as a supportive tool. Viewing video recordings of class lectures through mobile comes under the content-based category of m-learning. Context-based learning is a true mobile learning environment. A context-based learning application will focus learning objectives in the environment in which it is being used. Morrison et al.(2009) talks about context based application of M-learning describing how users of a mobile device can use the camera function to display a map in real time while application overlays meta-data on the map. Collaborative learning refers to the notion that a learner is not a passive participant when learning but takes an active part in the learning process as per Deegan and Rothwell (2010).Participating in forum discussion using a mobile device is an example of Collaborative usability of M-learning [1].

Adapted mobile learning systems aim to adapt learning content to each individual learner’s context in order to improve the effectiveness of accomplishing a learner activity. Personal digital assistants (PDAs) and mobile phones are used by a variety of learners in different environments. Awareness of context is important as it allows the environment to be used in a way that supports the learner. Machine learning techniques are commonly used for learner modeling because of the complex nature of relationships between learner contexts that are hard to be represented. Webb et al. listed four main issues related to the use of machine learning techniques for modeling purposes: the need for large data sets, the need for labelled data, concept drift and computational complexity. Most personalisation approaches depend on machine learning techniques that require a large amount of labelled data in order to provide proper results. The

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continuous changes in learners' interests and profiles are referred to as concept drift.

The main objective of this paper is to provide suitable learning content format for mobile learning application user using an adaptive neuro-fuzzy inference system (ANFIS) based on the obtained learner profile. Section II of this paper provides an overview of mobile learning. In section III, the ANFIS system modeling approach is introduced. Section IV presents the structure of the proposed ANFIS. Section V presents the evaluation of the proposed system. Finally, section VI presents concluding comments about future developments related to this work.

II. OVERVIEW OF MOBILE LEARNING

Ahmed Al-Hmouz et al. (2009) presented a new framework that depicts the process of adapting learning content to satisfy individual learner characteristics. In the case of a mobile learning adaptation, seven adaptation layers need to be considered (Fig.1).

Context Acquisition Layer
Information Classification Layer
Learner Model Layer
Information Extraction Layer
Learner Profile Representation
Reasoning Layer
Interface Layer

Fig.1.Adaptation Components [2]

Context Acquisition Layer: This layer is used to gather the information required for adaptation.It relies on both explicit and implicit information collection. Explicit information relies on information provided by the learner and implicit information is gathered by monitoring the learner's interactions with a system and making assumptions as to his/her needs.

Information Classification Layer: This layer deals with all data obtained from the previous layer by categorizing the data into several class types.

Learner Model Layer: A learner model is defined as a set of information structures designed to represent one or more of the following elements: goals, plans and preferences; characteristics of learners; learner stereotypes and learner behaviour.

Information Extraction Layer: This layer assesses,analyses, verifies, and filters the data based on the current learner's situation.

Learner Profile Representation: In order to achieve personalized services, we should be able to specify learner interests. Creating a learner profile allows for much more accurate results, given a sufficiently expressive keyword. Precise information allows the system to more accurately support learner decision making.

Reasoning Layer: The output of this layer is a set of structural descriptions of what has been learned about learner behaviour and interests.

Interface Layer: The layer is formed by the events that are processed by the adaptation system as well as the questions about the learner that it can answer.

In this paper, a solution to adapt learning contents through the use of mobile technology, based on modelling the learner and all possible contexts related to his/her current situation is proposed.

Ahmed Al-Hmouz et al. (2010) presented a new approach to combine learner information and contexts together to achieve maximum integration, which will result in information-rich learner profiles. The ultimate goal of the enhanced learner model is to enrich learner profile because they are the main inputs for the reasoning layer. This enhanced learner model consists of four main components, namely the representation of the Learner Status, the Situation Status, the Knowledge and Shared Properties Status and Educational Activity Status. In this paper, the focus is on how to model the learner and all possible contexts in an extensible way that can be used for personalization in mobile learning.

III. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

Adaptive Neuro Fuzzy Inference System(ANFIS) technique was originally presented by Jang in 1993[3].ANFIS is a simple data learning technique that uses a fuzzy logic to transform given inputs into a desired output throughout highly interconnected(Neural Networks)processing elements and information connections weights to map the numerical input into output.ANFIS constructs a fuzzy inference system(FIS) whose membership function parameters are adjusted using either a back propagation algorithm, or in combination with a least squares method(Fig.2).

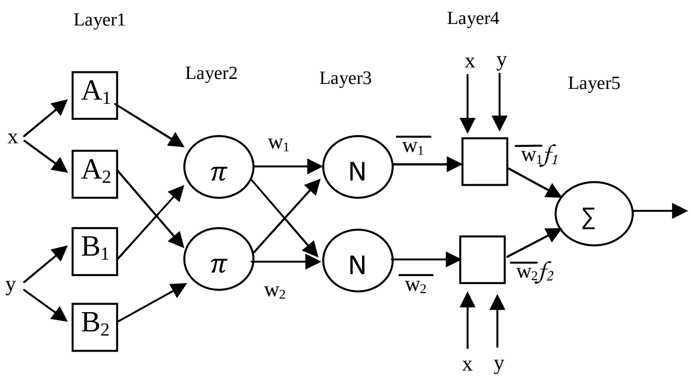

Fig.2. ANFIS structure with two inputs and one output [4]

A first-order Sugeno fuzzy inference system contains the following two rules:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$.

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 y + r_2$.

where x and y are the inputs, A_i and Bi are the fuzzy sets, f_i are the outputs, p_i, q_i and r_i are the design parameters that are determined during the training process.

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Adaptive neuro fuzzy inference system has basically five layer architectures [4]:

In the first Layer: For input fuzzification, the following equations are used.

$$O_{1,i} = \mu_{Ai}(x), \quad i = 1, 2 \qquad (1)$$

$$O_{1,i} = \mu_{Bi-2}(y), \quad i = 3, 4 \qquad (2)$$

where x,y is the input to node $_i$, and A_i , B_i is the linguistic label associated with this node function. $\mu\ A_i(x)$, $\mu\ B_{i-2}(y)$ can adopt any fuzzy membership function. For example, if the bell-shaped membership function is employed, $\mu\ A_i(x)$ is given by:

$$\mu_{Ai}(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]b_i} \quad , i = 1,2 \qquad (3)$$

where a_i , b_i and c_i are the parameters of the membership function.

In the second layer: This layer involves fuzzy operators, it uses the AND operator to fuzzify the inputs. Every node in this layer is labelled π, and each output represents the firing strength of the fuzzy control rule.

$$O_{2,i} = \omega_i = \mu_{A_i}(x) * \mu_{B_i}(y), \quad i = 1,2 \qquad (4)$$

In the third layer,every node in this layer is labelled N with function of normalization.

$$O_{3,i} = \bar{\omega}_i = \frac{\omega_i}{\omega_1+\omega_2} \quad , i = 1, 2 \qquad (5)$$

Outputs of this layer are called normalized firing strengths.

In the fourth layer: Every node in this layer is a square node.

$$o_{4,i} = \bar{\omega}_i f_i = \bar{\omega}_i\,(p_i x + q_i y + r_i) \quad i = 1, 2 \qquad (6)$$

Where $\bar{w}$ is the output of layer 3, and p_i, qi, ri are consequent parameters.

In the fifth layer, every single node in this layer is labelled $\sum$ with function of summation.

$$o_{5,i} = \sum_i \bar{\omega} f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \qquad (7)$$

IV. ANFIS APPLIED TO MOBILE LEARNING ADAPTATION

ANFIS is an intelligent Neuro-Fuzzzy technique used for the modelling and control of ill-defined and uncertain systems. ANFIS is based on the input/output data pairs of the system under consideration. ANFIS is selected to solve the problem of continuous changes in mobile learning environments, facilitating the delivery of adapted learning content. The proposed ANFIS model can be used for modelling the learner context. The steps required to apply ANFIS to learner modelling are: define input and output values; define fuzzy sets for input values; define fuzzy rules; and create and train the Neural Network [5].

To implement and test the proposed architecture, a development tool is required. MATLAB Fuzzy Logic Toolbox (FLT) from Math Works was selected as the development tool. This tool provides an environment to build and evaluate fuzzy systems using a graphical user interface. It consists of a FIS editor, the rule editor, a membership function editor, the fuzzy inference viewer, and the output surface viewer.

FIS editor displays general information about a fuzzy inference system. The membership function editor is the tool that displays and edits the membership functions associated with all input and output variables. The rule editor allows the user to construct the rule statements automatically, by clicking on and selecting one item in each output box, and one connection item. The rule viewer allows users to interpret the entire fuzzy inference process at once. The ANFIS editor GUI menu bar can be used to load a FIS, and open a new Sugeno system to interpret the trained FIS model.

Four input parameters were controlled, namely: Learner Location (LL), Network Bandwidth (NB), Battery Life (BL) and Device Software Capabilities (SC) and one output, Adapted Learner Content (ALC).GENFIS1 is the function used to generate an initial single-output Fuzzy Inference System (FIS) matrix from training data. Several experiments have been conducted to assess the proposed modelled ANFIS whether it has produced an acceptable result [6].

Overfitting is a common problem in ANFIS model building, which occurs when the data is over trained by ANFIS. Every data that trained using ANFIS has its maximum number of epochs before overfitting occurred which cause the predicted output to be over its accuracy. The optimal number of epochs can only be found through experiments. Therefore, overfitting is analysed by plotting the training and checking error values from the ANFIS simulation. To avoid overfitting problem, the model will be tested by setting training epoch equals 10, 20, 30 to find out the optimal epoch number with lowest Root Mean Squared Error RMSE which is defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(y_j - \hat{y}_j)^2} \qquad (8)$$

Where N is the total number of prediction, $\hat{y}_j$ is the predicted time series and y_j is the original series.

ANFIS Network Training is mapping inputs through input membership functions and mapping output through output membership functions. The parameters associated with each membership functions will keep changing throughout the learning process. ANFIS uses back propagation or a combination of least square estimation and back propagation for membership functions estimation. ANFIS training process starts by determining fuzzy sets and the number of sets of each input variable and shape of their membership function. All the training data pass through the ANN to adjust the input parameters to find the

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relationships between input/output and to minimize the error. RMSE (Root Mean Square Error) is the function used to monitor the training error.

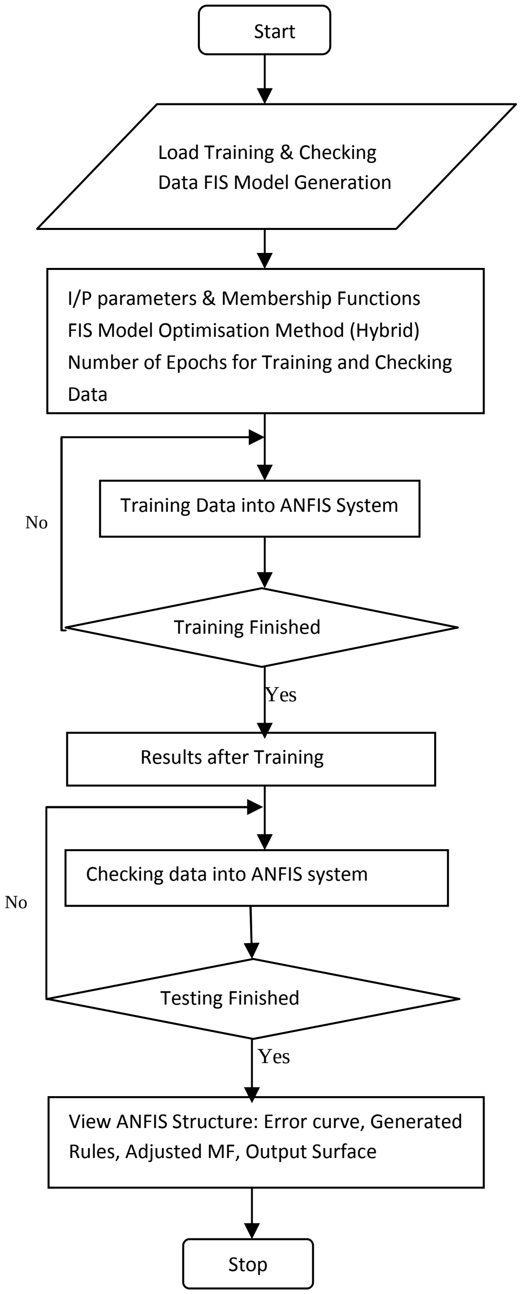

Fig 3. ANFIS training system [7]

V. RESULTS AND DISCUSSION

In order to find out the optimal model which will tackle the problem of mobile learning, a number of factors which play an important role in determining the optimal model need to be investigated. The optimal ANFIS model setting will be selected based on comparing RMSE values between different epoch numbers. The lowest RMSE indicates that the model is optimal and not being over-fit. The comparison is made between results obtained by human expert and ANFIS model using a checking data set. Two vectors are used in order to train the ANFIS, input vector and output vector. The training data set is used to find the initial premise parameters for the membership functions. A threshold value for the error between the actual and desired output is determined.

By comparing the experimental results, it can be concluded that because of the 20,40 and 60 rules were selected very carefully by human expert, the fuzzy base rule is consistent. However, not all situations are covered by human experts fuzzy rules and some missing rules are detected by ANFIS. All situations for all four inputs attributes are covered by the set of 81 rules and 180 rules, some of the rules have been found to have illogical decision because the training sample size not covering all possible cases.

The type of membership functions as well as the number of membership functions is important in building the ANFIS architecture. To investigate the effects of number of MFs and type, a total of 20, 40 and 60 training data and 40, 80 and 118 checking data were used to examine the effect of MFs number and type. There is no way to determine in advance the minimal number of membership functions needed to achieve a desired performance. In other words, the number of membership functions is chosen by trial and error values. The RMSE values were based to select the best membership function and epoch number in order to select the best fit model. From the results, Gaussian membership function with optimized epoch number of 10,20 and 30 in both model structure(4 3 3 5 and 3 3 3 3) was found to be the best model(in comparison with Triangular-shaped and Generalized bell-shaped MFs)with the lowest RMSE value in each test.

VI. CONCLUSION

This paper introduced the Adaptive Neuro-Fuzzy Inference System as a reasoning engine to deliver learning content for mobile learning applications. This study was conducted to illustrate the potential effectiveness of ANFIS with hybrid learning, for the adaptation of learning content format for mobile learning users. The performance of ANFIS was evaluated using standard error measurements which revealed the optimal setting necessary for better predictability. The numbers of fuzzy rules obtained from the human experts were insufficient, therefore, this paper adopted a hybrid approach that combined the Fuzzy Inference System with the Neural Network in determining a complete fuzzy rule system. The ANFIS approach has successfully solved the problem of incompleteness in the fuzzy rule base made by the human expert. By training the Neural Network to apply the human expert's fuzzy rule base to different training data, the Neural Network is expected to recognize other decisions that were previously not detected. Future research will revise the rules, inputs, number and type of membership functions, the epoch numbers used, and training sample to further refine the ANFIS model. The proposed future work will examine and increase the feasibility of developing a more effective and adaptive m-learning content delivery system.

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