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POWER CONTROL FOR MOBILE DS/CDMA SYSTEMS USING A MODIFIED ELMAN NEURAL NETWORK CONTROLLER

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Abstract — **It is well recognized that power control is an important technique to combat the near-far effect and increase the maximum capacity in Direct Sequence Code Division Multiple Access (DS/CDMA) cellular systems. In this paper, we propose a Modified Elman Neural Network (MENN) based multiple-model power control scheme to keep the received power almost constant at the base station. Unlike the conventional “bang-bang” control and fuzzy control, the MENN can identify the inverse dynamical characteristics of the channel by adaptive on-line learning. The inverse channel model is then used for reverse link power control. Hence, large overshoot and long rise time can be effectively avoided. Simulations show that the fluctuation of controlled received power is satisfactory. The overshoot and channel tracking error are small.**

I. INTRODUCTION

In recent years, mobile power control in Direct Sequence Code Division Multiple-Access (DS/CDMA) systems has been attracting growing research interests [1], [5], [10]. The aim of power control is to maintain all mobile users’ signal powers received at the base station nearly equal. This objective offers certain benefits: 1) the user capacity of the mobile CDMA system can be greatly increased [7], 2) near-far problem and co-channel interferences can be reduced, and 3) mobile battery life time may be prolonged.

The conventional power control methods used in DS/CDMA systems can be divided into *open loop* control and *closed loop* control. Due to the difference between the forward and reverse link propagation losses, it is impossible to use open loop control to get precise power control. Then the actual alternative is closed loop control. This means that the base station sends one-bit command to the user to either raise or lower mobile’s power by comparing the received power with the preset power level [1]. However, this method which creates a “bang-bang” like power control, usually has either poor system stability, large overshoot, or slow transient response. Recently, a fuzzy PI power control scheme was proposed in [2], which shows improved performance. However, the weakest point of the rule-based fuzzy control system is that human operation knowledge of the dynamics of the mobile fading channel must be obtained in advance to set up the critical decision table. The control system cannot automatically generate fuzzy control rules and improve its control performance by *learning* on line. It is also desirable to have high quality control performance when sudden changes in the mobile channel characteristics, such as the log-normal fading, multipath fading and varying mobile speed, are unavoidable realties.

This paper is organized as follows. In Section II, we first review the applied fading channel model. The Modified Elman Neural Network (MENN) structure and the inverse system power control scheme with multiple-model configuration are then introduced. In Section III, the proposed control scheme is applied to a reverse link power control in a cellular system with Rayleigh fading channel. The simulation results are provided with illustrative figures. Finally, we conclude this paper with a few remarks in Section IV.

II. MENN-BASED POWER CONTROL SCHEME FOR CDMA SYSTEMS

A. Fading Channel Model

A detailed description of modeling of Rayleigh fading radio channel was given by Jakes in [8]. In this paper, our channel simulator assumes the superposition of plane waves whose arrival angles are uniformly distributed. Different plane waves are associated with different Doppler shifts ranging from the minimum to the maximum specified by the mobile speed. The simulator consists of low frequency oscillators at these Doppler shift frequencies, and the frequency distribution results in a satisfactory approximation of the Rayleigh fading. The in-phase and quadrature components are formed by summing the appropriately weighted oscillator outputs. After multiplication with the corresponding carrier component, the signal is centered at the carrier frequency. Our carrier frequency was 1.8 GHz, the sampling rate of the baseband equivalent in-phase and quardrature components was 1 kHz, and the applied vehicle speed was 50 km/h (a "high speed" in an urban environment).

B. Structure of MENN and Power Control Scheme

The Elman neural network is a globally feed-forward locally recurrent network model [4]. It owns a set of *context* nodes to store the internal states. Thus, it has certain dynamical characteristics over static neural networks, e.g., multilayer perceptrons and radial-basis function networks. However, its training and converge speed are usually very slow and not suitable for time critical applications, such as on-line system identification and adaptive control. Hence, an improved Elman neural network, the Modified Elman Neural Network (MENN), was recently proposed and applied successfully to dynamical system identification [6]. The structure of MENN is given by Fig. 1.

An MENN-based power control system is shown in Fig. 2. Both the identification and control block use the MENN structure. By using an identification model, our system is self-adjusting, and it can improve its behavior by *learning* the varying inverse dynamics of the multipath fading channel in real time. The identification MENN is placed in parallel with the mobile channel to be modeled, and the received power from the mobile station is fed back to the controller. Single-user power estimation is a challenging problem in a CDMA environment. It will be a topic of our future research. The whole control process involves three highlights: 1) the unknown inverse dynamics of the channel are identified by an MENN, and the MENN also acts as the controller; 2) both identification and control are implemented in parallel; 3) multiple-model configuration makes our control scheme more robust to greatly varying system parameters and environment.

As the mobile channel is identified adaptively by the MENN, and the identification model is used immediately for control, we can obtain a smaller overshoot and better tracking error than in conventional control systems. This provides us with a very attractive approach toward a robust, autonomous, and self-tuning power control for mobile CDMA systems.

C. Principle of Neural Inverse Dynamical System Control

Generally, a linear or nonlinear system can be presented as follows

$$\begin{aligned} x(k+1) = \mathrm{f}\{ & x(k), x(k-1), \cdots, x(k-n), \\ & u(k), u(k-1), \cdots, u(k-m)\}, \end{aligned} \tag{1}$$

where *n* and *m* are the input and output order of the system, respectively. The goal of the control is to find the appropriate control actions $u(k), u(k-1) \cdots u(1)$ in order to drive the output $x(k)$ to track a specific reference signal $x^*(k)$. For a nonlinear function $y = \mathrm{f}(x)$, it has been proved that under certain easily-satisfied assumptions there exists an *inverse* function $\mathrm{g}(x)$ defined as

$$\mathrm{g}(x) = \mathrm{f}^{-1}(x), \tag{2}$$

which makes $\mathrm{g}[\mathrm{f}(x)] = x$. Therefore, the above control problem can be converted into solving the inverse function $g(x)$ to satisfy the following equation

$$\begin{aligned} u(k) = \mathrm{g}\{ & x^*(k+1), x(k), \cdots, x(k-n), \\ & u(k-1), u(k-2), \cdots, u(k-m)\}. \end{aligned} \tag{3}$$

Once the inverse model $\mathrm{g}(x)$ of the channel is obtained, it will be cascaded with $\mathrm{f}(x)$ so that the output of $\mathrm{g}(x)$ is the proper control input of $\mathrm{f}(x)$ with the desired output of $x^*(k)$. This control scheme may be considered as *inverse dynamic system control*. However, in practice, it is impossible to find the inverse function $\mathrm{g}(x)$ by any analytical method, especially when $\mathrm{f}(x)$ is unknown, as is the case with practical fading channels. It is well known that a neural network with one hidden layer of sigmoidal units can approximate any nonlinear function arbitrarily well, provided that there are enough neurons in the hidden layer [3]. Hence, by using the output and input data, a neural network can be employed to identify both the feedforward and inverse characteristics of the reverse link channel by adaptively adjusting its weights. This kind of identification approach is usually called *neural network-based dynamical system identification*.

Let $\hat{\mathrm{f}}(x)$ and $\hat{\mathrm{g}}(x)$ represent the neural network approximation forms of $\mathrm{f}(x)$ and $\mathrm{g}(x)$, respectively. There are two types of neural network-based inverse system identification structures, i.e., the *direct* method and the *indirect* method. In the direct method, the neural network is applied to identify the inverse model of $\mathrm{f}(x)$, and thus we can get $\hat{\mathrm{g}}(x)$ from it in the end. In the indirect method, one neural network is first employed to identify the feedforward model of $\mathrm{f}(x)$ in order to acquire $\hat{\mathrm{f}}(x)$. Another neural network is then serially connected with $\hat{\mathrm{f}}(x)$ to identify its inverse model instead of directly identifying the inverse model of $\mathrm{f}(x)$. The latter approach is also called the BTT (Backpropagation Through Time) method. The advantage of the indirect method is that it is suitable to be used in real time, while the direct method can be only used *off-line*. We consider the direct approach in this paper, and propose an improved version to be used for *on-line* power control.

In typical neuro-identification approaches, such as serial-parallel identification, the designer must know exactly how many past inputs and outputs should be fed into the neural network through tapped delay lines. This is not trivial under such conditions, when no prior information of the system to be identified is available. Due to its internal *context* nodes and adjustable connections, the Elman neural network has the great advantage of identifying dynamical systems without knowing their exact orders in advance. The MENN, shown in Fig. 1, includes advantageous feature of additional adjustable weights connecting context nodes and output nodes. This feature can greatly increase the converge speed of the MENN and make it suitable for on-line identification of nonlinear dynamical systems [6].

To keep the received power constant at the base station, the MENN must first identify the inverse characteristics of the fading channel, and then adjust the power output level using the inverse model. The control procedure can be divided into two steps. First, the MENN is employed to identify the inverse model of the channel. Because MENN has internal memory units, only the current power output of the channel $x(k)$ and one step delayed output $x(k-1)$ are needed to be fed into MENN. This alternative simplifies our identification structure and speeds up the training procedure. The power control input of the channel $u(k)$ is used as the reference output of MENN. The identification procedure can be done *off-line* to get a *rough* model without time limitations. At the second step, the MENN representing the inverse model of channel $\hat{g}(x)$ is cascaded with the channel to construct the closed loop control system. The set point signal $r(k)$ which has the general form of $r(k) = 0\,\text{dB}$ is fed into MENN as the given output in place of $x(k)$, while the feedback received power acts as $x(k-1)$. To make our MENN-based controller able to track the time-varying inverse characteristics of the channel, the identification procedure is carried out in parallel with the control procedure. In fact, the MENN controller is set to be a delayed replica of the MENN identifier. The time intervals T_i and T_c, over which the identification and control parameters are updated, are selected as: $T_i = \tau$ and $T_c = T_p = 3\tau$, where T_p is the power control sampling period. Hence, the control parameters are adjusted at a slower rate compared to the identification process. We also require that the whole procedure is performed at a higher rate than the rate of multipath fading to be compensated.

D. Multiple-Model Control Configuration

The fast time-varying channel environment, such as the velocity of mobile station, may affect the dynamic characteristics drastically. These sudden changes in the system parameters will deteriorate the control quality, i.e., large transient errors may occur, if the converge rate of identification is too slow. To attack this severe problem, a *multiple-model* control configuration [9], illustrated in Fig. 3, is used to further improve the power control performance. The main idea of multiple-model control is just like the *gain scheduling* paradigm widely employed, e.g., in flight control. After having considered the various possible models of the channel, several controllers, $C_1, C_2, \cdots, C_N$, and identification models, $M_1, M_2, \cdots, M_N$, are designed *off-line*. Switching among these controllers and identification models is decided by the judgment of the changes of the environment, system parameters, or some predetermined performance index. The multiple-model control configuration can improve the overall performance of the control system, and avoid large transient errors due to rapid changes in the channel and environment. Actually, the approximate mobile speed is chosen as the index for switching in our structure. We developed the following switching policy:

If mobile speed $\leq V_1$
  switch to controller-1
else if mobile speed $\leq V_2$
  switch to controller-2
else if
  ...
else
  switch to controller-N
end,

where $V_1, V_2, \cdots, V_N$ are the estimated mobile speeds. In our approach, three MENN based inverse models of the radio channel are set up for mobile speeds of 5 km/h, 50 km/h, and 100 km/h.

Besides switching among the different MENN-based inverse channel models, we also use another switch between the MENN and the direct *gain* control. This makes the controller more responsive to the occurrence of deep fading, and thus reduce the reaction time needed for the base station to compensate for such fading. Our control system switches to gain control using the following logic:

If deep fading happens, i.e., $x(k) - x(k-1) > E$
  let $u(k) = K$
else
  let $u(k) = u^E(k)$
end,

where E represents the threshold of deep fading, $u^E(k)$ denotes the control output of the MENN and K is an adjustable positive gain that should be chosen to make an approximate balance between the overshoot and the rise time of the response. From the classical control point of view, K is used to improve the performance of transient response, while MENN is left to handle other conditions. With the on-line inverse model identification and multiple-model switching configuration, our scheme can effectively cope with both slow and fast time-varying characteristics of the channel.

III. SIMULATIONS AND RESULTS

In our simulations, the velocity of the mobile station is assumed to be 50 km/h. The center frequency of the mobile transmitter is 1.8 GHz, and the sampling period is set to be 1 ms. An MENN with two input nodes, one output node, and ten hidden nodes is used in our simulations. The structure of MENN depends on the required control accuracy and complexity of the channel under consideration. A simulated random power input is used to illustrate the modeling capabilities of the MENN. These identification results of the inverse model are shown in Fig. 4. We can easily find that MENN gives us a fairly accurate inverse model of the channel. It is expected, however, that more hidden nodes and a longer training time could provide better identification results.

The reference power at the base station is set to be 0 dB. In practice, the power control command output to the mobile station may be implemented in two possible ways. One is to send the *incremental* power to the mobile users by using a one-bit control command, which either lowers or increases the relative power by a fixed amount. The other scheme is to send *full* power to the mobile users. Although this leads to better control performance than the fixed step method, it also increase the demand for the bit rate to be used. Fig. 5 shows the controlled received power using both full command and incremental control. It can be seen that the effects of deep fading are greatly compensated using our MENN control structure. In the worst case when the received power is -38 dB without power control, it is now about -17 dB with the MENN-based power control.

To make quantitative comparisons, two criteria are proposed to measure the control quality of our method. One is the commonly used control index, which gives us a general idea of the control accuracy of our scheme

$$J_1 = \frac{1}{2}\int_0^T e^2(t)dt\,, \tag{4}$$

or for the discrete time case:

$$J_1 = \frac{1}{2}\sum_{k=1}^{N} e^2(k)\,, \tag{5}$$

where e is the control error. To examine the capability of our control scheme to compensate the deep fading, another special control performance index is used here as well

$$J_2 = \max\left(\left|Power(k)\right|\right), \tag{6}$$

where *Power(k)* represents the received power in dB at the base station.

In the simulations, for the received power at the base station without control, i.e., $u(k) = 0\,\mathrm{dB}$, J_1=4200 and J_2=38. While in our full command control scheme, we get J_1=1900 and J_2=18. For the incremental control approach, J_1=3300 and J_2=16. It is clear that both of these control indexes are improved and the full command control method can offer the smoother power control performance.

IV. CONCLUSIONS

A modified Elman neural network-based power control approach is proposed for reverse link power control in DS/CDMA systems. Our simulations show that the Elman neural network is capable of identifying the time-varying inverse dynamics of the multipath fading channel, and the power control command generated by the neural network controller can effectively compensate for fast deep fading. To combat the effects of varying mobile velocity on the received power, a multiple-model reverse link power control configuration is presented. It can further improve the power control performance by selecting different Elman controllers for users at different mobile velocities.

Further research will be carried out on analyzing the performance under different conditions. Also, the single-user power estimation in a multi-user environment is an important topic of advanced research.

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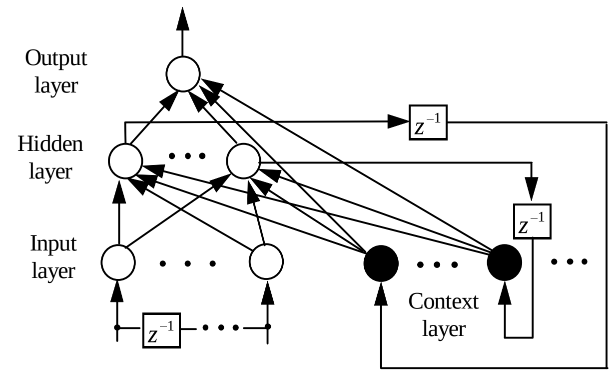

Fig. 1. Structure of MENN.

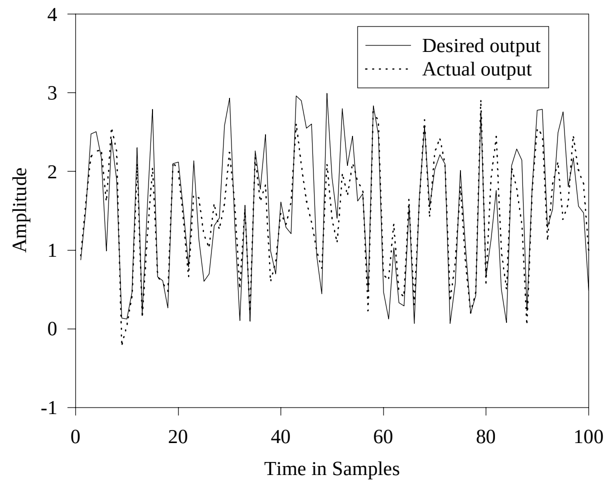

Fig. 4. Identification results of inverse channel model using MENN (random excitation).

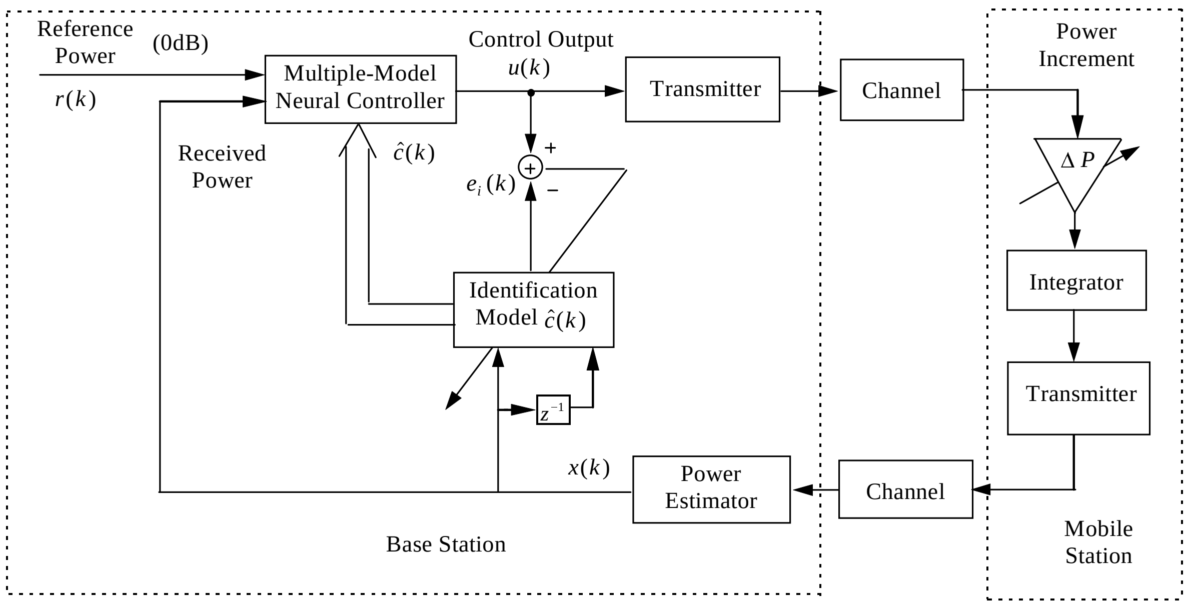

Fig. 2. Neural network-based power control system for DS/CDMA mobile channels.

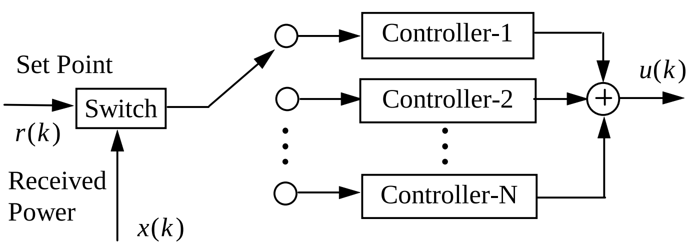

Fig. 3. MENN-based multiple-model reverse link power control structure.

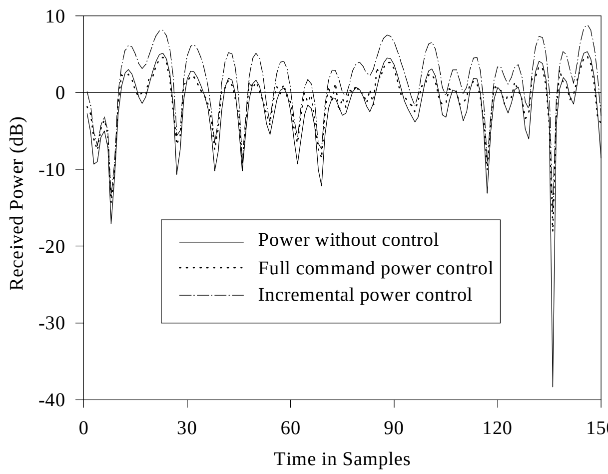

Fig. 5. Performance of MENN-based power control system.