*International Journal of Advancements in Electronics and Electrical Engineering– IJAEEE*
*Volume 4 : Issue 1* [ISSN : 2319-7498]
*Publication Date : 30 April, 2015*

# Biped Robot Control Using Cerebellar Model Articulation Controller

Chih-Hsuan Chen Chih-Min Lin Chang-Chih Chung

***Abstract*—This paper presents the design of a biped robot using the *Cerebellar Model Articulation Controller* (CMAC). An inertial navigation system (INS) including gyroscopes and accelerometers is used to measure the robot's attitude and acceleration for modifying the dynamic attitude of the robot. Moreover, a zero moment point (ZMP) compensator is used to on-line adjust the gait trajectories to improve the walking stability. Experimental results show that the developed system can achieve favorable control performance for the biped robot.**

***Keyword*–Biped robot, Cerebellar Model Articulation Controller (CMAC), Zero moment point (ZMP).**

## I. Introduction

Biped robots have received great attention in recent decades [1-3]. Due to their advanced mobility for different environments, biped robots have a wider range of applications. A method to prove stability at the zero moment point (ZMP) has been proposed by Vukobratovic *et al*. [4, 5]. This is important since the ZMP is the most important factor in a stable biped robot walking. If the ZMP is located in the region of a supporting sole, the robot will not fall down while walking [6]. While walking, the off-line planned swing foot trajectories might not be suitable for uneven surfaces [7]. Since the trajectories can be determined for biped robot control systems, the tracking controller should be designed to track the desired reference trajectories.

The cerebellar model articulation controller (CMAC) is a non-fully connected perceptron-like associative memory network with overlapping receptive fields [8]. CMAC has been already validated to approximate a nonlinear function over a domain of interest to any desired accuracy [9].

The advantages of a CMAC over neural network in some applications have been presented in recent study [10]. Thus, an adaptive CMAC is designed in this study for walking control of a biped robot. Finally, Experimental results will be given to illustrate the effectiveness of the designed system.

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## II. Zero Moment Point

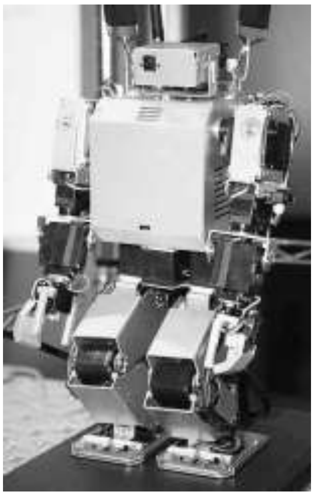
Figure 1The biped robot

A biped robot has a complex kinematic structure that includes the kinematic structure of the arms, the legs, the body, and the head. The designed biped robot has 27 joints altogether and this biped robot is composed of actuators, processor, sensors and other peripheral circuits, configured as shown in Fig. 1. The robot is equipped with various sensors such as accelerometer, gyroscope and force-sensing resistor (FSR) to identify and evaluate the surrounding environment, posture and position.

The zero moment point (ZMP) concept was proposed by Vukobratovic and Juricic in 1969 [4]. Since 1990, ZMP concept has been implemented in a biped robot and then became a criterion for walking balancing control of biped robots [5].

ZMP is equal to floor reaction with inertial and gravity whiling walking. However, a complete walking period is composed of single support phase and double support phase. To realize the actual ZMP via FSR measurement, each sensor reaction is shown as in Fig. 2. Thus the actual ZMP can be computed as

$$\boldsymbol{P}_{ZMP} = \frac{\sum_{i=1}^{n_z} f_i r_i}{\sum_{i=1}^{n_z} r_i} \tag{1}$$

where $n_z$ is the number of foot sensors, $r_i$ is the location of FSR within the feet and $f_i$ is the pressured reaction from the robot.

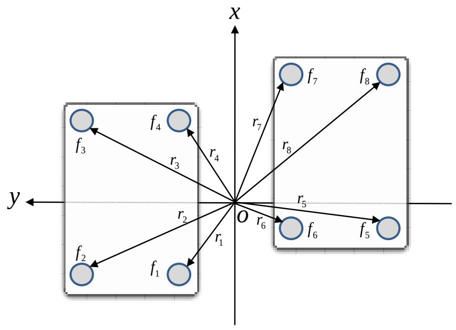


Figure 2 Vectors of FSR location for zero moment point

# III. Adaptive CMAC Control and ZMP Compensation Design

The cerebellar model articulation controllers CMACs have been widely used for closed-loop control for complex dynamic systems due to its fast learning property, good generalization capability and simple computation [9]. Since biped robots have highly nonlinear dynamic coupling characteristics, it is difficult to exactly formulate the complete dynamic model. Therefore, the adaptive CMAC-based intelligent control is designed to achieve walking dynamic stability.

## A. *Description of CMAC*

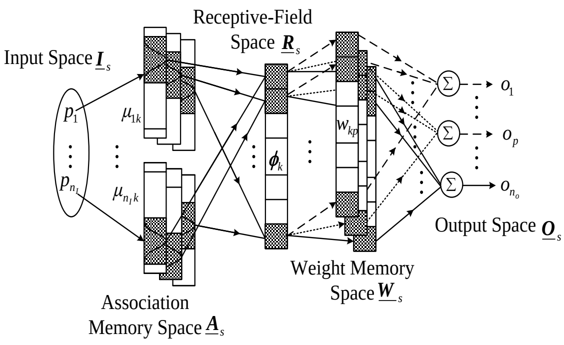


Figure 3 CMAC configuration

A CMAC is proposed as shown in Fig. 3. This CMAC is composed of input space, association memory space, receptive-field space, weight memory space and output space. The signal propagation and the basic function in each space are described as follows.

1) *Input space* $\underline{\boldsymbol{I}}$ : For a given $\boldsymbol{p}=[p_1, p_2, \cdots, p_{n_I}]^T \in \Re^{n_I}$, where $n_I$ is the number of input state variables, each input state variable $p_i$ can be quantized into discrete regions (called *elements*) according to the given control space. The number of elements, $n_e$, is referred to as a resolution.

2) *Association memory space* $\underline{\boldsymbol{A}}$ *:* Several elements can be accumulated as a *block*, and the number of blocks, $n_b$, is usually greater than or equal to two. $\underline{\boldsymbol{A}}$ denotes an association memory space with $n_R$ $(n_R = n_I \times n_b)$ components. In this space, each block performs a receptive-field basis function, and the Gaussian function is adopted here as the receptive-field basis function, which can be represented as

$$\mu_{ik} = exp\left[\frac{-(p_{ik}-m_{ik})^2}{v_{ik}^2}\right], \quad \text{for} \quad i=1,2,\cdots n_I,\ k=1,2,\cdots n_b \tag{2}$$

3) *Receptive-field space* $\underline{\boldsymbol{R}}$ : Areas formed by blocks, referred to as $B_{a1}B_{a2}$ and $B_{b1}B_{b2}$ are called receptive-fields. The number of receptive-fields, $n_d$, is equal to $n_b$ in this study. The $k$-th multi-dimensional receptive-field function is defined as

$$\phi_k(\boldsymbol{p},\boldsymbol{m}_k,\boldsymbol{v}_k) = \prod_{i=1}^{n_I}\mu_{ik} = exp\left[\sum_{i=1}^{n_I}\frac{-(p_{ik}-m_{ik})^2}{v_{ik}^2}\right] \quad \text{for} \quad k=1,2,\cdots n_d \tag{3}$$

where $\boldsymbol{m}_k = [m_{1k}, m_{2k}, \cdots, m_{n_I k}]^T \in \Re^{n_I}$ and $\boldsymbol{v}_k = [v_{1k}, v_{2k}, \cdots, v_{n_I k}]^T \in \Re^{n_I}$.

The multi-dimensional receptive-field functions can be expressed in vector form as

$$\boldsymbol{\Phi}(\boldsymbol{p},\boldsymbol{m},\boldsymbol{v}) = [\phi_1, \cdots, \phi_k, \cdots, \phi_{n_d}]^T \tag{4}$$

where $\boldsymbol{m} = [\boldsymbol{m}_1^T, \cdots, \boldsymbol{m}_k^T, \cdots, \boldsymbol{m}_{n_d}^T]^T \in \Re^{n_I n_d}$ and $\boldsymbol{v} = [\boldsymbol{v}_1^T, \cdots, \boldsymbol{v}_k^T, \cdots, \boldsymbol{v}_{n_d}^T]^T \in \Re^{n_I n_d}$.

4) *Weight memory space* $\underline{\boldsymbol{W}}$ *:* Each location of $\underline{\boldsymbol{R}}$ to a particular adjustable value in the weight memory space can be expressed as

$$W = [w_1, \cdots, w_p, \cdots, w_{n_o}] = \begin{bmatrix} w_{11} & \cdots & w_{1p} & \cdots & w_{1n_o} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ w_{k1} & \cdots & w_{kp} & \cdots & w_{kn_o} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ w_{n_d 1} & \cdots & w_{n_d p} & \cdots & w_{n_d n_o} \end{bmatrix} \in \Re^{n_d \times n_o} \tag{5}$$

where $\boldsymbol{w}_p = [w_{1p}, \cdots w_{kp}, \cdots w_{n_d p}]^T \in \Re^{n_d}$, and $w_{kp}$ denotes the connecting weight value of the $p$-th output associated with the $k$-th receptive-field.

5) *Output space* $\underline{\boldsymbol{O}}$ *:* The output of CMAC is the algebraic sum of the activated weights in the weight memory, and is expressed as

$$o_p = \boldsymbol{w}_p^T \boldsymbol{\Phi} = \sum_{k=1}^{n_d} w_{kp}\phi_k, \ \text{for} \ \ p=1,2,\cdots n_o \tag{6}$$

The outputs of CMAC can be expressed in vector notation as

$$\boldsymbol{o} = [o_1, \cdots o_p, \cdots o_{n_o}]^T = \boldsymbol{W}^T\boldsymbol{\Phi} \tag{7}$$

### B. *Online learning algorithm*

The online learning algorithm is done by means of the chain rule, and the method is generally referred to as the back-propagation learning rule. To describe the on-line learning algorithm of CMAC by using the supervised gradient decent method, the energy function is defined as

$$E = \frac{1}{2}(d_m - d)^2 = \frac{1}{2}e_m^2 \quad (8)$$

With this energy function, the error term to be propagated is defined as

$$\frac{\partial E}{\partial u_{ZMP}} \equiv \delta_{ZMP} \quad (9)$$

Based on back-propagation method, the learning law of $w_{kp}$ can be derived as

$$\Delta w_{kp} = -\eta_{zw}\frac{\partial E}{\partial w_{kp}} = -\eta_{zw}\frac{\partial E}{\partial u_{ZMP}}\frac{\partial u_{ZMP}}{\partial w_{kp}} = -\eta_{zw}\delta_{ZMP}\phi_k \quad (10)$$

where $\eta_{zw}$ is the learning-rate for all $\phi_k$. Moreover, the means and variances of the Gaussian receptive-field basis functions can be adjusted with (11) and (12), respectively:

$$\begin{aligned}\Delta m_{ik} &= -\eta_{zm}\frac{\partial E}{\partial m_{ik}} = -\eta_{zm}\frac{\partial E}{\partial u_{ZMP}}\frac{\partial u_{ZMP}}{\partial \phi_k}\frac{\partial \phi_k}{\partial m_{ik}} \\ &= -\eta_{zm}\delta_{ZMP}w_{kp}\phi_k\frac{2(p_{ik} - m_{ik})}{v_{ik}^2}\end{aligned} \quad (11)$$

$$\begin{aligned}\Delta v_{ik} &= -\eta_{zv}\frac{\partial E}{\partial v_{ik}} = -\eta_{zv}\frac{\partial E}{\partial u_{ZMP}}\frac{\partial u_{ZMP}}{\partial \phi_k}\frac{\partial \phi_k}{\partial v_{ik}} \\ &= -\eta_{zv}\delta_{ZMP}w_{kp}\phi_k\frac{2(p_{ik} - m_{ik})^2}{v_{ik}^3}\end{aligned} \quad (12)$$

where $\eta_{zm}$ and $\eta_{zv}$ are the learning-rates for means and variances, respectively. The error term of the system, $\delta_{ZMP}$, cannot be computed if the plant model is unknown. To overcome this problem, an approximation of this error term is used [11]:

$$\delta_{ZMP} \cong (\dot{d}_m - \dot{d}) + (d_m - d) = \Delta e_m + e_m \quad (13)$$

## IV. Experimental Results

The learning-rate parameters of the proposed dynamic balancing control system are selected as $\eta_{zw} = 0.01$ and $\eta_{zm} = \eta_{zv} = \eta_{zr} = 0.001$ . The proposed CMAC-based adaptive controller is applied to control this biped robot. Figure 4 shows the actual ZMP during walking including ZMP compensator. The simulation results show that the proposed control algorithm can achieve satisfactory control performance for the biped robot.

## V. Conclusions

This study has successfully designed an intelligent control system for a biped robot. The proposed intelligent control system consists of a CMAC-based controller and a ZMP compensator. Since the highly nonlinear models needed for a biped robot are difficult to obtain, the adaptation propagation law is adopted and an on-line learning algorithm of CMAC is achieved by the supervised gradient decent method. The experimental results have demonstrated favorable control performance for the walking control of a highly nonlinear biped robot.

### *Acknowledgment*

This work was supported by the National Science Council of the Republic of China under Grant 98-2221-E-155-058-MY3.

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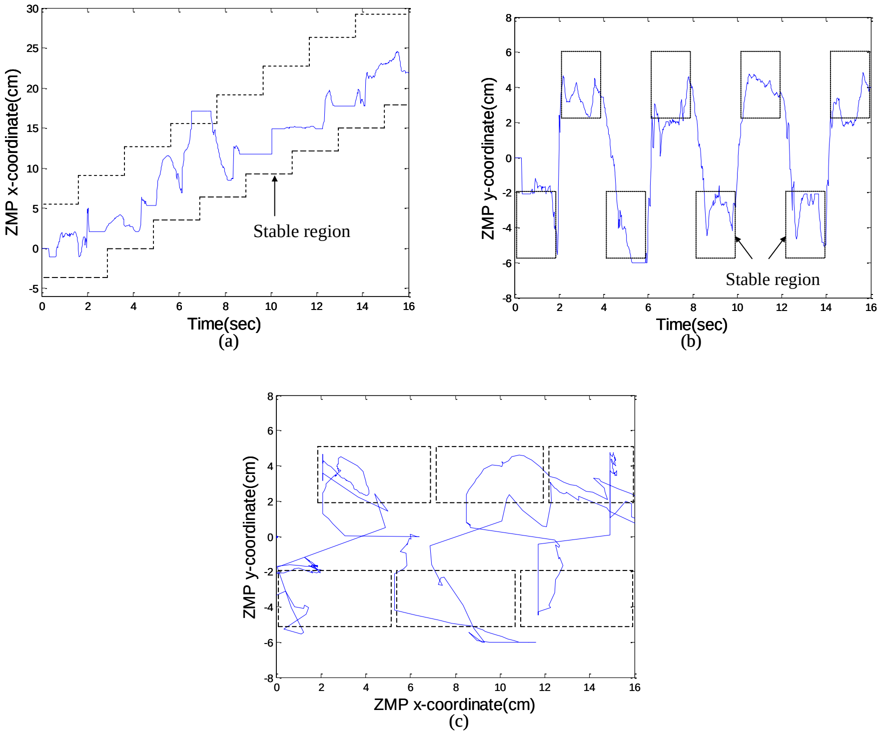


Figure 4 Walking pattern