Toward Developing a Computational Model for Bipedal Push Recovery–A Brief

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***Abstract*— The human being can negotiate with external push up to certain extent reactively. Grown up persons have better push recovery capability than kids and also the professional wrestlers acquire better push recovery capability than normal human being. The acquired push recovery capability, therefore, is based on learning. However, the mechanism of learning is not known to us. Researchers around the world are trying to explore this mystery through developing various models and implementing them on various humanoid robots. All the models based on conventional mechanics and controls have inherent limitations. We believe appropriate computational model based on learning will be able to effectively address this issue. Accordingly, we have collected extensively humanoid push recovery data using our innovative idea of exploiting the accelerometer sensor of smart phone. Through our experiments, we have studied the human push recovery by fusing data at feature level using physics toolbar accelerometer of android interface kit. The subjects for the experiments were selected both as right handed and left handed. Pushes were induced from the behind with close eyes to observe the motor action as well as with open eyes to observe learning-based reactive behaviors. A learning vector quantization-based classifier has been developed to identify the coordination between various push and hip and knee joints.**

***Index Terms*— Savitzky Golay filter (Sgolay), push recovery, LVQ, inverse kinematics, HMCD (Human Motion Capture Device).**

I. Introduction

We FORESEE in future, robots will perform the task in domestic and industrial environment just like as human beings. Any study help to understand the problem of elderly and disabled person. Push Recovery [1] is the capability of any human being to recover from any external push. Bipedal is much suitable then wheel robot due to dexterity and mobility over unstructured terrain. The robotics limbs which mimic the human locomotion gives rise of humanoid robot. The Human locomotion is a complex process which took almost years for stable gait. The emergence of human like robot benefited the society due to potential benefits in assistance of elderly people and help amputee to recover their gait. The human negotiate with push using three type of push recovery strategy (hip, knee & ankle) [2]. Fig. 1 describes the process of scientific investigation of humanoid push recovery. In our experiment we selected subject of different weight, height and age group to a push and captured their recovery mechanism for both male and female with left and right handed using wearable mobile phone embedded suit and compared the results with our earlier indigenously developed wearable HMCD [3] suit.

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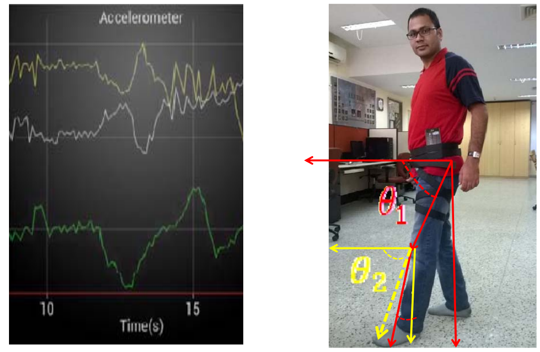

Fig. 1. Extracting data from accelerometer.

Algorithm 1 Extracting Data from Accelerometer to Biped's Configuration Space Using Inverse Kinematics - Complexity $\theta(n)$

Input:*LeftKnee*$_x$ $(x[n])$, *LeftKnee*$_y$ $(y[n])$, *length of thigh* (l_t), *length of shank* (l_s),*constant* $(k1)$ *& constant*$(k2)$
Output:$\theta_1[n], \theta_2[n]$
Initial:$l_t \leftarrow 5;\ l_s \leftarrow 4;$
Begin
  for i ← 1:n
    $tmp[i] = \frac{x[i]^2+y[i]^2-l_t^2-l_s^2}{2\times l_t \times l_s}$
  End for
  $tmp_{max} = \max(tmp)$ *% where 'max' will find the maximum*
  for i ← 1:n
    $cos\theta_2[i] = \frac{tmp[i]}{tmp_{max}}$
    $sin\theta_2 i = \sqrt{1-(cos\theta_2[i])^2}$
    $k1[i] = l_t + l_s \times cos\theta_2[i]$
    $k2[i] = l_s \times cos\theta_2[i]$
    $\theta_1[i] = atan2(y[i], x[i]) - atan2(k2[i], k1[i])$
    $\theta_2[i] = atan2(sin\theta_2[i], cos\theta_2[i])$
  End for
End Begin

A. Proposed Method

We designed the wearable accelerometer embedded mobile phone suit named HLPRDCD (Human Locomotion and Push Recovery Data Capture Device) to capture the data of different joint angles change (hip and knee) which is the manifestation of locomotion/push recovery. We fused the data collected into x, y, z direction and later using algorithm 1 we converted the capture data into biped's configuration space using inverse kinematics. Fig. 2 is the curve between theta vs time for left and right hip/knee. It is one step more advance of our

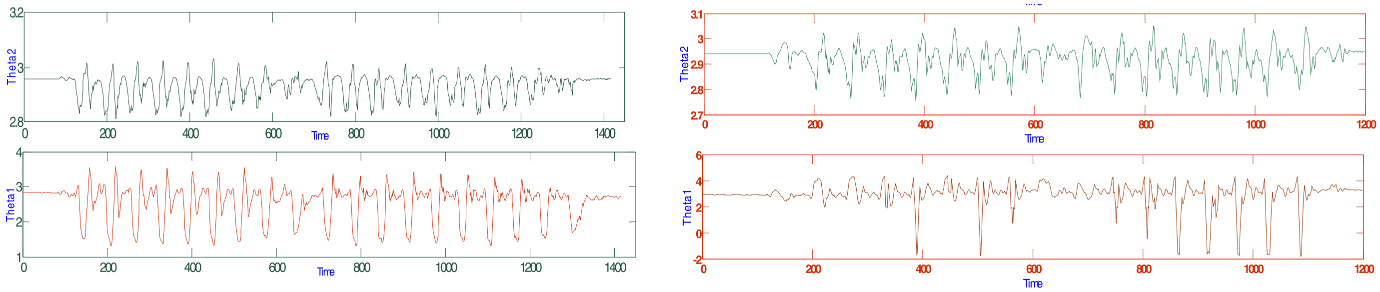

Fig. 2. Observed left hip, left knee and right hip, right knee joint curve for right and left leg.

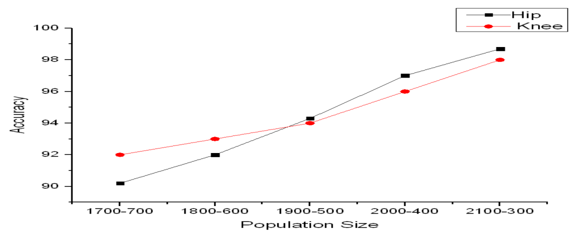

Fig. 3. Accuracy of classifier over different strategy.

previous research toward more sophisticated device with less error and more accuracy. Earlier we developed the HMCD suit [3] to capture the push recovery capability of human. To measure the value of applied push force we placed the force sensing resistor (FSR 3105) on the back between spinal chord and last rib of person. The measured value can convert into Newton using formula1 where f is the force in digital counts. Due to limited area of the forces sensor measured the value measure in digital count is between 1 to 100 Newton

$$\text{Force (Newton)} = f \times 9.8/1000. \quad (1)$$

B. Experimental Setup and Data Acquisition

We used the mobile phone embedded accelerometer to measure the joint angle before and after application of external push. We are calculating the applied force on the subject with the help of force sensor. We applied different magnitude push behind up to 25 Newton.

C. Data Correction and Smoothing

The ideal curve for hip and knee are disturbed due to push applied from behind, so we smoothed the data using Savitzky-Golay filter. The initial reading which we captured has certain value initially due to noise, so we corrected data using zero correction i.e. subtracted initial value from the all measured value.

II. RESULT

Fig. 3 describes the accuracy curve for the two push recovery strategies for different population size using LVQ (Learning Vector Quantization). It is a complex co-ordination of muscles and nerves i.e. motor system, sensory organ (sensation) and other parts of the brain which help co-ordination [5], [6].

Ideally a person has oscillatory motion in hip which is almost sinusoidal, has two sharp humps for ankle and two humps in knee joints curve for normal walking pattern without external force. The observed leg joint curve for right handed person's right and left leg is shown in Fig. 2. In our experiment, results have been noted for both left and right handed subjects with specific setting i.e. closed eyes without hand movement to produce robot like environment. Fig. 2 shows the graph of angle variation of hip and knee (in degree) versus time duration for a right handed person. In given graph we can see an oscillatory motion of hip, very close to ideal one [7], [8]. This can further be used in the analysis of crouch or abnormal subject [9].

III. CONCLUSION AND FUTURE WORK

We analyze the human push recovery using several experiments using HMCD as well as HLPRDCD as manifestation of knee, hip and ankle joint angle change. The mobile phone based data collection is very convenient and accurate compared to the potentiometer based HMCD. Using LVQ we observed that the push recovery capability depends on many factors including age, sex, weight, height, ambidextrous, race etc. It is an evolutionary process grows and decays with age and based on complex coordination between muscle and motor action our future research is directed towards developing an optimized computational model based on hybrid automata which can control the biped robot's push recovery in an as effective way as human beings.

REFERENCES

[1] B. Stephens, "Humanoid push recovery," in *Proc. 7th IEEE-RAS Int. Conf. Humanoid Robots*, Nov./Dec. 2007, pp. 589–595.
[2] J. Pratt, J. Carff, S. Drakunov, and A. Goswami, "Capture point: A step toward humanoid push recovery," in *Proc. 6th IEEE-RAS Int. Conf. Humanoid Robots*, Dec. 2006, pp. 200–207.
[3] V. B. Semwal, A. Bhushan, and G. C. Nandi, "Study of humanoid push recovery based on experiments," in *Proc. IEEE Int. Conf. CARE*, Dec. 2013, pp. 1–6.
[4] H. Martin Schepers, E. H. F. van Asseldonk, C. T. M. Baten, and P. H. Veltink, "Ambulatory estimation of foot placement during walking using inertial sensors," *J. Biomech.*, vol. 43, no. 16, pp. 3138–3143, 2010.
[5] V. B. Semwal, P. Chakraborty, and G. C. Nandi, "Less computationally intensive fuzzy logic (type-1)-based controller for humanoid push recovery," *Robot. Auto. Syst.*, vol. 63, pp. 122–135, Jan. 2014.
[6] V. B. Semwal, M. Raj, and G. C. Nandi, "Multilayer perceptron based biometric gait identification," *Robot. Auto. Syst.*, to be published.
[7] T. Liu, Y. Inoue, and K. Shibata, "A wearable ground reaction force sensor system and its application to the measurement of extrinsic gait variability," *Sensors*, vol. 10, no. 11, pp. 10240–10255, 2010.
[8] T. Liu, Y. Inoue, and K. Shibata, "Development of a wearable sensor system for quantitative gait analysis," *Measurement*, vol. 42, no. 7, pp. 978–988, 2009.
[9] V. B. Semwal, S. A. Katiyar, P. Chakraborty, and G. C. Nandi, "Biped model based on human gait pattern parameters for sagittal plane movement," in *Proc. Int. Conf. Control, Autom., Robot., Embedded Syst. (CARE)*, Dec. 2013, pp. 1–5.