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LVQ based speed adaptive swing and stance phase detection: An alternate to Foot Switch

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Abstract

This paper presents a novel method for stance and swing phase detection employing Learning Vector Quantization (LVQ), using knee angle information only. The results show detection accuracy of 95.9% in stance phase and 83.9% in swing phase. The research concludes an efficient replacement of footswitch for phase detection. The work can directly lead to low cost speed adaptive transtibial prosthesis where the knee angle measurement can be used to decide the damping in the prosthesis.

Keywords: *Adaptive, LVQ, Swing Phase, Stance Phase, Transtibial Prosthesis*

1 Introduction

Swing and stance phases are the important phases of walking pattern. Most of the popular prosthesis's performance depends on successful detection of these phases. The damping is decided by the control unit as per the determined phase. Besides in the prosthesis and orthosis, this phase detection is also useful in stimulation of nerves such as the peroneal nerve. Cross correlation was implemented on the data acquired from accelerometer, to detect the swing and stance phase [1]. The hardware available in the foot, i.e. foot switch, helps in detecting the gait phases, and is quite popular. Research has claimed that the combined use of the FSRs

(Force Sensitive Resistor) and the gyroscope together with an intelligent rule based detection algorithm leads to a very robust gait phase detection system [2]. Even a wireless portable gait phase detection system has been developed using foot switch and gyroscope [3]. In another research work a sensor system comprising of two accelerometers, two goniometers and a gyroscope was attached to lower leg for stance phase detection, using Artificial Neural Network (ANN). This has a potential application in FES (Functional Electrical Stimulation) assisted walking. A “gaitshoe” comprises of three orthogonal accelerometers, three orthogonal gyroscopes, four force sensors, two bidirectional bend sensors, two dynamic pressure sensors, as well as electric field height sensors is developed to quantify gait analysis. Further it was highly capable of heel strike, toe off, foot orientation and position [4]. A gait phase detection system was entirely embedded in a shoe insole and detects four phases of the gait cycle in real time: stance, heel-off, swing and heel-strike. The accelerometer attached to lumbar region was 98.2% and 99.8% reliable in the detection of heel contact events, whereas with the footswitch, the reliability ranges between 92.4% and 98.7% [5]. Foot switch, though inexpensive, suffers from the limitation in size and accurate placement for phase detection. The proposed scheme provides to overcome this limitation.

For Trans-tibial amputee prosthesis, hardware setup mentioned earlier does not work properly. Furthermore, synchronization of hardware is complicated process. Knee angle trajectory intrinsically contains the phase information. However, this information is corrupted due to non-unique mapping of knee angle amplitude in different phases. This ambiguity is eliminated by employing learning machines (specifically Artificial Neural Networks). Apart from knee angle, its derivative has been taken as the input for neural network. Linear Vector Quantization (LVQ) was the preferred choice for this work due the advantage of competitive layer - which requires less hidden layer neurons as well as less computation time. The tradeoff comes in the form of networks that may possibly be less generalized. Moreover LVQ eliminates the explicit need to tune multiple parameters while training like momentum, learning rate. Previously, variables such as joint angles (measured using potentiometer Goniometer), and the foot forces using a flexible force sensing insole, were used to detect gait phases employing inductive learning techniques [6]. Relatively few research works have been reported on using LVQ for phase detection in gait analysis. Distinction-Sensitive Learning Vector Quantization (DSLVQ) was used to automate feature selection of footsteps to identify adaptive identification of walkers [7].The difference between gait signatures, detected using SVM (Support Vector Machine) from basic kinetic and kinematic data [8] has also been presented. The key idea in the present method is the detection of the swing and stance phase using knee angle information only, which will directly lead to lower costs of transtibial prostheses. The accurate detection of swing and stance phase leads to precise switching of damping and hence leads to a smart speed adaptive prosthesis.

The other source of information can be the EMG for swing and stance phase detection. EMG based prosthesis performance is degraded by sweating in tropical region and needs a lot of training. EMG signal is easily corrupted by Electromagnetic noise and motion artifacts. Moreover achieving higher accuracy requires higher number of electrodes and complex signal processing. In contrast knee angle measurement does not get affected by any physiological parameter and may overcome the problem associated with EMG.

1.1 Swing and Stance

Stance phase represents about 60% of the gait cycle, and starts from initial contact with the ground. Swing phase is the phase of the normal gait cycle during which the foot is off the ground (Fig.1 (a)). The swing phase follows the stance phase and is divided into the initial swing, the midswing, and the terminal swing. Swing phase accounts for 40% in normal gait cycle (Fig.1 (b). Based on the switch status the phases are decided.

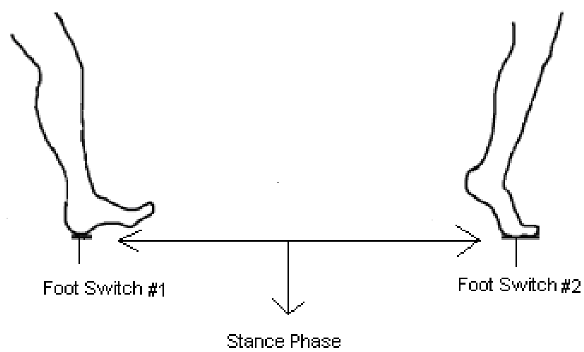

Fig. 1(a)

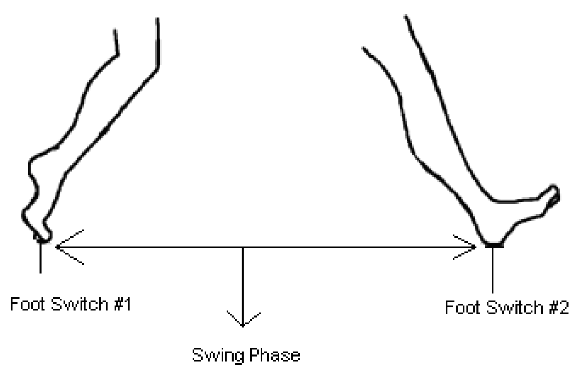

Fig. 1(b)

Table. 1. Table for swing and stance phase detection

Foot Switch#1	**Foot Switch#2**	**Gait Phase**
1	0	Stance
1	1	Stance
0	1	Stance
0	0	Swing

Foot switch are generally pressure sensitive resistive membrane. Table 1 gives the expression for phase identification based on status of switch. In prosthesis the foot switches are interfaced to microcontroller and based on their status the control action is taken. The Boolean expression from Table 1 can be written as K=A + B, where A, B are the states of toe and heel switches, respectively and K represents Stance (1) or Swing (0).

1.2 Linear Vector Quantization (LVQ)

Learning Vector Quantization (LVQ) is a supervised version of vector quantization. LVQ algorithms directly define class boundaries based on prototypes, a nearest-neighbor rule and a winner-takes-it-all paradigm. S^1 represents the subclasses in the competitive layer having S^1 competitive neurons while S^2 represents the output classes, also called linear layer, having S^2 linear neurons. R is the number of elements in the input vector. Neurons in competitive layer perform the distance from presented input vector to each row of the input weight matrix $\mathbf{IW}^{1,1}$, i.e. $-\| {}_i\mathbf{IW}^{1,1}-\mathbf{p}\|$, while the neurons at output layer performs linear function. $\mathbf{LW}^{2,1}$ represents the weight of neurons in competitive layer connected to linear layer.

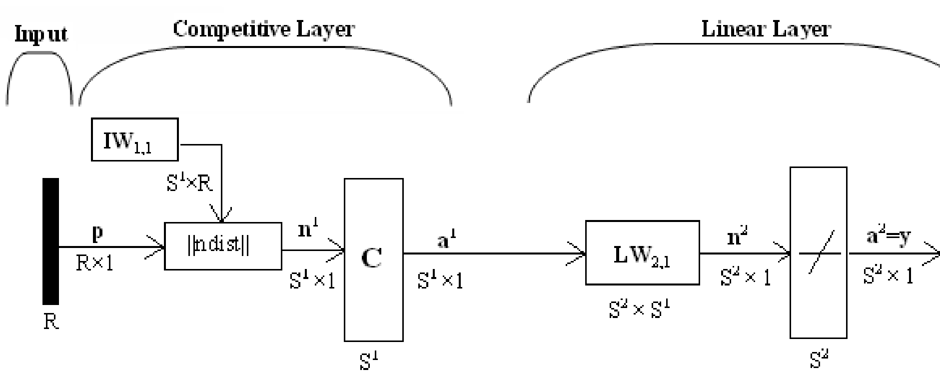

Fig.2 LVQ

Weight updating rule

If the input vector p is classified correctly and the neuron i^* wins the competition then the input weight matrices of the neuron is updated to move neuron closer to input vector, using following equation

$$ {}_{i^*}W^{1,1}(q) = {}_{i^*}W^{1,1}(q-1) + \alpha(p(q) - {}_{i^*}W^{1,1}(q-1) \quad \ldots\ldots\ldots\ldots\ldots\ldots (1) $$

On the other hand if p is classified incorrectly, then the input weight matrices of the neuron is updated to move the neuron away to the input vector using following equation

$$ {}_{i^*}W^{1,1}(q) = {}_{i^*}W^{1,1}(q-1) - \alpha(p(q) - {}_{i^*}W^{1,1}(q-1) \quad \ldots\ldots\ldots\ldots\ldots\ldots (2) $$

where **α** is the learning rate.

Such corrections move the hidden neuron toward vectors that fall into the class for which it forms a subclass, and away from vectors that fall into other classes.

2 Methods

Sixteen healthy adult male volunteers between the ages of 22 and 27 years with no obvious neurological or musculoskeletal deficiencies participated in this study. All participants provided written informed consent prior to testing. Data was collected in a 3 D motion analysis system using six CCD Cameras. EVA 7.0 and Orthotrak 6.2 software were used for data recording [9-10], gait analysis and for toe off and heel strike detection. Twenty five Cleveland markers were placed on the subjects. Confidentiality aspects prevent any visual data from being presented. Furthermore, all subject identification information was anonymized as well. Subjects were asked to habituate themselves with walking in the laboratory at their normal speed. They were further asked to walk with varying speeds.

2.1 Data Collection and Analysis

Training data was collected from human motion analysis lab, Defense Institute of Physiology and Allied Sciences (DIPAS), New Delhi. The initial contact in the Orthotrak software was used as the starting of stance phase and toe off was considered as swing phase. The corresponding collected data were used to train and test the network. The data collected were analyzed offline in order to develop suitable walking phase detection algorithm. Data recording began 2-3 minutes after the subjects began walking. This was done to habituate the subjects with the walk pathway. Seven to eight trials were performed for each locomotive task to get repetitive data for comparison and analysis. Data was collected at the sampling frequency of 120 Hz. The time duration to record the data for every trial was 3 seconds. Some of the trials were not included for analysis as they were corrupted due to incomplete information or excessive noise. Noise was eliminated from the gathered data using a low pass Butterworth filter with cut off of 6.0 Hz, and analyzed using Matlab 7.0. Out of 360 samples, only one gait cycle information was used, despite the availability of multiple cycles during recording phase. Even though analysis was performed for movements in frontal, transversal and sagittal planes, only sagittal analysis was considered relevant to this study, as most of the movement of knee is in sagittal plane.

Knee angle derivative was computed using first order difference. For a constant and uniform sampling rate if the walking speed changes temporal values of knee angle and its derivative also change. So data with various speeds were presented to LVQ.

2.2 LVQ Design

The optimal number of neurons in competitive layer is determined heuristically. In this research work it was three which was considered to be quite reasonable after visualizing the scatter diagram of knee angle and its derivative. LVQ being suitable in terms of training time and number of hidden units required is preferred over back propagation and Radial basis function. The lower dependence of LVQ on tuning parameters like learning rate and momentum makes it a preferable choice compared to BP (Back Propagation) algorithm.

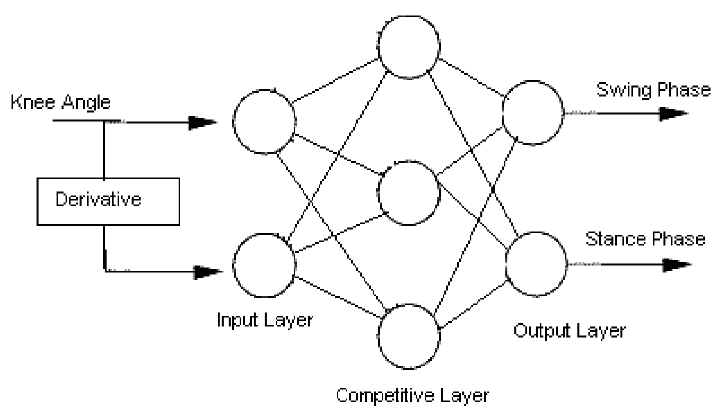

Fig.3 Design of LVQ Network

The input parameters for the network are knee angle and its derivative i.e. first order difference. Derivative having a good potential (significant difference in amplitude in sign) to discriminate between two phases was selected as input features. The neurons in competitive layer were selected two and then increased by one with each trail. The error with same number of epochs i.e. 25 was found minimum with 3 neurons in competitive layer. So finally the LVQ with three neurons in competitive layer was finalized to train the data.

3 Results

The average walking speed for slow, normal and fast gait was 82cm/sec, 112cm/sec and 138cm/sec, respectively. The network was trained with speeds of 81cm/sec, 112cm/sec, 116cm/sec and 138cm/sec. After training the network was tested with speeds of 92cm/sec, 109cm/sec and 143cm/sec. Fig.4 shows the successful training in as few as 25 epochs. Table3 summarize the accuracy of swing and stance phase.

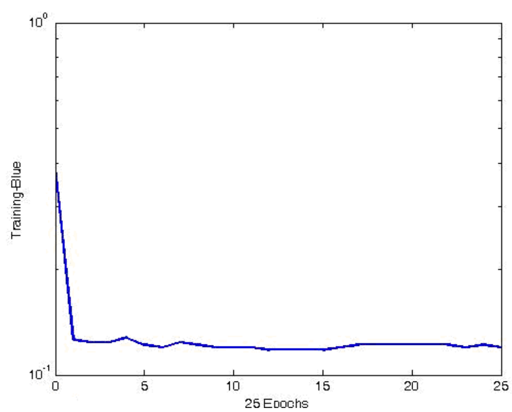

Fig.4 Error profile of network in 25 epochs

Table 2. Testing accuracy of the network

Walking Speed(cm/sec)	**Stance Phase Detection Accuracy (%)**	**Swing Phase Detection Accuracy (%)**
92 (below normal)	97.7	78.3
109 (normal)	96.5	82.5
143 (above normal)	93.6	90.9

The results show that the network is capable of detecting stance and swing phase with almost all average accuracy of 95.9% and 83.9% respectively. The authors also conclude that the detection performance depends on the walking speed rather the subjective nature. The results were verified from both left and right leg as well.

4 Discussion and Conclusion

This study developed an approach to the determination of the key gait events, swing and stance, based on knee angle data alone. The results show that the knee angle and its derivative are strong features to detect the gait phase accurately. Derivative calculation being quite easy to calculate in hardware adds an advantage for the hardware design of the proposed prosthesis. It also shows that the detection performance depends on the walking speed rather the subject. The available Foot switches have limitations in terms of dimension and their placement for accuracy.

This algorithm in this sense has an edge over it. Sensitivity of footswitch towards weight of the subject introduces undesirable subjective nature. The knee angle measurement, on the other hand, is independent of subject's physical parameter. The testing of algorithm has not been done with amputee. If the training data consist of amputee walking the network will have more accuracy for testing with amputee data. This work provides easily realizable and reliable approach for echo controlled prosthesis. There certainly is room for further studies, which will improve swing phase detection accuracy.

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