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## Accelerometer Based Static Gesture Recognition and Mobile Monitoring System Using Neural Networks

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### Abstract

Gesture recognition enables humans to communicate with the machine and interact naturally without any mechanical devices. A lot of research has been already done in the field of gesture recognition using different mechanism and algorithms. The majority of work in this field is done using Image processing techniques<sup>1</sup> and methodologies. This paper aims to propose a cost effective low power wearable wrist band to control the locomotion of robot using static gesture from hand which leads to the advance concept of unmanned vehicle. An artificial neural network (ANN) trained with a Learning Vector Quantization (LVQ) algorithm was used to train and recognize arm gesture. The results show that the system allows the control of a robot in an intuitive way. However, the achieved recognition rate of postures has a lot of scope for improvement by compromising the system response time.

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### Introduction

Gestures are very natural form of interaction between people, and also can be effectively used for human computer interaction applications. human gestures can be either static or dynamic in nature, static gestures are also known as postures. A significant amount of work on dynamic hand gesture recognition could be seen in Dynamic Hand gesture recognition using 3-axis accelerometer<sup>2</sup> and Using Motion Trajectories and Key Frames<sup>3</sup>. This paper aims to develop a cost effective low power wearable wrist band to control the locomotion of robot using static gesture from hand. One of the major application of this wearable band could be seen in wheelchair, suppose a handicapped person is controlling the motion of wheelchair by wearing this wrist band in his own hand. This device can be used to control things like unmanned vehicle, even intensity of light apart from wheelchair.

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Accelerometer based industrial robotic arms are already in use and the studies in this view have been in prevalence<sup>5</sup>. The gestures of different organs of the body are used to control the wheel chair and different intelligent mechanisms have been developed to control the intermediate mechanisms<sup>6</sup>. Hidden markov models and neural networks have always imparted a sense of intelligence to the controlling and classifying mechanisms in different industrial applications<sup>7</sup>. Accelerometers have also involved themselves in to the digital and hand written character recognition based on gesture classification<sup>8</sup>. The application of 3-axis accelerometers signal classification involves quite a very precision and uses different methods. The comparison among these classification methods has always been debatable<sup>9</sup>. LVQ is one of those mostly used methods, which proves to be given robust classification among many complicated patterns<sup>10</sup>. Many neural network algorithms have been repetitively applied for the purpose of classifying the signatures and gestures. The training and number of epochs have been significantly varied for improving the classification efficiency<sup>11</sup>.

## 1. Proposed Method

When the gesture is stationary, the accelerometer can measure the composed of the gravitation acceleration in three axes. We use the interrupt function inactivity of accelerometer (ADXL335). The accelerations of three axes can be read to determine the directions of the accelerators and recognize it as static gestures. Firstly, Data was acquired using the three-axis accelerometer, and then it was trained using LVQ algorithm in neural network. The neural network was trained using MATLAB software. This trained neural network will classify the data into three sets for forward, stop and left movement of the robot. Now a random input or gesture is given as an input via the accelerometer placed in the wearable band. This input will be classified into one of the three gestures already predefined by the neural network. So the neural network acts as the brains of the system. This recognized static gesture will then be transmitted to the receiver wirelessly through a bluetooth module. At the receiver end the movement of motors can be controlled based on the received signal. The block diagram for transmitter is shown in Fig. 1.

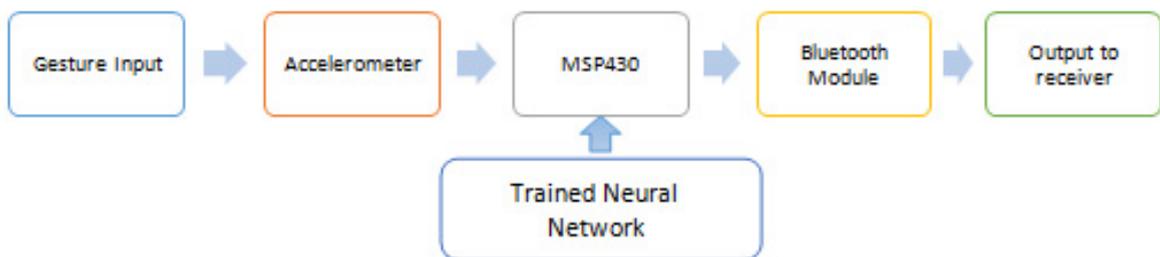


Fig. 1. Block Diagram for transmitter

### 1.1 Design Approach

For acquiring gesture, sensors like gyroscope, flex sensor or even an accelerometer can be used. A three-axis accelerometer has been opted to acquire gesture information. When it comes to wireless technology it can be RF, Zigbee or Bluetooth. Bluetooth has been opted as it is both moderate in cost and a standard feature in most laptops and smart phones. For its computing needs Texas Instruments MSP430 was used due to its low-cost, robustness and low power consumption, overall it offers good functionality with flexibility.

## 2. Static hand gestures

This Trained neural network will classify the data into three sets for forward, stop and left movement of the robot. Static hand gestures are shown in figure 2. The hands gesture movement is indicated on the mobile through the Bluetooth module and the same indication is also fed to the robotic vehicle wirelessly using MSP430 and Bluetooth module. The vehicles wheels are controlled by the gestures of the hand through the LVQ trained neural network.

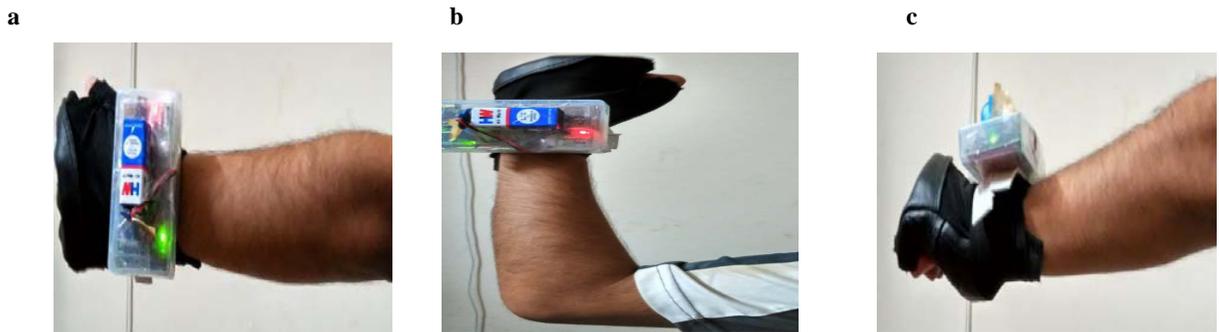


Fig. 2. (a) Forward control (b) Stop control (c) Left control

### 2.1 LVQ Algorithm

LVQ neural network combines the competitive learning with supervised learning and it can realize nonlinear classification effectively. It was first presented by Kohonen<sup>4</sup>.

The core of LVQ is based on the nearest-neighbour method by calculating the Euclidean distance. Let the  $x$  is the input vector and  $W$ , is the reference vector. The winner unit  $c$  would be found in the competitive process through this equation.

$$\|x(t) - W_c\| = \min \|x(t) - W_i\| \quad (1)$$

and the learning process is :

when  $i = c$  :if  $x$  and  $W_c$  belong to the same category

$$W_c(t+1) = W_c(t) + \mu(t)[x(t) - W_c(t)] \quad (2)$$

if  $x$  and  $W_c$  belong the different categories

$$W_c(t+1) = W_c(t) - \mu(t)[x(t) - W_c(t)] \quad (3)$$

Others :

$$W_i(t+1) = W_i(t) \text{ if } i \neq c \quad (4)$$

where  $\mu(t)$  is the learning rate . And

$$\mu(t) = \mu_0 (1 - t/T) \quad (5)$$

where  $0 < \mu_0 < 1$ , and  $T$  is a total number of learning iterations. Since the learning rate  $\mu(t)$  plays an important role for Convergence, professor Kohonen proposed an optimization method for quick convergence:

$$\mu(t) = \frac{\mu(t-1)}{1+s(t)\mu(t-1)} \quad (6)$$

where  $s(t) = 1$  if input vectore  $x(t)$  and the reference vector  $W_i$  belong to the same Category  $c$ ; otherwise  $s(t) = -1$  when they belong to the different categories.

For each gesture a total of 40 samples are taken. So a total of 120 gesture value readings are stored in the excel sheet in the form of rows and columns. The dimensions of the excel sheet is 3x120. After storing the sample values, target classes are defined. There are three gestures so three target classes are defined. These target values are stored in another excel file named target. After storing both the readings, they are imported in MATLABfile. Also targets

are clearly specified for incoming gestures which are used as training data. First forty gestures belong to target 1, next forty belong to target 2 and last forty to target 3. Learning rate alpha is set to 0.1 and weight vectors are initialised. For initialising of weight vectors initially one of the input gesture readings are used and they are further manipulated through LVQ algorithm to obtain the weight vectors. Epoch is set to 5, which means there will be 5 iterations of the entire code. For every iteration, the alpha value is reduced by 1/10. In every iteration Euclidean distance is calculated. Euclidean distance is calculated using the normal distance formula.

$$D = \sqrt{(x - x_1)^2 + (y - y_1)^2 + (z - z_1)^2} \tag{7}$$

So three Euclidean distances are calculated and they are compared against each other. The minimum distance is taken and the corresponding weight vectors are manipulated. Final weight vectors calculated are nothing but the centroid of 40 input samples of each static gesture position.

### 3. Results

Accelerometer readings of x-axis, y-axis and z-axis readings are show with blue, red and dark blue curve respectively presented as Fig. 3., Here ADC values of accelerometer after ADC(Rx) = 600 is constant this region shows static gesture while region between 0-600 signifies dynamic gesture.

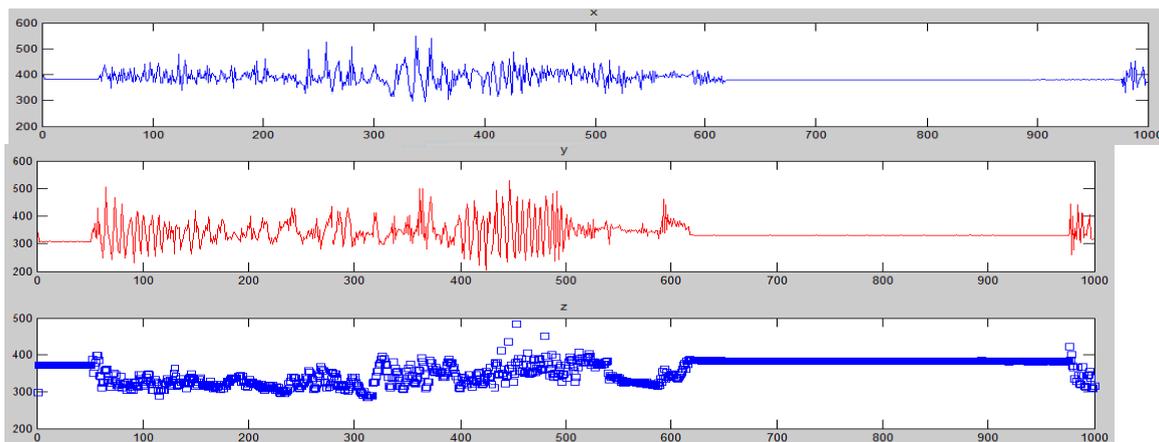


Fig. 3. X-axis, y-axis and z-axis curves of accelerometer

The data acquired from accelerometer for three static gestures presented as Fig. 4. Which shows three different clusters for each static gesture. After training the input data using LVQ algorithm centroid for each of these clusters is calculated and when a new input is given to the accelerometer it will be classified into one of the three gestures already predefined by the neural network. Thus the result is transmitted through a Bluetooth device to control a robot. The centroid values of these clusters are presented in table 1. (Number of training epochs 500).

Table 1. Centroid values obtained by LVQ algorithm

Gesture Input	X-axis	Y-axis	Z-axis
Gesture 1	430.25	388.80	375.45
Gesture 2	374.30	436.70	381.35
Gesture 3	317.50	384.80	377.70

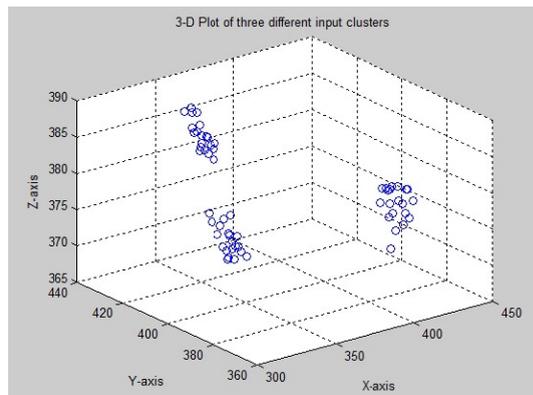


Fig. 4. 3-D Plot of three different input clusters

## 4. Conclusion

In this experimental validation, it was found that higher the training data and epochs, more accurate would be the decision making. So it is highly recommended to keep the training data and epochs as large as possible but keeping it very high is also not feasible as it increases the overall training time. Thus, the problem requires an optimal solution to counter this and could be done by keeping the training data and epoch somehow in between neither too large nor too small. A lot of improvement can be done in future version of this product which was not possible right now due to time constraints like making it to communicate with more than one Bluetooth device at a time and increasing its range for more than ten meters. Right now product is ready for low level application like the one which has been developed, controlling a robot. The achieved recognition rate of postures (93%) has a lot of scope for improvement by compromising the system response time (190 milliseconds). For more advanced application another prototype cycle is highly recommended.

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