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ANN Based Assistance for Exercise Patterns Using Accelerometer Data

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Abstract

Maintaining a good state of health is most challenging and necessary for all. In this regard, carrying out regular exercise with proper moves is important. Improper exercise moves often results is a strain, injury or no progress towards the goal. It is necessary to have a trained professional for proper guidance. Smart systems are in place, to help people in tracking their exercising activity, in the form of wearable bands or mobile apps. In this paper, an exercise assist tool is proposed to distinguish proper and improper exercise moves. Accelerometers were attached to upper limbs for data collections and an Artificial Neural Network (ANN) was used to classify them based on the features extracted. The proposed system was tested on five different volunteers for three different exercise movements. It was observed that the network was able to identify which axis the movement goes wrong.

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Keywords: Accelerometer, Artificial Neural Network, Pattern Classification, Wearable Systems

INTRODUCTION:

Notable applications have been developed in recognition field [1], ever since the invention of Human Interface Devices (HID). Nowadays, there are several devices that provide information from different phenomena, although each one delivers the information in its own way, and therefore each one needs a specific processing algorithm. Most commonly accelerometers play the sensing role in this gesture recognition field [2 - 3]. Digital Signal Processing techniques were used to process the collected data and extract features. Artificial Neural Network (ANN) has been the key in getting plausible recognition rates hand gesture recognition [4 - 6].

Nowadays, many people are keen towards physical fitness and as a matter of fact many tend to perform wrong postures which lead to muscular injuries [7 – 8]. Therefore a self-training device is essential. Recently many such devices and mobile applications were developed to support or monitor various aspects of exercising [9 -11].

In this work accelerometer-based movement recognition has been proposed for correcting body posture while doing exercise moves. Three basic moves, 'Hands Sideways', 'Hands Front Alternate' and 'Hands Sideways Circular', were considered in this work. These exercise moves are represented pictorially in Fig. 1, Fig. 2 and Fig. 3 respectively.

Here two accelerometers, for the two arms, along with Arduino Mega2650 are used. The schematic of the hardware is shown in Fig. 4. The data is collected using Arduino Support Package on Simulink. Signal features are extracted using DSP Tool Box and the neural network is trained using Neural Network Tool Box on MATLAB. A neural network was trained with data collected from professional fitness trainers of varied body dimensions. Later, when an individual tries to perform the same exercise, the network ensures if the person is performing it correctly and is able to correct the person.

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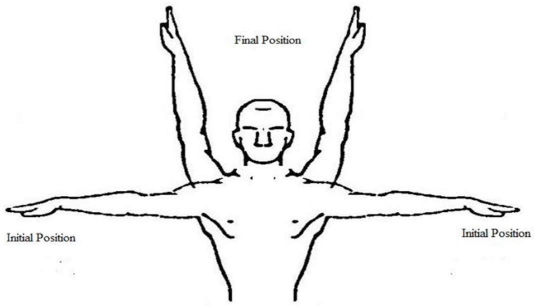

Fig.1. Hands Sideways – Exercise move

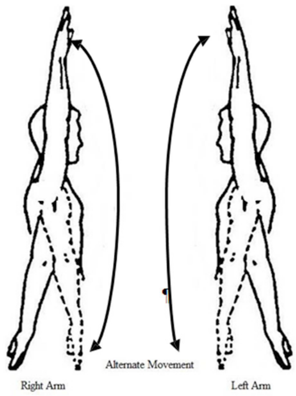

Fig.2. Hands Front Alternate – Exercise move

Fig.3. Hands Sideways Circular – Exercise move

METHODOLOGY:

Data Collection:

Two accelerometers, ADXL335, were hooked up to the upper side of the user's wrist by means of adhesive tape. The location for the mounting of the sensor was determined such that it ensures proper tracking of the hand movement with minimalistic error. The sensors were mounted at the centre of the wrist on both the hands. The wire was routed such that it doesn't restrict or strain any of the movements. Wires from both the sensors were routed from behind the neck to Arduino board which was mounted on the back side of user near the waist. The wiring diagram is shown in Fig.4.

Once mounted, check movements were performed to ensure proper data collection. The window size was determined by the time taken a complete movement. For instance, while doing the 'Hand Sideways' movement, complete movements were captured with a sample size of 41. Since the accelerometer is very sensitive to very small movements and vibrations, therefore the sample size of the analog inputs were kept at 30ms. Similarly, the other two exercise movements (Hands Alternate and Hands Sideways Circular) were recorded with sample window sizes 51 and 31 respectively.

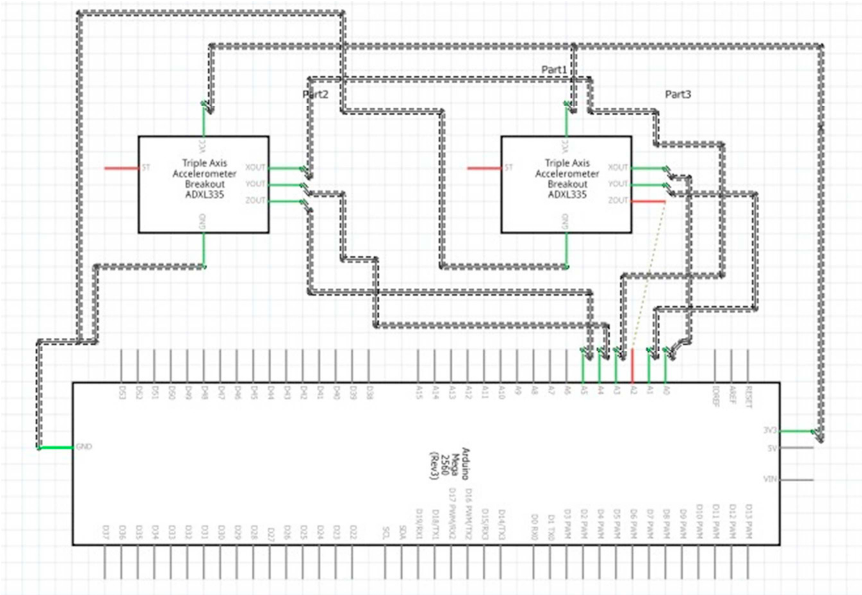

Fig.4. Arduino – Accelerometer Wiring Disgram

Pattern Classification:

From the entire collected pattern the following features were extracted for each coordinate.

1) *Max Value(**x1**)*- The maximum value of the output given by the sensor for the respective coordinate
2) *Min Value(**x2**)*- The minimum value of the output given by the sensor for the respective coordinate
3) *Mean Value(**x3**)*- Difference between max and min
4) *Zero Crossing(**x4**)*- Since an accelerometer only outputs positive values from 0 to 1023, once the mean was found, the signal was subtracted by the mean value to bring the signal about the origin. There after the number of times the signal crosses the origin was found. This feature was essential because the peak and the slope of the curve of the signal depends upon the speed of the movement.
5) *Index Value(**x5**)-* This is the number of samples between the maximum and minimum value.

After the data was collected and the features were extracted, the data was fed to a feed forward neural network, as shown in Fig.5, for training. The target was set as 1 for all the correct movements and as 0 for all the incorrect movements. Three different networks were trained for the three coordinates.

Once all the three networks for the three coordinates were trained the network was tested. The network was able to detect the wrong movements and suggest corrections needed terms of the exact coordinate axis.

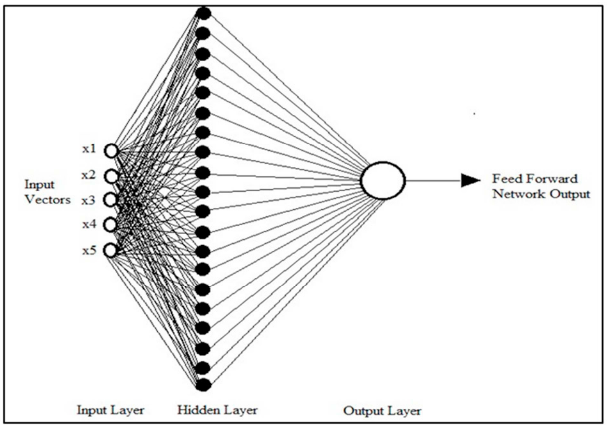

Fig.5. ANN Structure for Classification

RESULT:

For each exercise movement 10 patterns were collected from 5 different persons, which include 5 correct movement and 5 incorrect movement. In all 75 patterns were collected for correct movement and 75 for incorrect movement.

The captured waveforms from a volunteer for correct and incorrect movements, while performing 'Hands Sideways' are shown in Fig.6 and Fig.7 respectively. The corresponding features extracted are shown in Table.1.

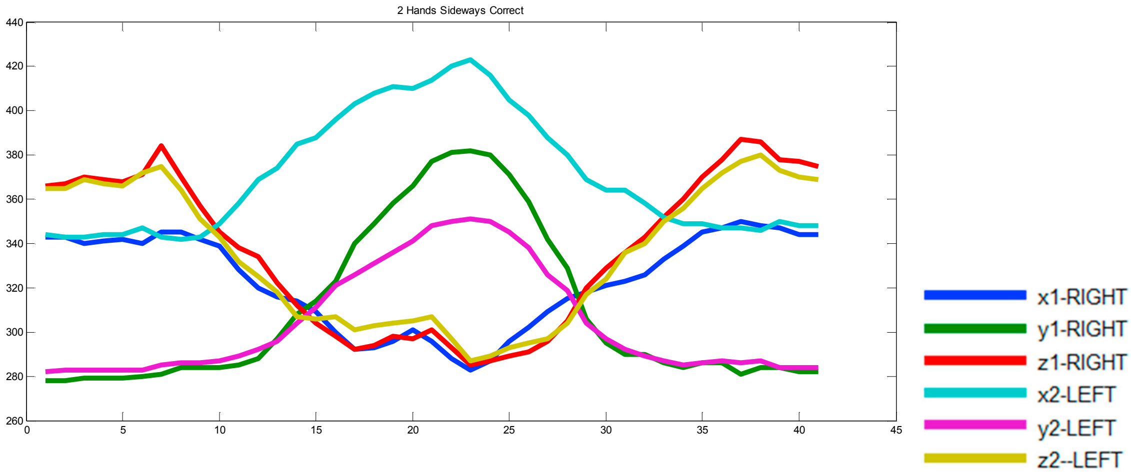

Fig.6. Signals acquired from both sensors while doing a 'Hands Sideways' move correctly

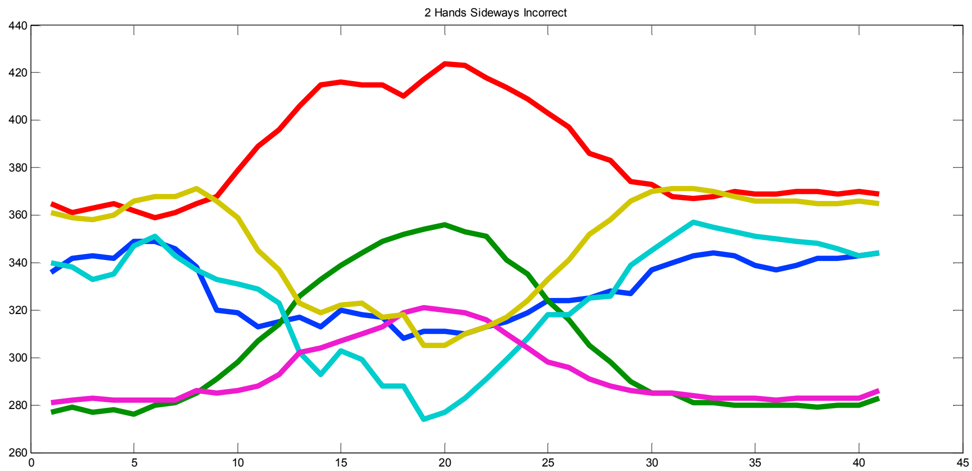

Fig.7. Signals acquired from both sensors while doing a 'Hands Sideways' move wrongly

Table.1. Features extracted while doing a 'Hands Sideways' move

	C						I					
Feature	**X1**	**Y1**	**Z1**	**X2**	**Y2**	**Z2**	**X1**	**Y1**	**Z1**	**X2**	**Y2**	**Z2**
Max	346	379	386	414	360	379	412	356	413	404	361	414
Min	270	277	280	340	282	277	301	276	324	284	289	326
Mean	308	328	333	377	321	328	357	316	369	344	325	370
Index	16	26	17	15	25	15	16	25	20	18	58	17
Zero Crossing	2	2	2	2	2	2	2	2	2	2	2	2

The recordings of correct and incorrect movements while performing 'Hands Alternate' are shown in Fig.8, Fig.9 and Table.2 shows the corresponding features extracted for classification.

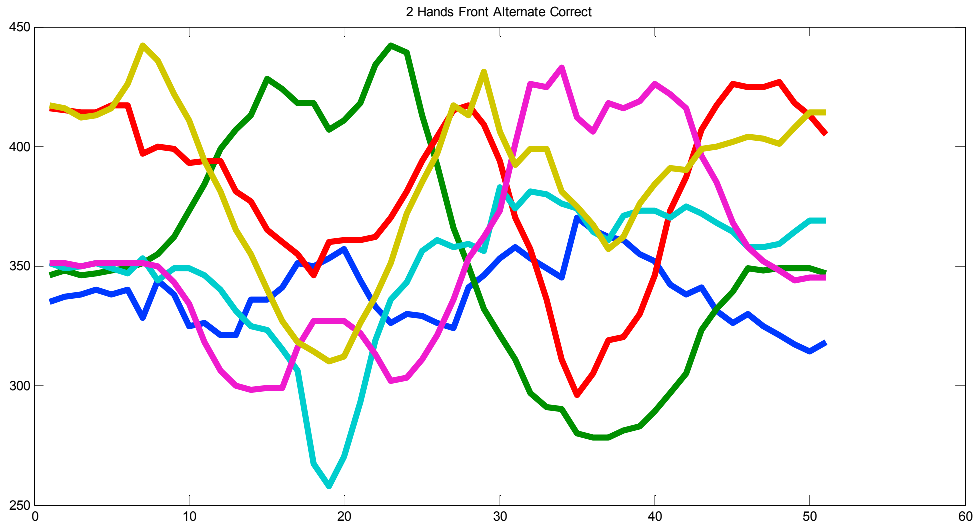

Fig.8. Signals acquired from both sensors while doing a 'Hands Front Alternate' move correctly

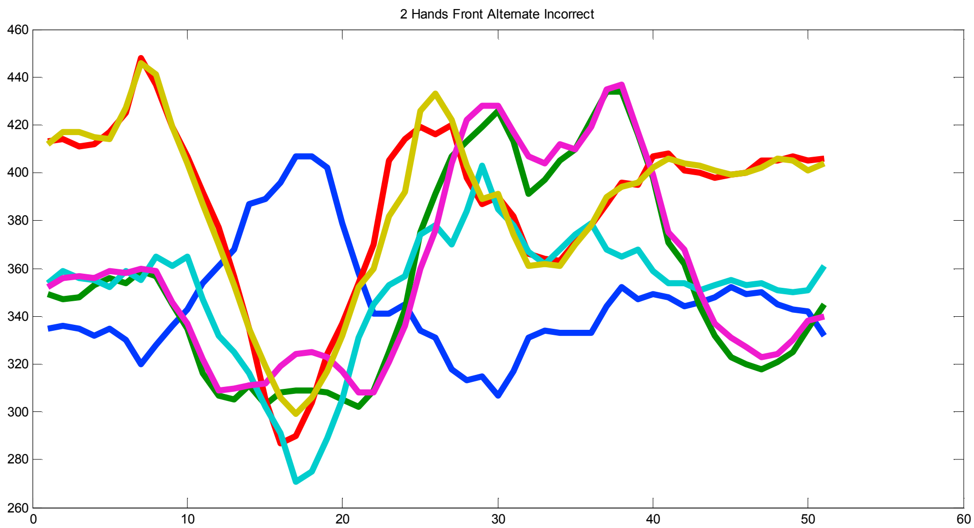

Fig.9. Signals acquired from both sensors while doing a 'Hands Front Alternate' move wrongly

Table.2. Features extracted while doing a 'Hands Front Alternate' move

	C						I					
Feature	**X1**	**Y1**	**Z1**	**X2**	**Y2**	**Z2**	**X1**	**Y1**	**Z1**	**X2**	**Y2**	**Z2**
Max	370	442	427	383	433	442	347	425	438	396	424	430
Min	314	278	296	258	298	310	314	279	347	336	297	367
Mean	342	360	362	321	366	376	331	352	393	366	361	399
Index	15	59	13	11	48	12	4	57	7	25	56	8
Zero Crossing	6	2	4	2	2	4	9	3	4	8	3	4

Similarly Fig.10 and Fig.11 display the sample waveforms of correct and incorrect movements for 'Hands Sideways Circular' exercise, while Table.3 presents the features extracted.

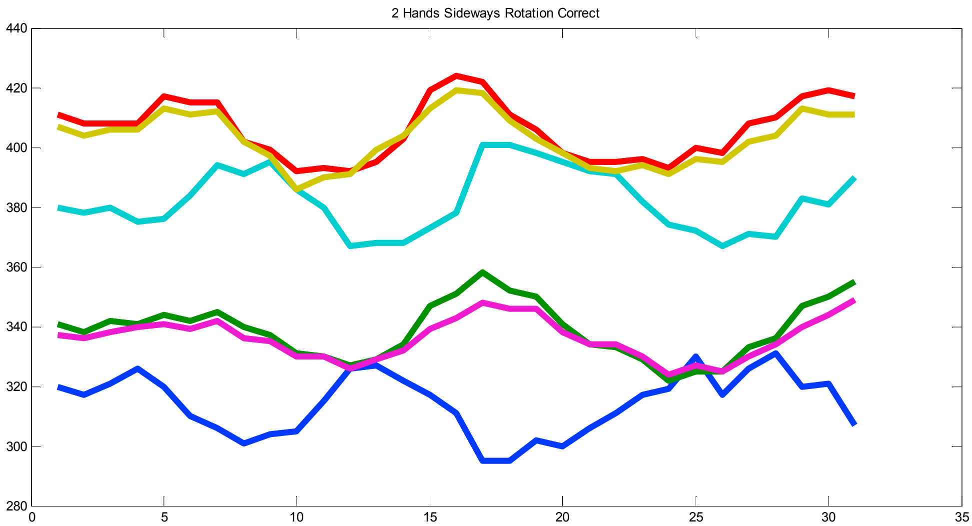

Fig.10. Signals acquired from both sensors while doing a 'Hands Sideways Circular' move correctly

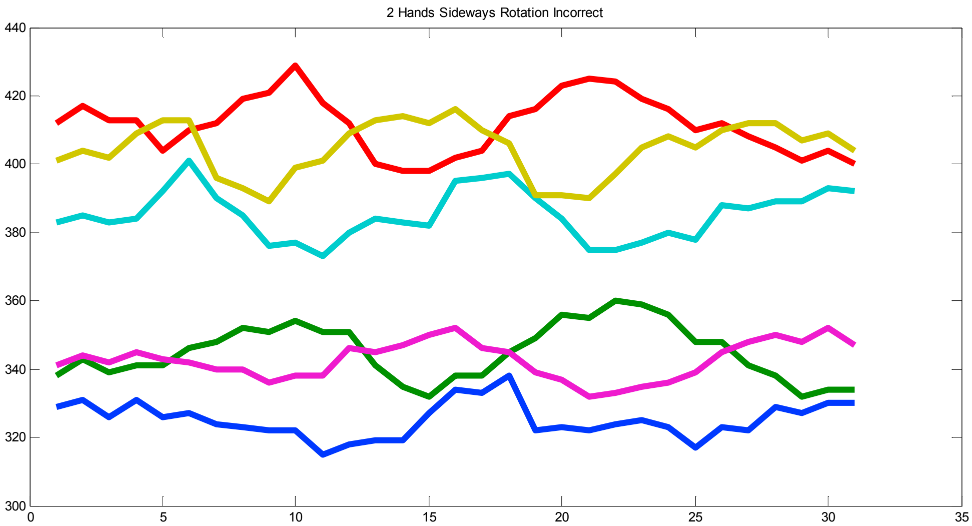

Fig.11. Signals acquired from both sensors while doing a 'Hands Sideways Circular' move wrongly

Table.3. Features extracted while doing a 'Hands Sideways Circular' move

	Correct						Incorrect					
Feature	**X1**	**Y1**	**Z1**	**X2**	**Y2**	**Z2**	**X1**	**Y1**	**Z1**	**X2**	**Y2**	**Z2**
Max	335	360	431	402	354	422	345	423	416	419	355	421
Min	305	328	391	361	328	390	306	335	349	373	335	377
Mean	320	344	411	382	341	406	326	379	383	396	345	399
Index	16	54	4	17	56	7	13	15	1	4	31	5
Zero Crossing	5	3	6	5	3	6	3	1	5	9	3	8

After performing the feature extraction using Digital Signal Processing Tools the training inputs for all coordinates formed with corresponding target values. 6 independent neural networks were trained for all 6 co-ordinate axis (3 for each arm). In the hidden layer 20 nodes were used.

Let us consider the training inputs taken/extracted from one person pertaining to the x-coordinate of the right hand while doing 'Hands Sideways' exercise.

x1:	346	344	350	345	342	374	365	349	412	388
x2:	270	292	283	282	286	269	264	308	301	305
x3:	308	318	317	314	314	322	315	329	357	347
x4:	16	23	14	14	17	15	17	13	16	5
x5:	2	2	2	2	2	2	2	2	2	4

In the sequence of the correct and incorrect data inputs, the targets were set as '1' or '0' respectively.

T= [1 1 1 1 1 0 0 0 0 0]

After the training the network was also tested for validation. A sample test report for x-axis recording while doing 'Hands Sideways' exercise is shown in Table.4.

Table.4. Sample test report while doing 'Hands Sideways Circular' move

ANN Inputs	ANN Output		ANN Inputs	ANN Output	
	Expected	Obtained		Expected	Obtained
348	1	0.9450	401	0	-0.1012
280			300		
314			351		
14			16		
2			2		

Similarly all the other 5 remaining networks were trained and the results were obtained. After all the 6 networks were trained and the desired results were achieved the network was tested with a new input and it was seen that the network was able to identify which direction the movement was going wrong by comparing the result values of the test data and the training data.

CONCLUSION:

With more number of data points, most certainly the ANN becomes stronger. Hence as we increase the number of sensors and tap more body parts, we can increase the number of exercises and at the same time improve their accuracy. For example: One accelerometer can be fixed on the head and all the head movements as well as inclination can be accounted while performing the exercise. Feet and leg exercises can be included by installing sensors near the two feet.

Also, this methodology doesn't only apply to exercises but can be used for innumerable applications such as training for swimming, running, dancing, gesture recognition and many more.
The prototype shown here had wired connections from the sensors to the controller but these can easily be replaced with button cell sized wireless modules that have 3-axis Accelerometer with Bluetooth connectivity on board. This would ensure easy hassle free harnessing of the sensors to the user.

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