American Sign Language Recognition Using Sensory Glove and Neural Network

Assistant Prof. Dr. Firas A. Raheem[a]*, Hadeer A.Raheem [b]

[a] *Assistant Prof. Dr. ,University of Technology , Baghdad , Iraq*

[b] *Engineer , University of Technology , Baghdad , Iraq*

[a]*Email: 60124@uotechnology.edu.iq*

[b]*Email: Hadeerasaad@gmail.com*

Abstract

a system was designed to recognize the Human hand manual alphabet of the American Sign Language utilizing artificial neural network that implemented to convert the (ASL) finger spilling alphabet into printed letters and using matlab to implement program that converting printed letters into animated (ASL) .the hardware system uses flex sensors these sensors were positioned on gloves to obtained The finger joint angle data when represent each letter of (ASL) and DAQ NI-6212 which was the interface between the sensors and the pc.DAQ produce 1000 readings per second the average of this readings is taken and normalization process is performed on the data and then applied to trained neural network to recognize which letter was performed by the hand and print it on the screen. On the other hand a matlab program was build using forward and inverse kinematics equations of human hand this program take normal language letters as input and produce an animated (ASL) letter as output. The hardware system have been trained and tested for (ASL) manual alphabet words and names recognition.

Keywords: ASL, Artificial neural network, forward kinematics, inverse kinematics, deaf, DOF.

تمييز لغة الاشارة الامريكية باستخدام القفاز المتحسس والشبكة العصبية

الخلاصة

تم تصميم نظام لتمييز الابجدية اليدوية المستخدمه في لغة الاشارة الامريكية باستخدام الشبكة العصبيه الاصطناعية التي صممت لتحويل لغة الاشارة الامريكية الى حروف مطبوعة .وتم استخدام برنامج (MATLAB) لتصميم برنامج يقوم بتحويل الحروف الابجدية الانكليزية الى اشكال الحروف في لغة الاشارة الامريكية .في الجزء العملي والخاص بتحويل لغة الاشارة الى حروف مطبوعه تم استخدام مستشعرات المرونة التي ثبتت على قفاز يتم ارتدائه من قبل الشخص الاصم هذه المستشعرات تقوم بقياس مقدار انحناء كل جزء في الاصبع عند تمثيل كل حرف من احرف لغة الاشارة الامريكية وارسال هذه القياسات الى الحاسبة عن طريق المعالج (DAQ 6212)

الذي يقوم بتسجيل ١٠٠٠ قراءة في الثانية يتم اخذ متوسط هذه القراءات واجراء عملية التسوية عليها ومن ثم ادخالها على الشبكة العصبية الاصطناعية المدربة للتعرف على الحرف الذي تم تمثيله باليد التي ترتدي القفاز وتقوم بتحويله الى حرف انكليزي مطبوع .من ناحية اخرى تم بناء برنامج باستخدام ال(MATLAB) هذا البرنامج يستخدم المعادلات الكينماتيكية باتجاه الامام والمعادلات الكينماتيكية باالتجاه المعاكس المشتقة من تحليل يد الانسان ،هذا البرنامج يقوم بتحويل احرف اللغة الانكليزية المكتوبه الى اشكال الاحرف في لغة الاشارة الامريكية.

الكلمات الدالة:لغة الاشارة الامريكية ،الشبكة العصبية الاصطناعية ،الكينماتيكية بأتجاه الامام ،الكينماتيكية باتجاه معاكس ،الاصم ،درجات الحرية.

1. Introduction

Deaf people have the same needs as the normal people of communicate with other people but they have the problem of describing that because they cannot speak. There are diverse sign languages throughout the world, similarly as there are diverse talked languages American Sign Language and British Sign Language are distinctive, commonly ambiguous the two languages grown autonomously because the American and British Deaf people group have no contact between one another,. French, Australian, Danish, Taiwan, Finnish, Thai, and Brazilian Sign Languages, what's more, numerous others have developed in communities of Deaf people, as the development happened in the groups of hearing people [1]. This languages help deaf people to communicate with each other and normal people who knew that languages. This work will depend on American Signe Language and concentrate on recognition of one important section of the ASL which is: ASL fingerspelling alphabet as shown in (Figure 1). In which deaf person made a sequence of hand shapes or hand trajectories to spell out a word corresponding to single letters. Unfortunately majority of normal people do not understand that language this causes the isolation of deaf people from general community. This language is expressed by using hand gesture .The human hand is a great complex system because its extensive number of (DOF) inside an essentially small space it's composed of nineteen links corresponding to the bones of the human and twenty-four DoF's [2].

In the last decade numerous researchers have studied communication through signing some of them take the way of converting normal English language into sign language [3, 4, 5], and the others take the reverse way by converting sign language into normal language, sign language recognition and Gesture recognition have been studied by large number of researchers, in any case, there are significant challenges because of intricacy of body and hand movement in the expression of sign language. Sign language and Gesture recognition researches will ordered to two portions: (a) based on computer vision [6, 7, 8, 9, 10] (b) based on data glove and movement sensor [11, 12, 13, 14].

in this paper we will using data glove to perform all gestures of (ASL) 28 letters both static and dynamic by processing the data using artificial neural network algorithms to recognize ASL letters, using new and economy hardware design by decreasing the sensors needed, and we will build a software program to covert normal English language into ASL using Matlab programming .so that we will gathering the two approaches in this paper.

2. American Sign Language

American Sign Language (ASL) developed by Thomas Hopkins Gallaudet who brought the sign language from Spain to America [15]. It is a complex language that utilizes signs made by moving the hand. It's the essential language of Americans who are deaf or hard of hearing and is one of several communication options used by deaf people. in the USA there are around two million people suffering from deafen. The most used non-English language after Spanish is the American Sign Language in the united state America .ASL consists of 36 hand shapes, 6000 words, and 26 letters [16]. These can be performed by using hand and body gestures. American Sign Language alphabet is shown in (figure 1).it used in performing names and spelling words. We will depend on ASL alphabet as a reference in our project.

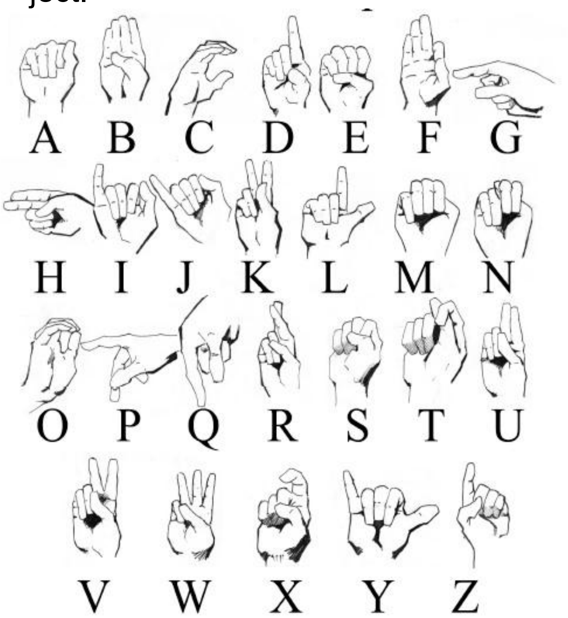


Figure 1: American Sign Language alphabet

3. Kinematic Modeling of human hand

The Human hand is one of the most complicated systems because of its ability to perform multiple tasks and its wide range of flexibility so that the human hand has 24 DOF and 19 links .in this project we will simplify this system to 20 DOF and 15 link because some links and joints does not effect on performing the letters of (ASL), we will derive one model to (thumb, middle, index, little, and ring) fingers. Where thumb has 3 links (metacarpal, proximal, and distal) links and three joints (metacarpophalangeal (MCP), interphalangeal (IP) and trapeziometacarpal (TMC)).as shown in (figure 2) The MCP and IP joints has one DOF for each one but TMC joint is universal joint and has two DOF one for adduction/abduction and one for flexion /extension (figure 3), (figure 4) shows the difference between flexion/extension and adduction/abduction. The other fingers (proximal, middle, and distal) also have 3 links. And three joints (proximal interphalangeal, Distal interphalangeal and metacarpophalangeal which have the following symbols respectively(PIP, DIP ,MCP)), The DIP and PIP joints has one DOF for each one but MCP joint is universal joint and has two DOF one for adduction /abduction and one for flexion/extension [2].

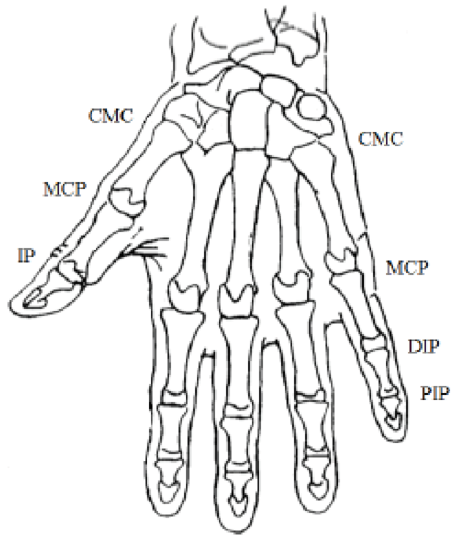


Figure 2: human hand skeleton [17].

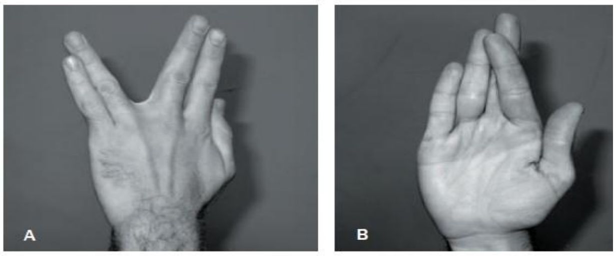


Figure 3: MCP abduction (A) and adduction (B) [18].

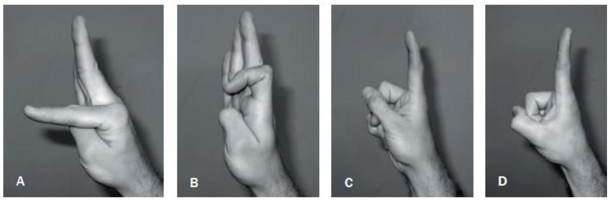


Figure 4: MCP flexion (A), PIP flexion (B), DIP flexion(C), and MCP, PIP, and DIP extension (D) [18].

3.1 forward kinematics

The forward kinematic was utilized to find the orientation and position of the finger tip depending on the finger joint angels. The Denavit-Hartenberg (D-H) parameters were used to calculate Model equations [19]. The rotation and translation of joints can be found using transformation matrix ${}^{i-1}_{i}T(\theta_i)$

$$ {}^{i-1}_{i}T(\theta_i)= \begin{bmatrix} C(\theta_i) & -S(\theta_i)C(\alpha_i) & S(\theta_i)S(\alpha_i) & a_iC(\theta_i) \\ S(\theta_i) & C(\theta_i)\ C(\alpha_i) & -C(\theta_i)\ S(\alpha_i) & a_iS(\theta_i) \\ 0 & S(\alpha_i) & C(\alpha_i) & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} $$

Where

C=cosine (θ_i)

S=sin (θ_i)

The D-H parameter for a single finger is shown in table(1) where joints defined by the variable θ. links are represent by the parameter a which is bone length since links(bones) are aligned d parameter is always zero, and the twist angel is α . θ_1, θ_2, θ_3, θ_4 are the angels of rotation for adduction\abduction of TMC joint ,flexion\extension of TMC joint ,MCP joint, and IP joint for the thumb finger and the angels of rotation for adduction \abduction of MCP joint , flexion\extension of MCP joint, The DIP, and PIP (for the rest of fingers)respectively. And L_1, L_2, L_3 are the length of bones. Frame -1 is the wrist frame and represents the base frame for all fingers.

Table (1): D-H parameter for a single finger

joint	***θ***	d	a	α
1	θ_1	0	0	pi/2
2	θ_2	0	L_1	0
3	θ_3	0	L_2	0
4	θ_4	0	L_3	0

Equation 1 represents the direct kinematics equation for finger

$$ \mathrm{p} = {}^{-1}_{0}\mathrm{T}(\mathrm{u})\,{}^{0}_{1}\mathrm{T}(\theta_1)\,{}^{1}_{2}\mathrm{T}(\theta_2)\,{}^{2}_{3}\mathrm{T}(\theta_3)\,{}^{3}_{4}\mathrm{T}(\theta_4) \quad (1) $$

The direct kinematics equation can be solve by finding Homogeneous matrixes for the finger which are

$$ {}^{0}_{1}T(\theta_1)= \begin{bmatrix} C(\theta_1) & 0 & S(\theta_i) & 0 \\ S(\theta_1) & 0 & -C(\theta_i) & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2) $$

$$ {}^{1}_{2}T(\theta_2) = \begin{bmatrix} C(\theta_2) & -S(\theta_2) & 0 & L_1C(\theta_2) \\ S(\theta_2) & C(\theta_2) & 0 & L_2S(\theta_2) \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (3) $$

$$ {}^{2}_{3}T(\theta_3)= \begin{bmatrix} C(\theta_3) & -S(\theta_3) & 0 & L_2C(\theta_3) \\ S(\theta_3) & C(\theta_3) & 0 & L_2S(\theta_3) \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (4) $$

$$
{}^{3}_{4}T(\theta_4) = \begin{bmatrix} C(\theta_4) & -S(\theta_4) & 0 & L_3C(\theta_4) \\ S(\theta_4) & C(\theta_4) & 0 & L_3S(\theta_4) \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (5)
$$

To find the thumb position and orientation or other fingers to the base (wrist) frame the transformation identity matrix was used for the rotational part and the position of frame zero with respect to frame -1 so that the transformation matrix become

$$
{}^{-1}_{0}T(U_{thumb}) = \begin{bmatrix} 1 & 0 & 0 & u_{t,x} \\ 0 & 1 & 0 & u_{t,y} \\ 0 & 0 & 1 & u_{t,z} \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (6)
$$

$$
{}^{0}_{4}T = \begin{bmatrix} n_{t,x} & s_{t,x} & a_{t,x} & p_{t,x} \\ n_{t,y} & s_{t,y} & a_{t,y} & p_{t,y} \\ n_{t,z} & s_{t,z} & a_{t,z} & p_{t,z} \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (7)
$$

Where:

$$n_{t,x}=(C_3C_2C_1 - C_3S_2S_1)C_4 +(-S_3C_1C_2 - C_3C_1S_2)S_4 \quad (8)$$

$$n_{t,y} =(S_1C_3C_2 - S_1S_3S_2)C_4 + (-S_3S_1C_2 - S_1C_3S_2)S_4 \quad (9)$$

$$n_{t,z} =(C_3S_2 - S_3C_2)C_4(-S_3S_2 + C_3C_2)S_4 \quad (10)$$

$$s_{t,x} =-(C_1C_3C_2 - S_3C_1S_2)S_4 +(-C_1S_3C_2 - C_3C_1S_2)C_4 \quad (11)$$

$$s_{t,y}=(-S_3S_1C_2 - C_3S_1S_2)C_4 - (S_1C_3C_2 - S_1S_3S_2)S_4 \quad (12)$$

$$s_{t,z} =-(C_3S_2 - S_3C_2)S_4 + (-S_3S_2 + C_3C_2)C_4 \quad (13)$$

$$a_{t,x} = S_1 \quad (14)$$

$$a_{t,y} = -C_1 \quad (15)$$

$$a_{t,z} = 0 \quad (16)$$

$$p_{t,x}= (C_1C_3C_2 - C_1S_3S_2)C_4L_3 +(-C_1S_3C_2 - C_1C_3S_2)S_4L_3+(C_1C_3C_2 - C_1S_3S_2)L_2 + C_2L_1C_1 \quad (17)$$

$$p_{t,y}=(S_1C_3C_2 - S_1S_3S_2)C_4L_3 +(S_1C_3C_2 - S_1S_3S_2)L_2 + (-S_1S_3C_2 - S_1C_3S_2)S_4L_3 + C_2S_1L_1 \quad (18)$$

$$p_{t,z} =(C_3S_2 - S_3C_2)C_4L_3 +(C_3S_2 + S_3C_2)L_2 + (-S_3S_2 + C_3C_2)S_4L_3 + S_2L_1 \quad (19)$$

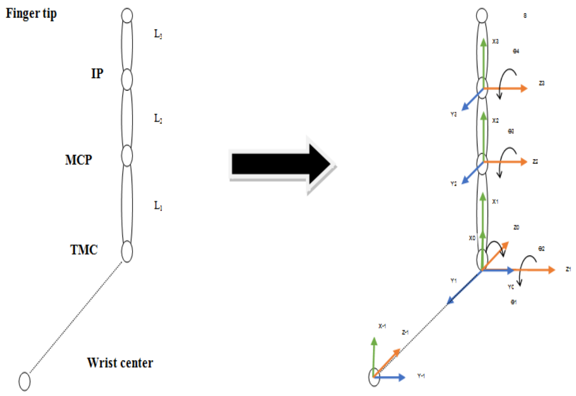


Figure 5: D-H coordinate assignment for one finger of human hand

3.2 Inverse kinematics

The inverse kinematics solution can be derived either geometrically or algebraically. Geometrically like triangles relation. The positive and the negative movements with respect to a reference line for some joints can perform by the hand [20, 21]. Or algebraically by finding relations between the elements of the final transformation matrix that derived in the forward kinematics [19]. In the solution of the inverse kinematics first we find Xc, Yc, Zc which denoted the component of the base frame (frame 1) by using transformation matrix (Equ.7).and we can find φ from it.

$$\varphi = atan2 \frac{n_{1z}}{s_{1z}} \quad (20)$$

Where

$$\varphi = \theta_2 + \theta_3 + \theta_4 \quad (21)$$

By using geometrical method and as shown in (figure 6):

$$\theta_1 = atan2 \frac{Yc}{Xc} \quad (22)$$

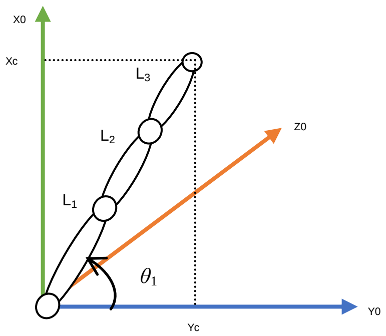


Figure 6: projection of the finger onto $x_0 - z_0$ plane.

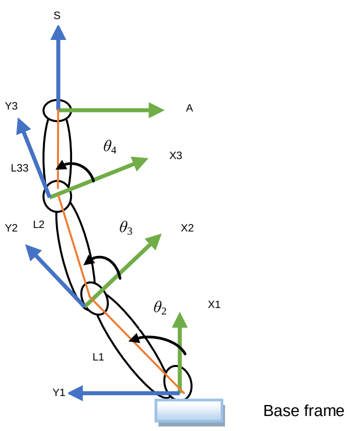


Figure 7: projection of the finger onto $x_0 - y_0$ Plane.

From basic trigonometry and (figure 7), the finger tip position and orientation can be written in joint coordinates terms as following:

$$X = L_2 \cos(\theta_{2+}\theta_3) + L_1 \cos\theta_2 + L_3 \cos(\theta_2 + \theta_3 + \theta_4) \quad (23)$$

$$Y = L_2 \sin(\theta_{2+}\theta_3) + L_1 \sin\theta_2 \, L_3 \sin(\theta_2 + \theta_3 + \theta_4) \quad (24)$$

Joint coordinates to a given finger tip coordinates (X, Y, φ) can be found by solving the nonlinear equations (21,23,24) for θ_2, θ_3 *and* θ_4.by Substituting equation (21)in equations(23,24) θ_4 can be eliminated . Then, the above two equations became in term of θ_2 *and* θ_3 as follow:

$$X - L_3 \cos(\varphi) = L_1 \cos\theta_2 + L_2 \cos(\theta_{2+}\theta_3) \quad (25)$$

$$Y - L_3 \sin(\varphi) = L_1 \sin\theta_2 + L_2 \sin(\theta_{2+}\theta_3) \quad (26)$$

The right hand side contains the unknowns. While the known are grouped in the left hand side. Now, by replacing the names of the left hand sides by X' *and* Y' where $X' = X - L_3 \cos(\varphi)$ and $Y' = Y - L3 \sin(\varphi)$, by terms rearranging and adding both sides in each equation after squaring them, a single nonlinear equation in θ_2 will be getting:

$$2L_1 X' \cos\theta_2 + 2L_1 Y' \sin\theta_2 + \left(L_2^2 - L_1^2 - X'^2 - Y'^2\right) = 0 \quad (27)$$

There are two solutions for $\theta_2$in the above equation given by

$$\theta_2 = arctan2(Y', X') \pm \arccos\left(\frac{L_1^2 + X'^2 + Y'^2 - L_2^2}{2L_1\sqrt{X'^2 + Y'^2}}\right) \quad (28)$$

By taking any one of these solutions and substituting it gives us:

$\theta_3 = arctan2(\ Y' - L_1 \sin\theta_2\,, X' - L_1 \cos\theta_2) - \theta_2$
(29)

Substituting $\theta_3$and θ_2 in (21) to findθ_4. Thus, for each solution forθ_2, there is one solution for $\theta_3$andθ_4.

4. Simulation of human hand manual alphabet (ASL).

Depending on the derived kinematics of human hand simulation of every (ASL)letter was build using matlab programming where each finger have specific position and orientation in each letter representation these values were used to implement every part of the simulated human hand by substitute these values in the kinematics equations for example letter(A).

Table (2): angels of fingers that perform letter A

angels	thumb	index	middle	ring	little
θ_1	π*0.08	0	0	0	0
θ_2	π/4.55	π*1.25	π*1.25	π*1.25	π*1.25
θ_3	π/4.5	π/2	π/2	π/2	π/2
θ_4	π/4	π/2	π/2	π/2	π/2

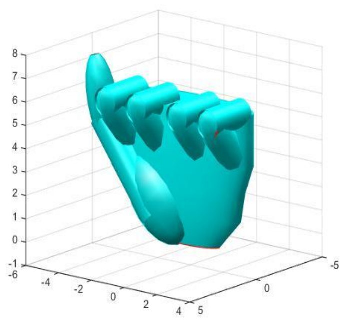


Figure 8: representation of letter (A) in Matlab

5. Design methodology

The hardware system contains

- Glove having six sensors:-five for every finger and one on the wrist.
- National instrument DAQ NI-6212.
- 5 V power supply.
- Six resistances of 10 kΩ .
- Six ceramic capacitors.
- Six electrolytic capacitors.

5.1. Block diagram

Flex sensors sending data that depending on the bending of human hand and fingers to the DAQ for processing and then the DAQ sending the data as inputs to PC, as shown in (figure 9).

5.2. Measurements normalization

The output data of the DAQ was used as input to Neural network program but this neural network has a specific rang of measurements so we use a function to normalize the output data of DAQ to the neural network rang this function is:

$S_{o} = \left(\frac{2*S_i - 2.8}{2.25}\right) - 1$
(30)

Where:

S_o= Sensor output after normalization.

S_i= Sensor output before normalization.

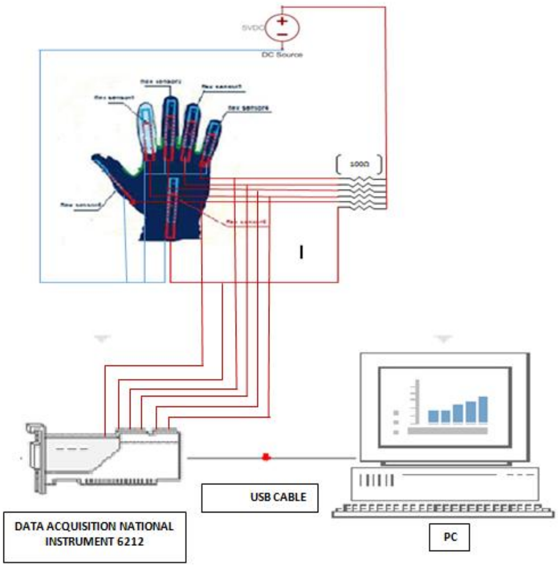


Figure 9: block diagram of the system

6. Artificial neural network

The algorithm used to train the ANN model was a backpropagation algorithm. we summarized the fundamental structure and implementation of this algorithm in this section. Training a neural network includes calculating weights in order to find the result output according to a specific input within Limits of error. The target vector and input vector perform a training pair. The algorithm of backpropagation contains this procedure [21]:

1. Apply the input vector of the 1st training pair to the neural network.
2. Compute the corresponding output of the neural network.
3. Make a comparison between the real output and desired target then calculate the error.
4. To reduce the error Modify the weights.

This procedure is iterated until the value of error is reached in our project the error chosen to be (e=1e-25). In step 2, sets of output are computed for test inputs. If the difference between the real output and desired target is within the given error limits, then the neural network have been learn the case, and the weights at that time (when the error is within the limits) are saved to be used when the using the neural network.ANN having multi-layer was used to recognize the manual alphabet of ASL. The inputs to the ANN were six elements which representing the flex sensors output. the designed ANN was a feed-forward network having multilayer ,this network consist of (6 ,50 and 20) neurons in input, first hidden, second hidden layers respectively while the output layer having single layer as shown in (figure 10).

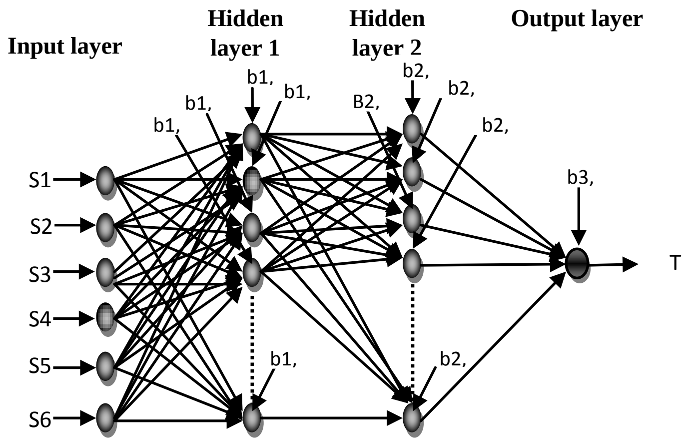


Figure 10: proposed neural network design structure

Where $W_{1,ji}$: Weights between the first hidden layer and input layer. $W_{2,rj}$: Weights between first and second hidden layers and $W_{3,kr}$: Weights between the output layer and the second hidden layer, while($B_{1,j}$, $B_{2,r}, B_{2,r}$) bias values of the first hidden, second hidden, output neurons respectively .

Equation (31) will calculate the result of the input layer

$$net_i = I_i$$

(31)

$$y_{net_i} = f\,[I_i] = I_i \qquad i = 1,2,3, \ldots . n$$

I=input vector values.

y_{net}=output of the neuron .

In this proposed design I refer to the sensor and i is the sensor number, $n =$ ber, $n = 6$.

.

Equation (32) will calculate the result of the first hidden layer.

$$net_{1,j} = \sum_{i=1}^{n} W_{1,ji} I_i + B_{1,j} \quad (32)$$

$$y_{1,j} = f\left[y_{net_{1,j}}\right] \quad j = 1,2,3,\ldots,m$$

Since the first hidden layer have sigmoid activation function

$$f\left[y_{net_{1,j}}\right] = \frac{1}{1-e^{-y_{net_{1,j}}}}$$

In this proposed design m =50; number of neurons in the first hidden layer.

Equation (33) will calculate the result of the second hidden layer.

$$net_{2,r} = \sum_{j=1}^{m} W_{2,rj} y_{1,j} + B_{2,r} \quad (3٣)$$

$$y_{2,r} = f\left[y_{net_{2,r}}\right] \quad r = 1,2,3,\ldots,h$$

Since the second hidden layer have sigmoid activation function

$$f\left[y_{net_{2,r}}\right] = \frac{1}{1-e^{-y_{net_{2,r}}}}$$

In this proposed design r =20; where r= neurons in second hidden layer.

Equation (34) will calculate the result of the output layer.

$$y_{net_{3,k}} = \sum_{r=1}^{h} W_{3,kr} y_{2,r} + B_{3,k} \quad (34)$$

$$y_{3,k} = f\left[y_{net_{3,k}}\right] \qquad k = 1,2,3,\ldots,t$$

Since the output layer have linear activation function

$$f\left[y_{net_{3,k}}\right] = y_{net_{3,k}}$$

In this proposed design t =1; number of neurons in the output layer.

6.1 measurements for training

For training the neural network five reading for every letter in each reading there are six values one for each sensor as shown in table [3].

Table 3: sensors readings used for training neural network

No.	Input1	Input1	Input1	Input1	Input1	Input1	output
1	١.٨٣٠٠	١.٦٣٠٠	٢.٢٧٠٠	٢.٢٢٠٠	٢.٢١٠٠	١.٤١٠٠	A
2	١.٧٥٠٠	١.٥٥٠٠	٢.١٢٠٠	١.٦٦٠٠	٢.٠٦٠٠	١.٣٧٠٠	A
3	١.٨٧٠٠	١.٦٦٠٠	٢.٢٦٠٠	٢.٢٥٠٠	٢.٢١٠٠	١.٤٥٠٠	A
4	١.٨٣٠٠	١.٦٢٠٠	٢.٢٥٠٠	٢.٢٠٠٠	٢.٢٩٠٠	١.٣٧٠٠	A
5	١.٧٥٠٠	١.٥٥٠٠	٢.١٨٠٠	٢.١٥٠٠	٢.٣١٠٠	١.٣٥٠٠	A
6	٣.١٨٠٠	٣.١٢٠٠	٣.٤٥٠٠	٣.٣٧٠٠	١.٨٤٠٠	١.٢٤٠٠	B
7	٣.١٨٠٠	٣.١١٠٠	٣.٤٦٠٠	٣.٣٣٠٠	١.٧٩٠٠	١.٢٤٠٠	B
8	٣.١٦٠٠	٣.٠٣٠٠	٣.٤٤٠٠	٣.٣٣٠٠	١.٨١٠٠	١.٢٥٠٠	B
9	٣.٢١٠٠	٣.٠٦٠٠	٣.٤٤٠٠	٣.٣٦٠٠	١.٨٢٠٠	١.٣٠٠٠	B
10	٣.١١٠٠	٣.٠٠٠٠	٣.٤١٠٠	٣.٣٥٠٠	١.٨٨٠٠	١.٣٢٠٠	B
11	٢.١٨٠٠	١.٩١٠٠	٢.٣٥٠٠	٢.٥١٠٠	١.٩٠٠٠	١.٢٩٠٠	C
12	٢.٢٥٠٠	١.٩٥٠٠	٢.٤٩٠٠	٢.١٦٠٠	١.٩٦٠٠	١.٢٧٠٠	C
13	٢.١٦٠٠	١.٩٤٠٠	٢.٤٣٠٠	٢.٥٥٠٠	٢.٠٠٠٠	١.١٩٠٠	C
14	٢.٣٠٠٠	١.٩٦٠٠	٢.٤١٠٠	٢.٥٥٠٠	٢.٠٥٠٠	١.١٨٠٠	C
15	٢.٣١٠٠	٢.٠٤٠٠	٢.٤٩٠٠	٢.٦٤٠٠	٢.٠٤٠٠	١.٢١٠٠	C
16	٢.١٠٠٠	١.٨٢٠٠	٢.٢٩٠٠	٣.٣٥٠٠	٢.٢٤٠٠	١.١٤٠٠	D
17	٢.٠١٠٠	١.٨٣٠٠	٢.٣٠٠٠	٣.٣٤٠٠	٢.٢٦٠٠	١.١٦٠٠	D
18	٢.٠٩٠٠	١.٨١٠٠	٢.٢٦٠٠	٣.٣٤٠٠	٢.٢٤٠٠	١.١٤٠	D
19	٢.٠٩٠٠	١.٨٠٠٠	٢.٢٨٠٠	٣.٣٥٠٠	٢.٣٧٠٠	١.١٦٠	D
20	٢.١٣٠٠	١.٨٢٠٠	٢.٢٣٠٠	٣.٣٥٠٠	٢.٣١٠٠	١.١٧٠٠	D
21	١.٩٤٠٠	١.٧٤٠٠	٢.٢٧٠٠	٢.٢٤٠٠	١.٦٢٠٠	١.٤٠٠٠	E
22	١.٩٥٠٠	١.٧٨٠٠	٢.٢٩٠٠	٢.٢٨٠٠	١.٥٧٠٠	١.٦٢٠٠	E
23	١.٩٥٠٠	١.٧٥٠	٢.٣٠٠	٢.٣٣٠	١.٥٩٠	١.٦٢٠	E

		٠	٠	٠	٠	٠	
24	١.٩٦٠٠	١.٧٦٠٠	٢.٣١٠٠	٢.٣٣٠٠	١.٦٣٠٠	١.٦١٠٠	E
25	١.٩٧٠٠	١.٨٠٠٠	٢.٣٢٠٠	٢.٣٣٠٠	١.٥٩٠٠	١.٦٢٠٠	E
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

7. Results and discussion

7.1 simulation results

The ASL letters were represented successfully in the matlab where the equations of forward kinematics for human hand were used to performing shape of letter and then we used the program to perform complete word and the result was successful and the aim was achieved from this simulation which was converting typed normal language into animated sign language, [figure 12] shows the results of typing word (ADAM) in the program ,and [figure 13] shows the trajectories of angels every joint in the thumb finger.

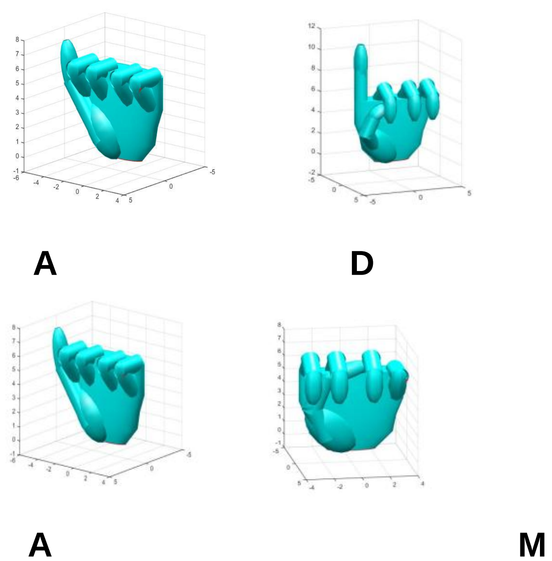


Figure 12: simulation of word (ADAM)

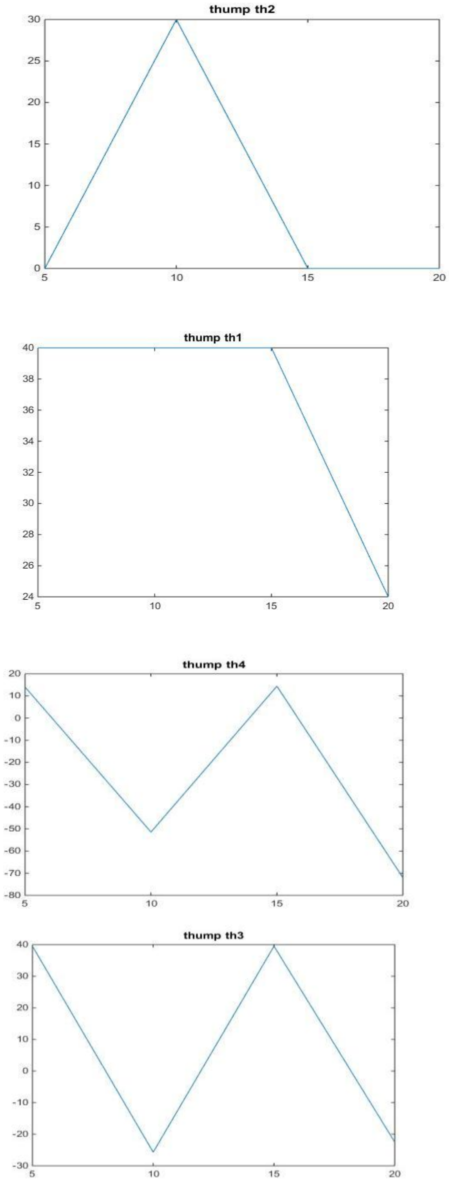
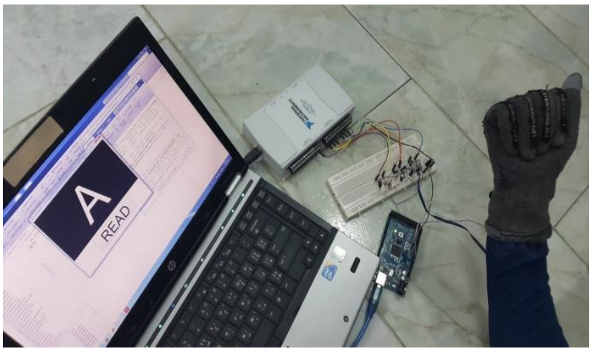


Figure 13: The trajectories of thumb joints angel.

7.2 experimental results

The developed ASL alphabet recognition ANN model was first trained with data as one for every letter. When that was not successful, we trained with two, three, and ten, finally, five readings for each letter which was effective and the neural network operate successfully and the ASL alphabet letters were recognized figure [14] shows the recognition of letters (A,D,A,M) of ASL alphabet.



A

D

A

M

Figure 14: ASL alphabet recognition

Conclusion

a complete system have been build to help deaf people to communicate with normal people as well as to help normal people to communicate with deaf people by building a system using sensory gloves, DAQ NI-6212 and ANN to convert ASL finger spelling into written letters and words, and software program that convert letters and words into animated ASL finger spelling. This system has been trained to recognize all letters of ASL and then tested by representing different words the recognition results have the accuracy of 96% and the software system for converting printed English names and words into (ASL) have 100% accuracy. And the system was able to spell all letters of ASL and convert it into normal letters.

References

[1] D. M. Perlmutter. “what is sign language,” Linguistic Society of America. Washington, DC 20036-6501. Available: https://www.lsadc.org/.

[2] Cobos, Salvador, et al. "Simplified human hand models for manipulation tasks." *Cutting Edge Robotics 2010*. InTech, 2010.

[3] Huenerfauth, Matt. "A multi-path architecture for machine translation of English text into American Sign language animation." *Proceedings of the Student Research Workshop at HLT-NAACL 2004*. Association for Computational Linguistics, 2004.

[4] Zhao, Liwei, et al. "A machine translation system from English to American Sign Language." *Envisioning machine translation in the information future* (2000): 191-193.

[5] Morrissey, Sara, and Andy Way. "An example-based approach to translating sign language." (2005).

[6] Kim, Taehwan, Karen Livescu, and Gregory Shakhnarovich. "American sign language fingerspelling recognition with phonological feature-based tandem models." *Spoken Language Technology Workshop (SLT), 2012 IEEE*. IEEE, 2012.

[7] Pugeault, Nicolas, and Richard Bowden. "Spelling it out: Real-time asl fingerspelling recognition." *Computer Vision Workshops (ICCV Workshops), 2011 IEEE International Conference on*. IEEE, 2011.

[8] Wysoski, Simei G., et al. "A rotation invariant approach on static-gesture recognition using boundary histograms and neural networks." *Neural Information Processing, 2002. ICONIP'02. Proceedings of the 9th International Conference on*. Vol. 4. IEEE, 2002.

[9] Pansare, Jayashree R., Shravan H. Gawande, and Maya Ingle. "Real-time static hand gesture recognition for American Sign Language (ASL) in complex background." *Journal of Signal and Information Processing* 3.03 (2012): 364.

[10] Dong, Cao, Ming C. Leu, and Zhaozheng Yin. "American sign language alphabet recognition using microsoft kinect." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*. 2015.

[11] Allen, Jerome M., Pierre K. Asselin, and Richard Foulds. "American Sign Language finger spelling recognition system." *Bioengineering Conference, 2003 IEEE 29th Annual, Proceedings of*. IEEE, 2003.

[12] Shembade, Yateen P. *Design and Simulation of a Mechanical Hand*. Rochester Institute of Technology, 2012.

[13] De Marco, Robert Michael, and R. A. Foulds. "Data recording and analysis of American Sign Language." *Bioengineering Conference, 2003 IEEE 29th Annual, Proceedings of*. IEEE, 2003.

[14] Wang, Honggang, Ming C. Leu, and Cemil Oz. "American Sign Language Recognition Using Multi-dimensional Hidden Markov Models." *Journal of Information Science and Engineering* 22.5 (2006): 1109-1123.

[15] Butterworth, Rod R. *The Perigee Visual Dictionary of Signing: An A-to-Z Guide to Over 1,350 Signs of American Sign Language*. Penguin, 1995.

[16] Sternberg, Martin LA. *American sign language dictionary*. HarperPerennial, 1998.

[17] van der Hulst, Frank PJ, et al. "A functional anatomy based kinematic human hand model with simple size adaptation." *Robotics and Automation (ICRA), 2012 IEEE International Conference on*. IEEE, 2012.

[18] Lowe, Whitney. *Orthopedic Assessment in Massage Therapy*. Daviau Scott, 2006.

[19] Schilling, Robert J. *Fundamentals of robotics: analysis and control*. Simon & Schuster Trade, 1996.

[20] Spong, Mark W., Seth Hutchinson, and Mathukumalli Vidyasagar. *Robot modeling and control*. Vol. 3. New York: Wiley, 2006.

[21] Firas A. Raheem, Azad R. Kareem and Amjad J. Humaidi, 'Inverse Kinematics Solution of Robot Manipulator End-Effector Position Using Multi-Neural Networks', Eng. &Tech.Journal, Vol.34,Part (A), No.7, 2016.