# ANN-models for jaw-research.

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## Abstract:

**ANN models for the opening jaw starting from the closed position are studied here. The models link final tension values in four active jaw muscles to final jaw positions and final tensions in the remaining muscles. The models assume the jaw opens in the midline: thus, right- and left-side muscles have equal tensions, and jaw motion is in two dimensions. We have examined two ANN jaw models. One gives jaw motion and passive muscle tensions given active muscle tensions. The other, possibly of practical use, gives jaw motion given active muscle tensions; passive muscle tensions appear as signals inside the model.**

## I Introduction.

An electrical engineer spends much of his life modelling electrical phonema, so modelling becomes second nature and M.P.B. has been fascinated by Artificial Neural Nets not so much to model life systems directly, as to produce fast and teachable processors which can be taught to produce much the same results as those from "in vivo" measurements or from a suitable biomechanical simulator. High speed arises by processing in parallel: teachability arises from the Back-Propagation Method for setting circuit weights. "Cause" and "Effect" data only are required.. The jaw is complex physiologically, and it is generally believed that at least 16 muscles are used to produce jaw motion. The active set provides muscle tensions to overcome inertia, to move the jaw against a food bolus if present, and so on; and the inactive muscles develop tensions to resist stretch passively. Early possibilities of using ANNs to model jaw behaviour were pointed out by [9], but here we are working to develop an essentially steady-state model of the jaw. Recently [5], the Peck-Langenbach-Hannam (PLH) dynamic model has been developed at U.B.C for the human jaw. It is based on published musculoskeletal data, and uses complex computing techniques to produce plausible, wide, jaw-opening. Each of the jaw muscles is modelled from appropriate anatomical and physical properties as a single-line actuator [10] which include an active component representing motor drive by the central nervous system, and a passive component determined by local muscle stretch. The actuators create forces on a jaw with average geometrical and inertial properties, and cause realistic jaw motions. By contributing to a better understanding of operational principles, simulators like this offer bioengineering solutions to problems encountered by practitioners in various fields of therapy.

The above simulator is a rich source of data with which to train the present ANN-jaw models. The system is assumed to be symmetrical, and jaw position is given by the x-coordinate, miptx, and y-coordinate, mipty, of a midline incisal point relative to an origin at the closed position. Due to symmetry, 16 muscle tensions are represented by 8 pairs of data. The measurements in Table 1 represent those for jaw opening only. Two opener muscle pairs were activated, namely the anterior belly of the digastric, dg, and the inferior head of the lateral pterygoid, ip. The other muscles were not activated, but they developed passive tensions due to their viscoelastic properties and changes in muscle length as the jaw moved. The measurements are for steady-state only. By this is meant that, e.g. for column i=2, if steady muscle tensions dg=0 Newtons and ip=1.5 Newtons, then the jaw will open by an amount miptx = 0.0173 Meter and mipty = 0.0037 Meter; the remaining six muscle-pairs will settle to tensions indicated. The ANN model which solves equation (1) below is based on this table.



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**Abstract**

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Table 1: 3 sets from a 59–set of steady–state measurements of T(m;i) from the PLH simulator.

| | m | Set i=1 | Set i=2 | Set i=3 |
|---|---|---|---|---|
| dg | 1 | 0.0 | 0.0 | 0.0 |
| ip | 2 | 0.0 | 1.5 | 3.0 |
| x | 3 | .001 | .017 | .025 |
| y | 4 | -.004 | .004 | .008 |
| at | 5 | .384 | .431 | .379 |
| mt | 6 | .172 | .334 | .401 |
| pt | 7 | .136 | .608 | .702 |
| sm | 8 | .394 | .302 | .348 |
| dm | 9 | .147 | .156 | .167 |
| mp | 10 | .315 | .321 | .324 |

Legend: T(m;i) = "target" value of muscle tension or jaw displacement. x =jaw–displacement miptx (meters), y = jaw-displacement mipty (meters). dg and ip are active muscle tensions, all other quantitites are tensions of passive muscles. All tensions are expressed in Newtons.

# II.I The ANN Jaw Model.

The field of Artificial Neural Networks is mature and many applications are reported. Current texts in the field are [1,4,7]. A convenient starting point to the ANN design is to consider the 10 x 59 matrix of experimental data (the first 3 sets are shown in Table 1). The first two row entries, dg and ip, are the "cause" of "effects" shown in the other rows, x = miptx, y = mipty, ...... mp. Suppose we discount cross-information between the effects, then a simple effect–cause equation can be written:

$$T(m;i) = F\{m;[T(1;i),T(2;i)]\} \qquad (1)$$

where T(1;i) is the ith value of dg, and T(2;i) is the ith value of ip. The left-hand terms are "target" values for m = 3–10, and i = 1–59. For a particular m, we have two inputs. What ANN configuration would solve this?

"Theorem 1.1: A 2–layer neural network with 2N+1 neurons in the first (hidden) layer and with suitable transformations of the input signals, can exactly implement any function in an N-dimensional input space (N≥2)" Annema 1995).For N=2, the hidden layer should have 5 or more processing elements. We assumed that the theorem referred to a lower limit, and we found that somewhat better results were obtained with 8 neurons in the hidden layer. Thus, the 2–8–1 configuration in Figure 1.

Eight separate networks, (Figure 1) realized equation (1) with O(m;i) replacing T(m;i); the two are about equal. Details of training and other matters were reported in [2]. NMSE() will be less than 0.003 after a small amount of training. (Incisor motion anterior, miptx, with 281 architecture has a fairly large error, but this can be reduced by a factor of 3 using a 3–layer ANN with architecture 2641.)

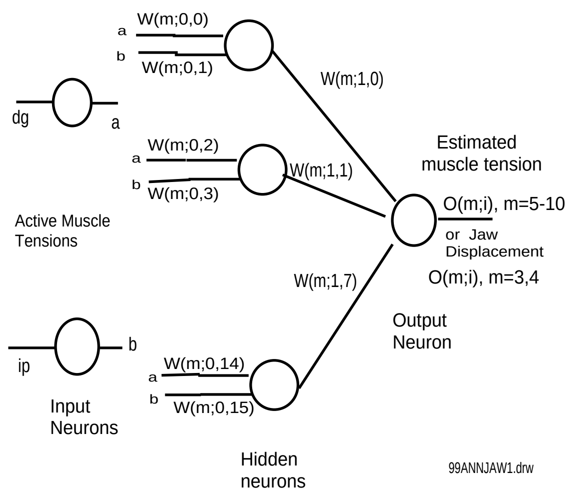


Figure 1: mth 2–8–1 two-layer ANN for realizing equation (1).

# II.II Free-moving jaw, Feedback Model ANN2

The first two rows of Table 1 give input causing jaw opening; the next two rows give resulting jaw movements. We would like our ANN jaw model to work only with these quantities but to give, in passing, the data from the remaining rows. This can be done using two interconnected networks which respectively obey equations (2) and (3). Given data (Table 1) will again be denoted T(m;i): data produced by the ANN2 will be denoted O(m;i).

Jaw opening, miptx, mipty,

$$O(3,4;i) = F_1\{T(1;i), T(2;i), O(5;i), O(6;i), , O(10;i)\} \tag{2}$$

Passive muscle tensions,

$$O(5,6,, ,10;i) = F_2\{T(3;i), T(4;i)\} \tag{3}$$

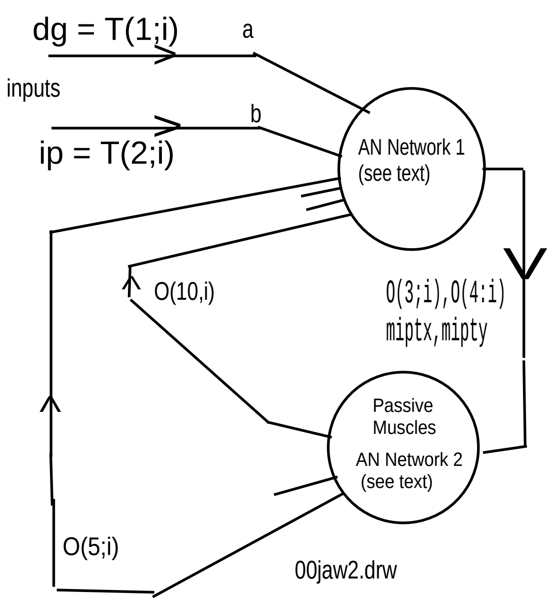


Figure 2: ANNs for 2 active muscle-pairs and 6 passive muscle–pairs for the free-moving jaw, ANN2.

We shall train network 1, to realize equation (2): this will be a 8–X–2 network where X is yet to be determined.. Network 2 realizing equation (3) requires an architecture of 2–Y-6 where Y had yet to be determined. We found that 8–20–2 and 2–30–6, a total of 68 processing elements, give ANNs which can be trained to give an NMSE of less than 0.0002.

# III Discussion.

The ANN jaw model of Figure 1 seems adequate to represent the various steady muscle tensions and jaw movements listed in Table 1 by obeying equation 1. Similarly, The ANN2 (Figure 2) gives useful relations between "cause" dg ip, and "effect" miptx, mipty, etc.. The ANN models will produce results in a fraction of the time needed by the non-linear biomechanical model.

A "spline" approach [8, 11] using the data of Table 1 was proposed and implemented recently by Dr. Iead Rezek and Dr. Stephen J. Roberts, both at Imperial College London but now at University of Oxford England. Good results were obtained. This approach merits further work.

ANN2 is of special interest. Suppose we teach a new 2–20–2 network, say ANN3, to produce outputs dg, ip for inputs miptx, mipty. Then, ANN3 can drive ANN2 with inputs miptx, mipty and final outputs expected values of miptx and mipty. ANN2 will produce muscle tension pairs O(5;i) – O(10;i). Thus, for any jaw displacement in our teaching set, we can get corresponding muscle tensions. If the ANNs can generalize from what they have been taught, it may be possible to get muscle tensions for jaw displacments not in the training set.

Two main questions remain.
Does the work apply to the asymmetrical case? If so, we might consider the full range of responses normally available to humans, including motions used for mastication and other acts involving the differential activation of muscles across the neuraxis.?
Is it possible to develop a Neural Network with delays which will solve the dynamic jaw motion problem? Hints at elaborate solutions are contained in references [3,6]. Consider a sampled version of ANN2 in which i is now the sampling index. It has been trained to obey equations 2 and 3. We wish to produce jaw movement from one steady-state, i = $I_0$ and terminating at another steady-state i = $I_F$. As it stands, our ANN2 will consistently under-predict miptx and mipty because jaw inertia was not included in the training.

A suggested solution follows. Alter equation (2) and (3) to include previous samples of the output:

$$O(3,4;i) = F_3\left\{\begin{array}{c} T(1;i), T(2;i), T(3,i-1), T(4,i-1), \\ T(3,i-2), T(4,i-2), O(5,i), , , O(10,i) \end{array}\right\} \tag{4}$$

$$\left\{\begin{array}{c} O(3;i-1), O(4;i-1), O(3;i-2), \\ O(4;i-2), O(5;i), , , O(10;i) \end{array}\right\} = F_3\{T(3;i), T(4;i)\} \tag{5}$$

A new network similar to that in Figure 2 but having feedback links is described by equations (4) and (5). We suggest training it with the Backpropagation Method. Training sets can be obtained from the PLH model. The training sets will have special interest because we want the network to generalize by predicting near-correct outputs whatever the shape of the driving set T(1,i); T(2,i). We can obtain training sets with differing waves linking the terminal startng and stopping points. Another matter: How does the network behave when the starting and stopping points themselves are altered? The Artificial Network of equations (4) and (5) should be able to mimic the moving jaw under these variations of dg and ip and we hope, in time, to demonstrate this experimentally.

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