Using Fuzzy Logic in Psychophysical Experiments to Separate Hits, False Positives and Guesses in Posturally Perturbed Standing Subjects

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Abstract— **In a 2-Alternative Forced Choice Interval task (2AFCi), a standing subject is required to press a button once or twice to signal in which of two 4 s sequential intervals that (s)he thought that a short ≤16 mm postural perturbation had occurred. The perturbation might or might not result in transient changes of the subject's Anterior-Posterior Center of Pressure (APCOP) or in other measures. This paper used fuzzy inference to explore whether the correctness of a subject's stimulus detection can be gleaned from analyzing changes in one of more metrics related to changes in the APCOP. Also, distinguishing guesses from correct responses is a critical issue in any psychophysical detection paradigm. Biomechanical and psychophysical data are used to design a prediction model based on fuzzy inference that is able to discriminate correct responses from guesses.**

1. INTRODUCTION

With the growing number of ageing people and increasing life expectancy of the older population, postural stability is becoming more critical. As people grow older, they are increasingly at risk of falling and consequent injuries, especially after age 65. Coogler reports that one third to one half of the older population experiences fall every year [1]. The number of fall deaths in the over 80 population is nearly as high as the number of motor vehicle accident deaths in the 15 to 29 year old population [2]. Falls can happen when people cannot control their posture during unexpected displacement. Postural control is the ability to keep the body's center of pressure above its base of support. Detecting perturbations plays a significant role in preventing a slippage that can lead to a fall.

The Sliding Investigative Platform for Assessing Lower Limb Stability (SLIP-FALLS) is a unique tool for studying human balance control [3]. It utilizes a linear motor and air bearing slides to drive small translational horizontal movements (0.25 to 16mm) that are in the subject's natural sway range while the subject stands on the platform. Simultaneously, data from platform position and acceleration, 3-axis head acceleration, platform load cells (to compute AP and ML centers of pressure [COPs]) and EMG raw signals are stored at 1000Hz and processed into engineering units stored at 100Hz. A 2-Alternative Force Choice (2AFCi) psychophysical procedure is used to determine the acceleration threshold at displacements of 1, 4 and 16mm [3].

In any psychophysical detection experiment, discriminating guesses from right answers is a baffling issue. Our primary objective in this paper is to use the initial knowledge of the subject's COP position to predict whether the subject will correctly detect the perturbation or not, and also to discriminate guesses from correct answers. Consequently, we may be able to use this knowledge to design a feedback control system to force a person's COP to remain within his/her base of support at the initiation of slippage (e.g., smart shoes to decrease the risk of fall).

In this study, a fuzzy logic base model was designed to take Center of Pressure (APCOP) time series data and the subject's psychophysical responses as inputs for predicting perturbation detection. Also, the model is able to distinguish guesses from right answers. It is an extension of the work first carried out by Bhatkar et al [4].

2. METHODS

2.1. Participants and Test Protocol

The study participants were 10 healthy adults over 49 y.o. and without diabetes or lower limb peripheral neuropathy. This data was collected at the Shreveport VA Medical Center under an Institutional Review Board (IRB) approved protocol. In each 2AFC trial, a subject heard four verbal instructions from the headphone: "ready", "one", "two" and "decide". Each interval was 4 s long. When the subject heard the word "decide", (s)he had to press the wireless doorbell button once or twice based on perceiving a movement in the interval one or two. The subject was forced to choose either the first or the second interval even if (s)he could not detect any movement. The length of the platform movement was 16 mm, and a set of maximum 30 trials was collected for each subject. The data collected per trial were: platform position and acceleration, anterior-posterior and medial-lateral centers of pressure (APCOP and MLCOP), lower limb EMG signals and head acceleration in X, Y and Z directions.

2.2. Modeling 2AFC Response

In our 2AFC experiment, a subject was presented with two sequential intervals, in one of which movement happened. The subject was forced to select an interval, and the experimental outcome was recorded as a correct or incorrect response. Based on the subject's responses to the perturbations, each interval of movement can be categorized into [4]:

- Hit (stimulus present, subject response "present")
- Miss (stimulus present, subject response "absent")
- False Alarm (stimulus absent, subject response "present")
- Correct Rejection (stimulus absent, subject response "absent").

Our hypothesis was that detection of a marked abnormality during interval one or two in APCOP data was a key for the perception of the correct platform movement interval [4]. Our proposed model is based on following assumptions:

(a) If the stimulus was very small, the signal-to-noise ratio was small, therefore the subject's APCOP data did not contain an acceptable difference between APCOP changes in interval one vs. two; and the subject made a guess.

(b) If the stimulus was larger, it would cause a marked change in the subject's APCOP data in the stimulus interval.

Therefore, if APCOP was more affected by movement in interval 1, we predicted that the platform moved in interval 1; and if it was more affected in interval 2, the prediction was for interval 2.

2.3. Selection of Significant APCOP Parameters to Predict Platform Movement Interval

We first present an analysis of 30 trials of 16mm perturbation data from a 66 year-old blindfolded healthy female (f66z067) without diabetes or lower limb peripheral neuropathy (as verified by clinical nerve conduction velocity testing). Four seconds each of the subject's APCOP in interval one and two were analyzed and 12 parameters produced (7 in the time domain and 5 in the frequency domain). The time domain parameters include following characteristics:

- The mean displacement of APCOP (MD);
- Root mean square of APCOP (RMS);
- The maximum distance between two points of APCOP travel trajectory (MXD);
- The total distance of the APCOP trajectory (TX);
- The mean velocity of the APCOP (MV);
- The Mean APCOP frequency in Hz (MF);
- The estimation of APCOP area (SA);

Also the frequency domain is characterized by following parameters:

- Total Power of APCOP (TP);
- The frequency range that spectral mass is concentrated or centroidal frequency (CF);
- The diversity in frequency component or frequency dispersion (FD);
- The frequency range over which 50% percent of the power spectrum is concentrated (P50);
- The frequency range that 95% of the power spectrum is concentrated (P95);

These parameters are standard parameters for evaluating subject sway and have been used by other researchers [5-9]. Each trial had 24 calculated sway evaluation parameters (12 for each interval).We used an adaptive neuro-fuzzy inference system (ANFIS) to find which of the APCOP parameters were most significant in predicting the platform movement interval. Our significant inputs selection technique is closely related to the work of J.S. Jang [10], and is based on the fact that the ANFIS model with the smallest root mean squared error (RMSE) after one epoch of training has a stronger probability of carrying out a lower RMSE when run for more epochs of training [10].

In our case we only wanted to find the two most significant APCOP parameters that predicted the platform movement interval. We constructed 276 (C_2^{24} =276) fuzzy ANFIS models each with two inputs (i.e., a combination of 2 of the 24 APCOP parameters in 30 trials), and one output (platform movement interval in 30 trials) in a single epoch of ANFIS training. The objective of using ANFIS in this study was not to train our main fuzzy model with ANFIS, but to find significant APCOP parameters for perturbation interval prediction.

3. RESULTS

3.1 Maximum Difference as Biomechanical Response Index

The training root mean squared errors for all constructed models are shown in Fig. 1. Because we were searching for the pair(s) that had the minimum RMSE, we can infer from Fig. 1 that pairing APCOP maximum distance, RMS and/ or its mean has the potential to be used as predictor(s) of the platform movement interval. As such, we analyzed the APCOP mean and RMS in both intervals to extract rules for our fuzzy model, but this did not give satisfactory results.

The subtraction of APCOP maximum distance (peak to peak) in interval one and interval two (MXD2-MXD1) shows a strong correlation between the APCOP maximum distance difference and the actual stimulus interval. Fig. 2a shows the logistic curve that we used to demonstrate this correlation for a 57 y.o. healthy female subject (f57z088) in 30 trials. Fig. 2b illustrates this relationship across 10 subjects and 289 trials with the psychometric logistic function plotted. The trials were sorted based on platform movement interval (0 if stimulus was in interval 1, 1 if in interval 2) and the APCOP maximum distance differences.

A positive difference was associated with an increased APCOP maximum distance in interval 2, and a negative difference was associated with an increased APCOP maximum distance in interval 1. In our classification MXD1 and MXD2 were the APCOP maximum distances during interval 1 and interval 2, respectively. The biomechanical

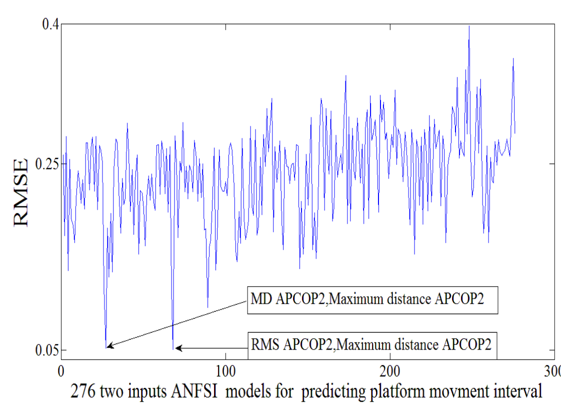


Fig. 1. Root mean squared error plot for 276 two input fuzzy models for platform interval movement prediction.

response was calculated based on the difference between these two values.

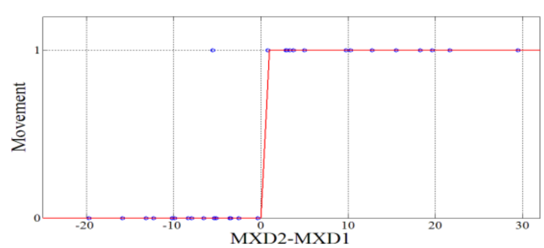
When the difference between these two numbers was smaller or greater than specified values (upper and lower thresholds), the biomechanical response was set to the stimulus interval with the greater maximum distance value (see Fig.4). For example, if MXD1 > MXD2, the biomechanical response was set to interval 1. Inversely, if MXD1 < MXD2, then it was set to interval 2. When this difference was between upper threshold (75% in logistic curve) and lower thresholds (25% in logistic curve), biomechanical response was set to Guess (i.e., there was an insignificant contrast between interval 1 and interval 2 maximum distance difference).

3.2 Designing the Fuzzy Model

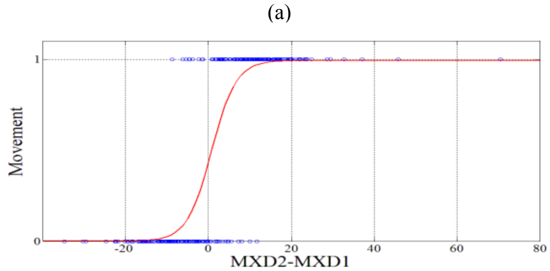
The design of the subject stimulus detection prediction fuzzy model is shown in Fig. 3, where the inputs are the APCOP maximum distance differences and the subjects' psychophysical responses. Fig. 4 then shows the APCOP membership functions and a logistic curve of all the data in the same plot with the absolute threshold set to 0.8 (50% in logistic curve). Fig. 5a shows the first input membership functions that include three membership functions: *Interval 1* (platform moved in interval 1), *Interval 2* (platform moved in interval 2), and *Guess* (there was no clear stimulus signal present in the APCoP difference data). A logistic regression model of all the data was used to set an absolute threshold for the APCOP maximum distance difference.

Fig. 5b shows the second input membership functions that include the subject's psychophysical response and has two membership functions: *Click1* (the subject pushed the button once), and *Click2* (the subject pushed twice).

Figs. 5c, 5d show the fuzzy model output membership functions. *Output 1* is active when the subject pushed the bell once and includes three membership functions: Hit, False Alarm, and Guess. *Output 2* is active if the subject pushed the bell twice and includes three membership functions: Miss, Correct Rejection, and Guess.



(a)



(b)

Fig. 2. The correlation between difference in the APCOP maximum distance and stimulus interval. (a) The logistic model fit for a subject (f57z088). (b) The logistic model fit for 10 subjects.

Based on the defined membership functions, the following fuzzy rule base was used to map the outputs from inputs:

- If the subject pushes the button once (Click 1) and APCOP is interval 1, then Output1 is Hit.
- If the subject pushes the button once (Click 1) and APCOP is interval 2, then Output1 is False Alarm.
- If the subject pushes the button once (Click 1) and APCOP is Guess, then Output1 is Guess.
- If the subject pushes the button twice (Click 2) and APCOP is interval 1, then Output2 is Miss.
- If the subject pushes the button twice (Click 2) and APCOP is interval 2, then Output2 is Correct Rejection.
- If the subject pushed the button twice (Click 2) and APCOP is Guess, then Output2 is Guess.

3.3 Performance

The fuzzy model was built using the fuzzyTECH^{TM} software, and the data sets of 289 trials were collected over 10 healthy subjects. The model was applied to predict perturbation detection in all subjects. Table 1 shows accuracy of the designed fuzzy model for each subject and all data sets. As can be seen in Table 1, the designed prediction detection model has 95.1 percent accuracy for all data sets. This implies that something related to the differences in APCOP is linked to successful detection.

4. DISCUSSION

We proposed to design a stimulus detection prediction model based on finding differences in one or more of a subject's biomechanical variables that corresponded to the subject's correct stimulus detection. We analyzed pairs of APCOP metrics abstracted from time series data and found that the APCOP maximum distance difference can be used as predictor(s) of the platform movement interval.

An adaptive neuro-fuzzy inference system (ANFIS) was used to extract the significant APCOP parameter for

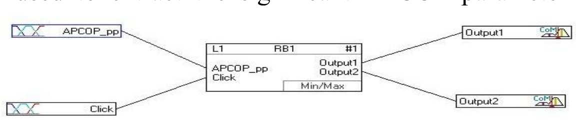


Fig. 3. Subject stimulus detection prediction fuzzy model.

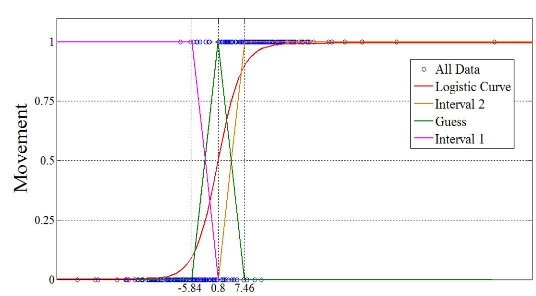


Fig. 4. APCOP membership functions and logistic curve for all 10 data sets (red).

predicting platform movement. Our model used psychophysical and biomechanical data to predict a subject's perturbation detection. Its novelty was that it could discriminate guesses from correct responses where traditional signal detection theory cannot. The "Guess" category could be considered as an inappropriate name, as the better description might be that it picked out trials in which signal noise ratio was small and the APCOP distance difference did not include sufficient information. In this case, the subject might have used other information to avoid a pure guess.

A conceptual error in our model might be the premise that the APCOP distance difference provided the sole information about which interval contained the stimulus. However, our model accuracy (95%) showed that the APCOP difference did contain significant information about the reaction to a short external translational perturbation in blindfolded, standing subjects. But what does that imply? It might be that one or more of the following changes provide this information: 1) distribution of pressures on foot soles (e.g., heels vs. balls); 2) lower limb muscle activity (e.g., TA vs. GN); and/or 3) within the vestibular system (otoliths?). Our lab is now isolating and investigating these various sources. Knowing which source(s) and how the input(s) vary with age and the presence of diabetes is currently being investigated, as is how they might link with fall potential in these groups.

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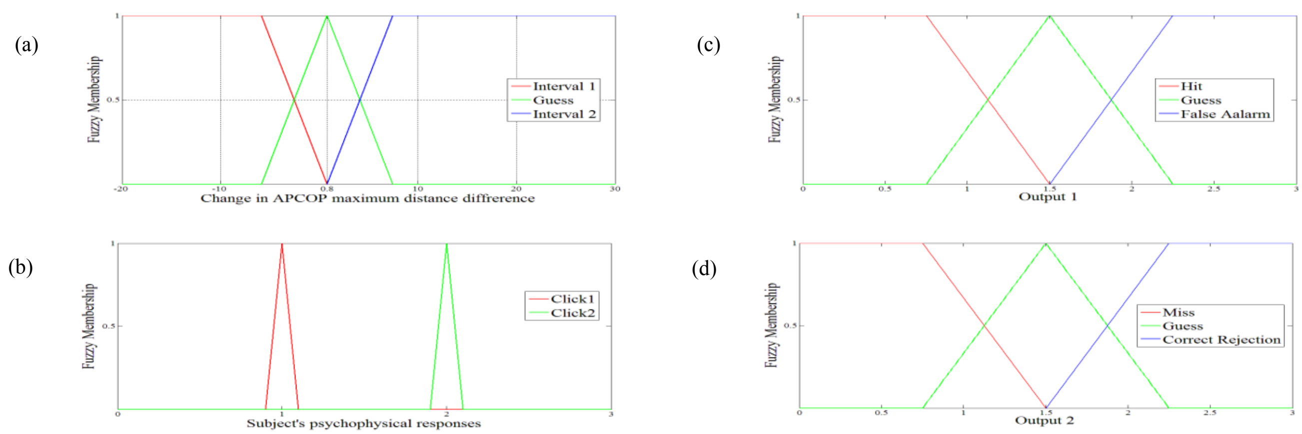

Fig. 5. Stimulus detection prediction model's fuzzy inputs and outputs

Table.1. Performance of designed prediction model in all data sets.

Subject	Hit	Miss	Correct Rejection	False Alarm	Guess	Wrong Prediction	Accuracy	Trials
f51z065	7	2	10	5	6	2	93.50%	30
f51z160	12	2	13	0	3	0	100%	30
f57z088	13	2	8	1	6	1	97%	30
f58z097	12	1	11	2	4	3	90%	30
f60z025	7	0	8	3	2	0	100%	20
f62z021	12	1	13	2	1	1	97%	30
f66z067	5	6	7	2	9	3	90%	29
f67z125	10	5	8	4	3	1	97%	30
f67z161	8	5	10	5	2	2	93.50%	30
m64z011	12	1	9	3	5	1	97.50%	30
Total	**98**	**25**	**97**	**27**	**41**	**14**	**95.10%**	**289**