

Research Article

A Development of Clinical Decision Support System for Video Head Impulse Test Based on Fuzzy Inference System

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This paper represents the clinical decision support system for video head impulse test (vHIT) based on fuzzy inference system. It examines the eye and head movement recorded by the eye movement tracking device, calculates the vestibulo-ocular reflex (VOR) gain, and applies fuzzy inference system to output the normality and artifact index of the test result. The position VOR gain and the proportion of covert and overt catch-up saccades (CUS) within the dataset are used as the input of the inference system. In addition, this system yields one more factor, the artifact index, which represents the current interference in the dataset. Data of fifteen vestibular neuritis patients and two of normal subjects were evaluated. The artifact index appears to be very high in the lesion side of vestibular neuritis (VN) patients, indicating highly theoretical contradictions, which are low gain but without CUS, or normal gain with the appearance of CUS. Both intact side and normal subject show high normality and low artifact index, even though the intact side has slightly lower normality and higher artifact index. In conclusion, this is a robust system, which is the first one that takes gain and CUS into account, to output not only the normality of the vHIT dataset, but also the artifacts.

1. Introduction

The vestibulo-ocular reflex (VOR) is a dynamic vestibular function, which helps humans to maintain balance and clear vision during head rotations or translations. This reflex, which depends on the vestibule, the acceleration detectors of the inner ear, generates eye movements at short latency (<15 ms) to compensate for head movement (rotations or displacements—translations) [1]. The VOR gain, the compensation ratio of the eye movement to head movement, accordingly, is the decisive factor to measure this dynamic vestibular function. However, there are many systems, apart from the semicircular canals, controlling eye movements [1]. Voluntary saccadic, smooth pursuit, visual (optokinetic) input, or cervical input, can all control eye movements, and in order to test semicircular canal function specifically, the contribution of these additional sources of control must be excluded [2]. Fortunately, only the VOR reflexes appear in high-frequency movement. Hence, in order to examine the

patient's function at particularly high acceleration, the head impulse test was first described by Cremer et al. and Weber et al. and became a specialized clinical assessment for VOR function. This test examines the function of semicircular canals in the inner ear at the high angular acceleration ($2000^{\circ}/s^2$ – $4000^{\circ}/s^2$) with the narrow angular extent of 5° – 15° [3–9]. In order to perform this test properly, scleral search coil technique was innovated. However, this system is bulky and not practical, especially in frontline healthcare. That is the reason why it has recently been replaced by the portable video head impulse test (vHIT) which enables this test to examine all six semicircular canals in both ears and detect the eye movements that are imperceptible to the naked eye. However, the practical assessment for vHIT still confronts with lots of artifacts; 72% had abnormal disruptive saccades, 44% had at least one artifact, and 42% were uninterpretable. These might come from the recording device (goggle slippage, improper pupil tracking algorithm, etc.), from the patient cases (eye disorders, kids, etc.), and

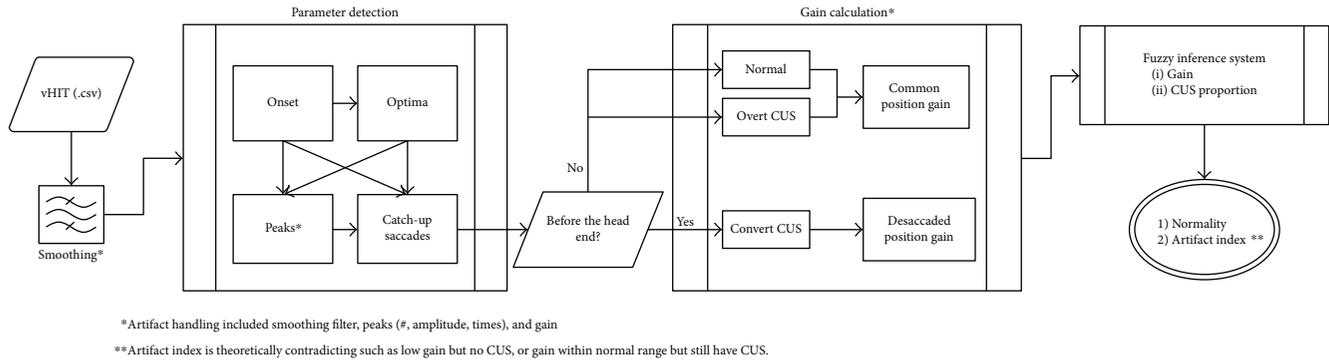


FIGURE 1: System block diagram. After loading the data file (.csv), the head impulse and eye response are first smoothed, then used for detecting parameters. Those include onset, minimum and maximum values, significant peaks, and catch-up saccades (CUS). If the CUS appears before the head impulse end, it is labeled as covert CUS, and the gain is calculated via desaccaded position gain algorithm. Otherwise, it can be a normal response, or contains overt CUS, which can be separated due to the number and time of significant peaks. After all, the gain and CUS proportion is calculated and inputted to fuzzy inference system to obtain normality and artifact index. *Artifact handling included smoothing filter, peaks (#, amplitude, and times), and gain. **Artifact index is theoretically contradicting such as low gain but no CUS, or gain within normal range but still have CUS.

the examining environment (lighting). As a result, expert assessment and interpretation of vHIT results are still required [10]. To overcome this drawback, this research proposes a clinical decision support system specialized in interpretation of video head impulse test's examination result using fuzzy logic. A clinical decision support system is a health information technology system that is designed to provide physicians and other health professionals with clinical decision support, that is, assistance with clinical decision-making tasks [11, 12]. Furthermore, fuzzy logic was applied in this research due to its compliance with the partial truth, in which the true value might range between fully truthful or false. Instead of defining one specific value into a bivalent if-then condition, a membership function for each subrange of each variable was employed, which describes how much one value partially belongs to one subrange. As a result, the fuzzy set extends the classical set, extending the fuzzy inference system to multivalued logic and the conventional if-then condition to linguistic variables, making it close to the natural languages and human reasoning. That is the reason why we applied the fuzzy logic theory into clinical decision support system, which can resemble the clinical experts in vHIT assessment.

Two important factors in vHIT are the normality and the artifact of the dataset. The normality is defined based on the VOR gain and catch-up saccades (CUS) presented in that dataset. The VOR gain and CUS of the impulse, however, are feeble toward artifacts so it is sometimes not reliable enough to determine the VOR purely based on the VOR gain and the appearance of CUS, especially without reviewing individual impulses because one noisy impulse can lead to wrongly detect the CUS in the whole set. Hence, this system combines both VOR gain and the proportion of CUS to yield the normality and the artifact index using one knowledge-based clinical decision support system. This system is an upgraded version for the previous fuzzy logic-based recommendation system [13]. In [13], two types of normality were employed based on gain and/or covert CUS and obtained by

the two inference systems. The first system uses only gain as an input, whereas the second one uses both gain and covert CUS appearance. This system, however, is naïve to the artifact and implements only covert CUS appearance which is not enough to define the normality of the dataset. In our new system, the inputs were updated to the proportion of both covert and overt CUS and VOR gain. Furthermore, it outputs the artifact index, which represents how conflicting it is theoretically. The new fuzzy inference system's block diagram is shown in Figure 1.

2. Methods

2.1. Catch-Up Saccade Detection. During the head impulse test, if VOR eye movements fail to keep the eyes on target, the difference between the head and eye positions triggers some adaptive motor responses, providing additional eye compensatory pursuit of eye to head movement, so-called CUS. These corrective saccadic movements might occur after head impulses, resulting in overt catch-up saccades, which are visible and can be detected by an experienced examiner during the bedside test without any additional equipment. If the position difference between the head and eye is predicted early enough, resulting in the short saccadic latency, catch-up saccades can happen during head impulses, become invisible to the clinician's naked eye, resulting in covert catch-up saccades. These kinds of eye movements are practically impossible to detect without specialized equipment and are not likely to reposition the eyes exactly on the target when the head impulses are unpredictable. The latency of catch-up saccades (100 ms) is considerably more than the latency of VOR eye movements (15 ms) because of the cortical involvement [1]. The CUS was statistically found with three conditions of refixation saccades occurred frequently in cases with abnormal hVOR: isolated covert saccades (13.7%), isolated overt saccades (34.3%), and the combination of overt and covert saccades (52.0%) [14]. Another motor response, which appears in vHIT eye velocity, is spontaneous

nystagmus. This is a rapid involuntary movement of the eyes and is mainly caused by a central lesion [15]. In this study, a spontaneous nystagmus was ignored and grouped with overt catch-up saccades for further examination.

One problem is that the covert CUS occurs during the head impulse. Consequently, it strongly influences on the gain calculation.

In this research, one catch-up saccade is categorized into covert set if its peak occurs from head peak until the zero crossing of head movement. On the other hand, overt catch-up saccades appear after the head impulse. So, if the saccades' peak is detected after zero crossing of the head movement, but not later than 450 ms after the head movement onset, that peak is defined as overt catch-up saccade. The peaks that appear later than 450 ms, however, are neglected.

2.2. VOR Gain Calculation. The VOR gain represents the compensation of the eye movement to the head movement. Cremer et al. have reported that unilateral vestibular lesions result in a permanent reduction in the VOR gain during sudden head thrusts toward the side of the lesion [3]. In normal cases, the VOR gain is close to one, then gradually decreases when the head velocity peak is higher than 200°/s. In unilateral vestibular deficit cases, the VOR gain is significantly below one for head impulses toward the side of lesion and declines rapidly with increasing head velocity. In the intact side, the VOR gain is similar but not as much as in the lesion side. In bilateral vestibular deficit, the VOR gain toward both sides is significantly less than one [6].

The VOR gain calculated based on the head and eye movements can be defined based on velocity, acceleration, or position. At first, velocity VOR gain is widely used and calculated by several approaches. As in [6], horizontal velocity VOR gain was calculated as the ratio of mean eye velocity over mean head velocity during a 40 msec window centered at the peak head acceleration. Or else, velocity VOR gain in [16] was calculated for each subject by dividing the length of the total eye velocity vector (eye speed) by the length of the head velocity vector (head speed). The disadvantage of the device that uses velocity VOR gain as patient output is that it requires a lot of careful calibration. Moreover, the recorded velocity is easier to be affected by noise (from device, clinician, and subject) as compared to position VOR gain [17]. Consequently, the position VOR gain is used in this research. Its mechanism is that firstly the head movement is the head velocity cumulated from the head onset until the next zero crossing of head velocity trace. Then, the eye movement is the eye velocity cumulated from the eye onset until the next zero crossing of the eye velocity trace. Finally, the VOR gain is the ratio of the eye movement to the head movement. This calculation is different from ICS device, which uses the frame of calculating gain between the head onset until its zero crossing [6]. This might be unstable due to the eye response's timing, which is theoretically 15 ms after the head movement [1]. In our dataset, the eye response might occur earlier or has bigger latency.

In addition, the position VOR gain calculation was optimized by removing covert CUS, because this type of CUS strongly influences on gain calculation. This method is called

desaccaded position gain [7]. In this study, after a covert CUS is detected, a line drawn from the valley of covert CUS to the next zero crossing of eye movement is used to remove the covert CUS. Afterwards, the position VOR gain is calculated as mentioned above.

2.3. Artifact Handling

2.3.1. Smoothing Filter. The velocity traces of both the head and eye contain small ripples, which possibly influence on the gain calculation and saccade detection. Hence, a smoothing filter is recommended. We choose Savitzky-Golay smoothing filter (SGF), a digital filter which minimizes the least squares error in fitting a low-degree polynomial to partial windows of a noisy data. Furthermore, it performs better than standard averaging finite impulse response filters, because the velocity traces do not contain frequent noise, but white noise. The disadvantage of SGF is that it is less successful than the conventional one at rejecting noise. However, in our application, signal preservation has prior consideration. In this research, SGF with the third order and window size of 13 was found as an optima parameter for head velocity trace [18].

2.3.2. vHIT's Artifact. One problem that might appear is that the plot will look extremely noisy if there are so many impulses, or one noisy impulse contains more than three high-eye velocity peaks. This could lead to the clinician confusion with the CUS, resulting in wrong detection. Then the proportion should be taken into account.

As the counting method, the combination of gain and proportion of catch-up saccades contains two cases contradicting with the theory when assessing the vHIT dataset. One is the response's gain is within normal or high range, but there is CUS. This might be the goggle slippage and so on. The second one is the patient has low gain but no CUS. This has an unknown reason.

The fuzzy inference system does come with an output of abnormality, in which can be defined into two indices: known reason and unknown reason.

2.4. Patients. Eight different types of vHIT's artifacts: phase shift, inappropriately high gain, pseudo-saccades, multiple VOR peaks, excessive post-HIT bounce, eye moves opposite the expected slow phase VOR direction, trace oscillations (noisy baseline), and unclassifiable artifacts (i.e., multiple different artifact morphologies or unrecognizable morphologies that were clearly nonphysiologic). These artifacts might come from patient factor, human error, detection algorithm, or unknown artifacts [10]. With an assumption, the normality of the response will decrease with the increase of the proportion.

The datasets of fifteen vestibular neuritis (VN) subjects and two normal controls were used to evaluate this system. All fifteen patients had acute unilateral vestibular neuritis diagnosed from clinical symptoms and a vestibular function test (mean 46 years, age range 22–69, and one female). The first twelve VN subjects have vestibular deficit on the left side; the last three have on the right side.

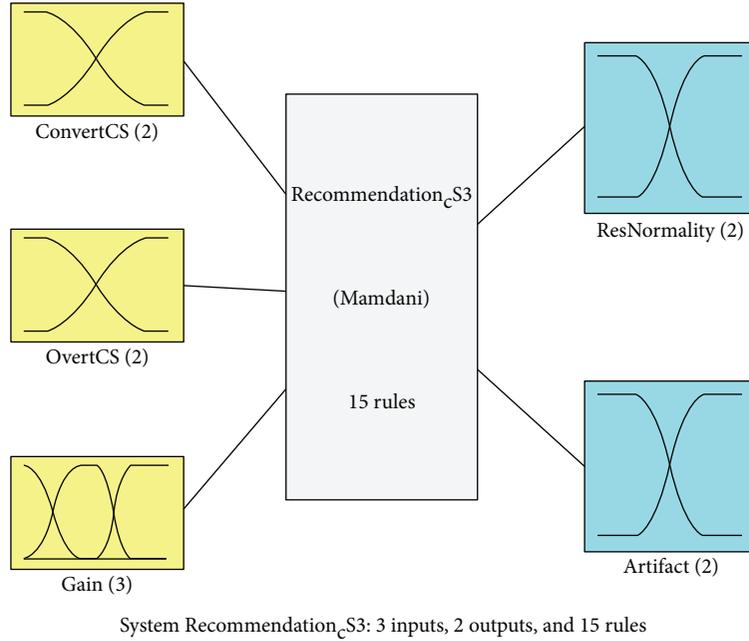


FIGURE 2: Fuzzy inference system with three inputs: covert CUS proportion, overt CUS proportion, and gain; two outputs, normality and artifact. This system has a rule set of 15 weighted rules, which are built based on personal knowledge.

2.5. Fuzzy Logic Inference System. Fuzzy logic is an extension of Boolean logic based on the mathematical theory of fuzzy sets. By introducing fuzziness, called the membership function, thus enabling a conditional state other than just true or false, fuzzy logic provides valuable and flexible reasoning, which makes it possible to take into account inaccuracies and uncertainties. One advantage of using fuzzy logic to formalize human reasoning is that its rules are set in natural language. That is why fuzzy logic is applicable for constructing a human-readable collaborative recommendation application [19, 20]. In the conventional Boolean logic, for instance, a gain of 0.6 is categorized into abnormal set, but it is not truly deficient in defining the gain. On the other way, the fuzzy set gives a degree of truth for that exact value, for example, 0.6 is abnormal, but 0.4 is normal.

Fuzzy inference is a method that interprets the values in the input vector and, based on some set of rules, assigns values to the output vector. Fuzzy inference system helps to bring out the input-output mapping using fuzzy logic. In order to do so, its structure consists of three main parts: membership function, logical operation, and if-then rules. The structure of fuzzy inference system consists of five parts: fuzzification of the input variables, application of the fuzzy operator (AND or OR) in the antecedent, implication from the antecedent to the consequent, aggregation of the consequents across the rules, and finally defuzzification. All of these steps will be described below [21, 22].

In this CDSS, we have five membership functions: three inputs (CovertCS, OvertCS, and Gain) and two outputs (ResNormality, Artifact) as shown in Figure 2. Velocity VOR gain was used in this reference system with the normal range: 0.8–1.2. The normal range of position VOR gain in this inference system is 0.8–1.2, which is higher than that of velocity

VOR gain. This is because position VOR gain contains variance due to the fluctuation during the whole period of head impulse. Overt CUS is detected as the CUS after the head stop, but not later than 550 ms. Covert CUS is the CUS occurring during the head impulse. Both the CUS proportions were partially defined by Z-shaped membership function as in 1 (LowProportion; 0.1, 0.9) and S-shaped membership function as in 2 (HighProportion; 0.1, 0.9), as shown in Figure 3(a). The gain membership function is partially divided into three π -shaped functions defined by 3: (LowGain; 0, 0, 0, and 0.8), (NormalGain; 0, 0.8, 1, and 1.5), and (HighGain; 1, 1.5, 2, and 2), as shown in Figure 3(b). The membership functions for normality (ResNormality) have two π -shaped functions (AbnormalRes; 0, 0, 0.25, and 0.75) and (NormalRes; 0.25, 0.75, and 1, 1), as shown in Figure 3(c). The membership functions for artifact index (artifact) was defined by two π -shaped functions (LowArtifact; 0, 0, 0.25, and 0.75) and (HighArtifact; 0.25, 0.75, and 1, 1) as shown in Figure 3(d). Consequently, once the crisp input is presented, it will be fuzzified into a set of values for each of its membership functions.

(i) Z-shaped membership function:

$$f_{Z\text{-shaped}}(x; a, b) = \begin{cases} 1, & x \leq a, \\ 1 - 2\left(\frac{x-a}{b-a}\right)^2, & a < x \leq \frac{a+b}{2}, \\ 2\left(\frac{x-b}{b-a}\right)^2, & \frac{a+b}{2} < x \leq b, \\ 0, & x > b. \end{cases} \quad (1)$$

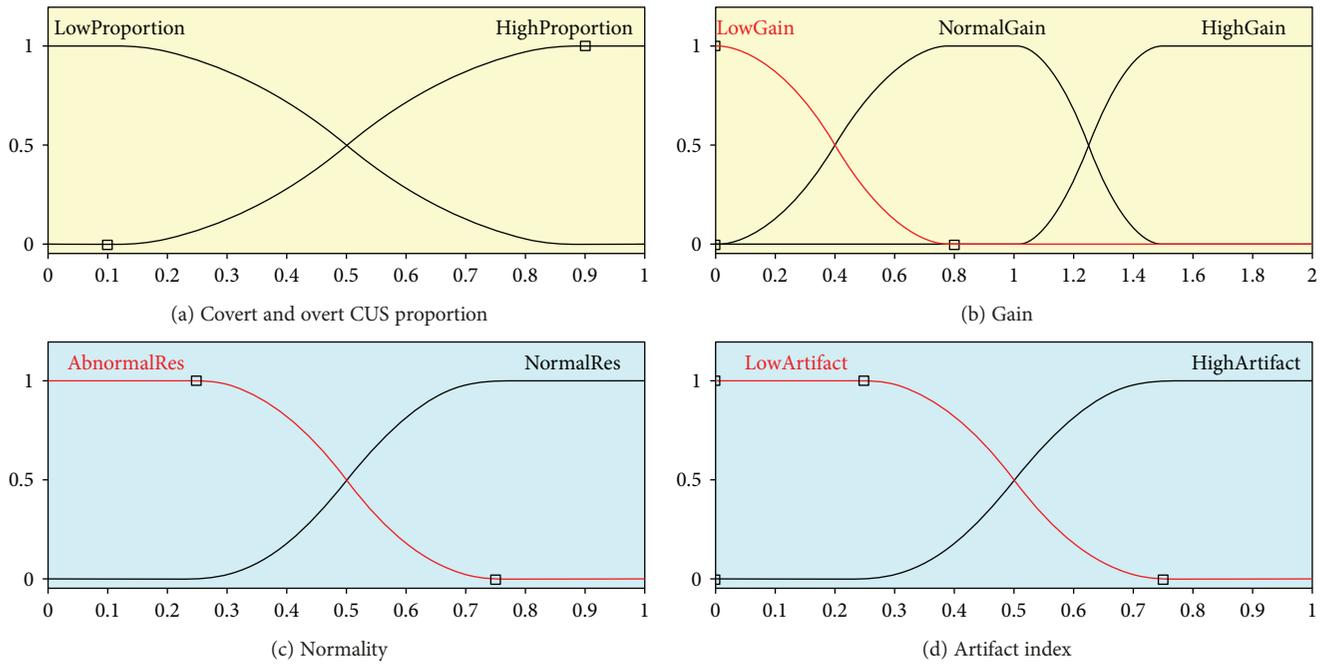


FIGURE 3: Membership function for each input and output.

(ii) S-shaped membership function:

$$f_{S\text{-shaped}}(x; a, b) = \begin{cases} 0, & x \leq a, \\ 2 \left(\frac{x-a}{b-a} \right)^2, & a < x \leq \frac{a+b}{2}, \\ 1 - 2 \left(\frac{x-b}{b-a} \right)^2, & \frac{a+b}{2} < x \leq b, \\ 1, & x > b. \end{cases} \quad (2)$$

(iii) π -shaped membership function:

$$f_{\pi\text{-shaped}}(x; a, b, c, d) = \begin{cases} 0, & x \leq a, \\ 2 \left(\frac{x-a}{b-a} \right)^2, & a < x \leq \frac{a+b}{2}, \\ 1 - 2 \left(\frac{x-b}{b-a} \right)^2, & \frac{a+b}{2} < x \leq b, \\ 1, & b < x \leq c, \\ 1 - 2 \left(\frac{x-c}{d-c} \right)^2, & c < x \leq \frac{c+d}{2}, \\ 2 \left(\frac{x-d}{d-c} \right)^2, & \frac{c+d}{2} < x \leq d, \\ 0, & x > d. \end{cases} \quad (3)$$

After the membership function was specified, the set of 15 if-then rules for three inputs and two outputs was independently defined as shown in Figure 4. These rule sets represent the relationship among each input and output

using linguistic values of each parameter. The antecedent, if statement of inputs, combines the value set of input which was obtained from membership function using fuzzy operator. In this CDSS, we use AND operator. Afterwards, these results will be implicated using the rule's weight. The implication method in this research is min operator. Then the result is summed up, so-called the aggregation, and finally, the outputs are defuzzified into specified value. Based on different implication relations, different outputs were derived. In this research, we used Mamdani-type inference system because of its intuitiveness as human input and its wide acceptance. The input-output mapping was represented in Figure 5.

Finally, yet importantly, the membership function, rule set, and rule's weight were intuitively defined based on clinical assessment and under supervision of the experts. Moreover, with sufficient data, this system can be converted to Sugeno-type fuzzy inference, which can be upgraded to the adaptive neural inference system in order to implicitly learn from the database.

3. Results

3.1. Fuzzy Inference System. The new application consists of two recommendation applications. In the previous systems, the fuzzy inference system was used to convert position gain and appearance of covert catch-up saccades (from experiment 1) into the efficiency of the subject's vestibule function, which is more significant to the application user. In contrast, in the new system, these two applications are a Mamdani type, where the implementation method is minimum, the aggregate method is maximum, and defuzzification is the minimum of the maximum. The first is Recommendation 1, one input for which is position gain. The

1. If (CovertCS is LowProportion) and (OvertCS is LowProportion) and (Gain is LowGain) then (ResNormality is NormalRes)(Artifact is LowArtifact) (0.2)
2. If (CovertCS is LowProportion) and (OvertCS is HighProportion) and (Gain is LowGain) then (ResNormality is AbnormalRes)(Artifact is LowArtifact) (1)
3. If (CovertCS is HighProportion) and (OvertCS is LowProportion) and (Gain is LowGain) then (ResNormality is AbnormalRes)(Artifact is LowArtifact) (1)
4. If (CovertCS is HighProportion) and (OvertCS is HighProportion) and (Gain is LowGain) then (ResNormality is AbnormalRes)(Artifact is LowArtifact) (1)
5. If (CovertCS is LowProportion) and (OvertCS is LowProportion) and (Gain is NormalGain) then (ResNormality is NormalRes)(Artifact is LowArtifact) (1)
6. If (CovertCS is LowProportion) and (OvertCS is HighProportion) and (Gain is NormalGain) then (ResNormality is AbnormalRes)(Artifact is HighArtifact) (0.8)
7. If (CovertCS is HighProportion) and (OvertCS is LowProportion) and (Gain is NormalGain) then (ResNormality is AbnormalRes)(Artifact is HighArtifact) (0.5)
8. If (CovertCS is HighProportion) and (OvertCS is HighProportion) and (Gain is NormalGain) then (ResNormality is AbnormalRes)(Artifact is HighArtifact) (0.7)
9. If (CovertCS is LowProportion) and (OvertCS is LowProportion) and (Gain is HighGain) then (ResNormality is NormalRes)(Artifact is HighArtifact) (0.7)
10. If (CovertCS is LowProportion) and (OvertCS is HighProportion) and (Gain is HighGain) then (ResNormality is AbnormalRes)(Artifact is HighArtifact) (0.7)
11. If (CovertCS is HighProportion) and (OvertCS is LowProportion) and (Gain is HighGain) then (ResNormality is AbnormalRes)(Artifact is HighArtifact) (0.7)
12. If (CovertCS is HighProportion) and (OvertCS is HighProportion) and (Gain is HighGain) then (ResNormality is AbnormalRes)(Artifact is HighArtifact) (1)
13. If (CovertCS is LowProportion) and (OvertCS is HighProportion) and (Gain is NormalGain) then (ResNormality is NormalRes)(Artifact is HighArtifact) (0.5)
14. If (CovertCS is LowProportion) and (OvertCS is LowProportion) and (Gain is LowGain) then (ResNormality is AbnormalRes)(Artifact is LowArtifact) (0.2)
15. If (CovertCS is HighProportion) and (OvertCS is LowProportion) and (Gain is NormalGain) then (ResNormality is NormalRes)(Artifact is HighArtifact) (0.5)

FIGURE 4: Rule list.

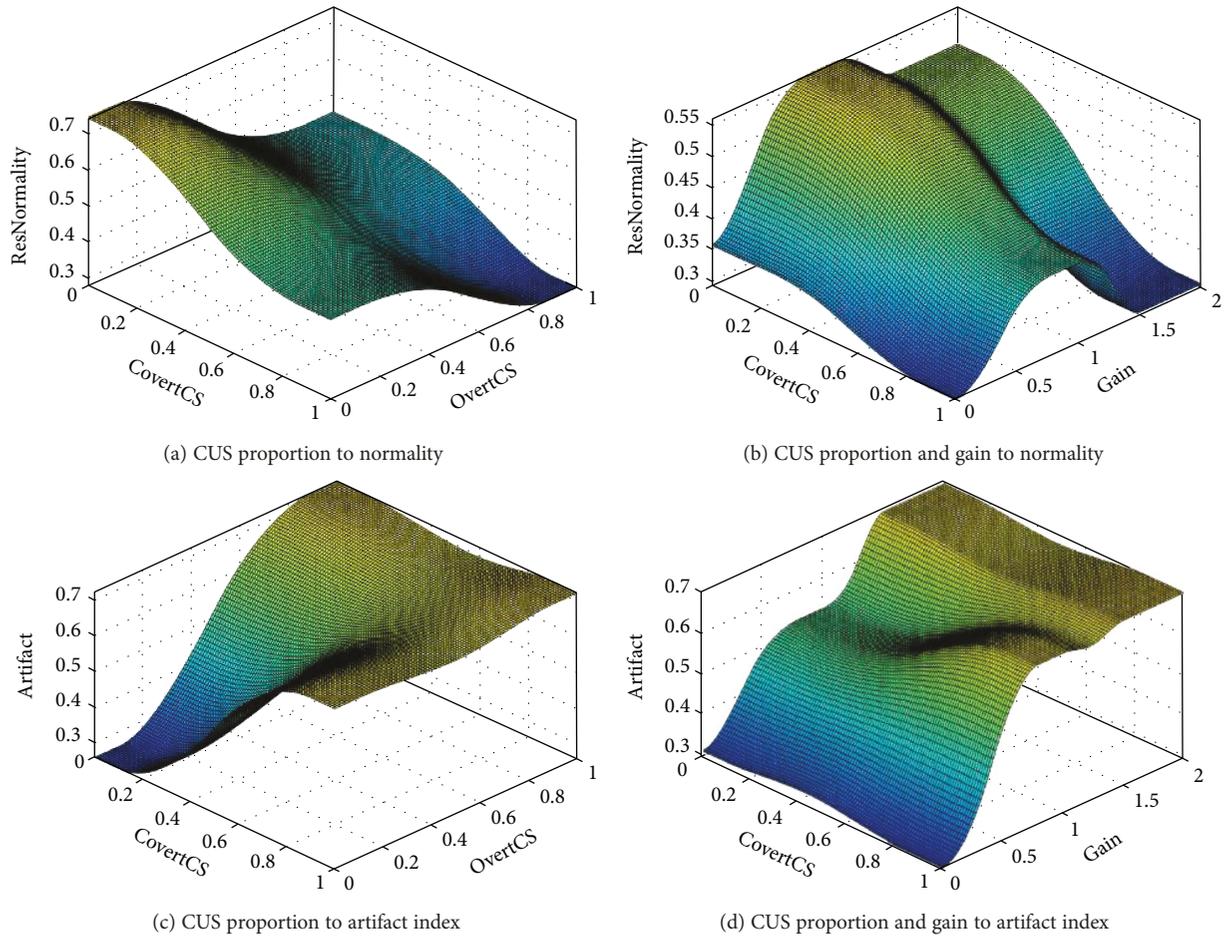


FIGURE 5: Membership function for each input and output. (a) Covert and overt CUS proportion. (b) Gain, (c) normality, (d) artifact.

second is Recommendation 2, with two inputs: position gain and appearance of covert CUS. The purpose of the design for the Recommendation 1 application is to reduce the confusion of variety in VOR gain. The second recommendation, Recommendation 2, will give the clinician a different output after combining CUS occurrence and position gain. Recommendation 2 requires one more input of covert CUS detection. The obtained normality, however, just somehow represents the effect of covert CUS on the diagnostic decision. Consequently, the new system was built to overcome the drawback

TABLE 1: System evaluation with the data of two controls and both sides.

Number	Covert CUS	Overt CUS	Gain	Normality	AI
Normal1_L	0.00	0.00	1.23	0.92	0.36
Normal1_R	0.19	0.05	1.10	0.96	0.10
Normal2_L	0.00	0.00	1.07	0.99	0.04
Normal2_R	0.18	0.05	1.14	0.94	0.16

TABLE 2: System evaluation with the data of 15 VN subjects.

Side number	Lesion				AI	Intact				
	Covert CUS	Overt CUS	Gain	Normality		Covert CUS	Overt CUS	Gain	Normality	AI
1	0.63	1.00	0.48	0.19	0.62	0.36	0.39	1.19	0.65	0.53
2	0.19	0.56	0.45	0.45	0.49	0.40	0.27	0.53	0.68	0.34
3	0.73	0.00	0.72	0.53	0.82	0.09	0.00	0.68	0.98	0.01
4	0.33	1.00	0.58	0.34	0.81	0.00	0.09	0.95	1.00	0.00
5	0.31	0.47	0.84	0.63	0.53	0.55	0.21	0.93	0.64	0.59
6	0.39	0.57	0.95	0.50	0.70	0.55	0.18	1.08	0.64	0.59
7	0.74	1.00	0.45	0.13	0.54	0.41	0.15	0.72	0.79	0.32
8	0.86	0.96	0.59	0.08	0.78	0.27	0.09	0.98	0.93	0.11
9	1.00	0.52	1.04	0.32	0.89	0.42	0.03	1.22	0.73	0.51
10	0.32	1.00	0.37	0.23	0.47	0.45	0.21	0.63	0.70	0.40
11	0.40	1.00	0.92	0.35	0.92	0.00	0.00	1.09	0.98	0.05
12	0.50	0.92	1.05	0.30	0.90	0.20	0.20	1.07	0.93	0.11
13	0.04	0.15	0.17	0.56	0.14	0.09	0.13	0.74	0.99	0.01
14	0.95	0.05	0.92	0.50	0.93	0.61	0.10	0.96	0.60	0.70
15	0.08	0.50	0.82	0.63	0.55	0.11	0.28	1.02	0.90	0.15
	Mean			0.38	0.67				0.81	0.29

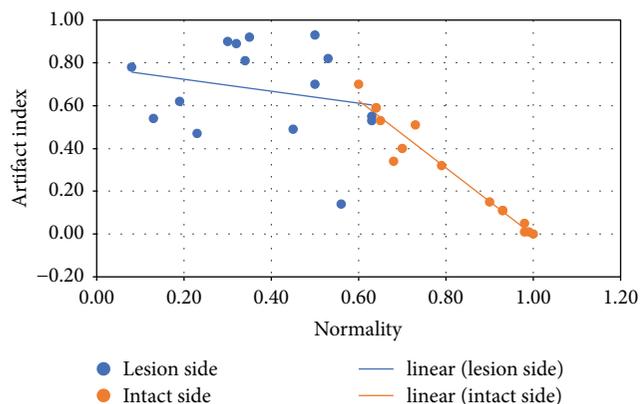


FIGURE 6: Artifact index versus normality in lesion side and intact side of 15 VN subjects.

of the previous system, using new inputs and new membership function, and produces one more factor of artifact index. The membership functions were built for three inputs: gain, proportion of covert catch-up saccades, and proportion of overt catch-up saccade as shown in Figure 5.

3.2. System Evaluation. Table 1 shows the evaluations from the dataset of two controls with both sides, and Table 2 shows the evaluation's result from the dataset of 15 VN subjects. In VN patient's population, in the lesion side, the normality is 0.38 ± 0.17 , with the artifact index of 0.67 ± 0.21 , for the intact side, the normality is 0.81 ± 0.29 , with the artifact index of 0.29 ± 0.24 ; whereas for normal subjects, the normality is 0.95 ± 0.03 , with the artifact index of 0.16 ± 0.34 . The linear relation of artifact index and normality in VN population was plotted in Figure 6. This relationship is more random on the lesion side, whereas it is more linear on the intact side.

The artifact index appears to be very high in the lesion side of VN patients, indicating highly theoretical contradictions, which are low gain but without CUS, or normal gain with the appearance of CUS. Both intact sides and normal subject show high normality and low artifact index, even though the intact side has slightly lower normality and higher artifact index. The fifth and fifteenth subjects' lesion side responses both have the highest normality of 0.63 among the lesion side's data, with relatively low artifact indices of 0.53 and 0.55, correspondingly. These results might indicate the lower severe condition compared to others, because of the high normality and low artifact index.

In addition, this program also gives out the optima point table, which could help the examiner review the maxima and minima point in the dataset with the number of optima points, their timing, and amplitude. The one with different value from the group could be the inference to gain calculation, hence should be removed.

4. Discussion

The software was built with a friendly graphical user interface (GUI), including plot, descriptive statistics for head and eye onset and zero crossing, gain, CUS timing and amplitude, and so on. In addition, it gave out an interface with the statistics of gain and CUS, plot of normal, covert and overt CUS-contained impulses, and normality and artifact. The whole GUI is mentioned in Figures 7–9. Normality represents the response's status by combining CUS proportion and gain using fuzzy inference system. The artifact index is an output from the fuzzy inference system, in which the impulse is contradicting with theory, that is, low gain but no CUS, or gain above 0.8 but still have CUS(s). The artifact index seems to be associated with the pattern of the whole dataset, which cannot be removed manually, and the clinician should

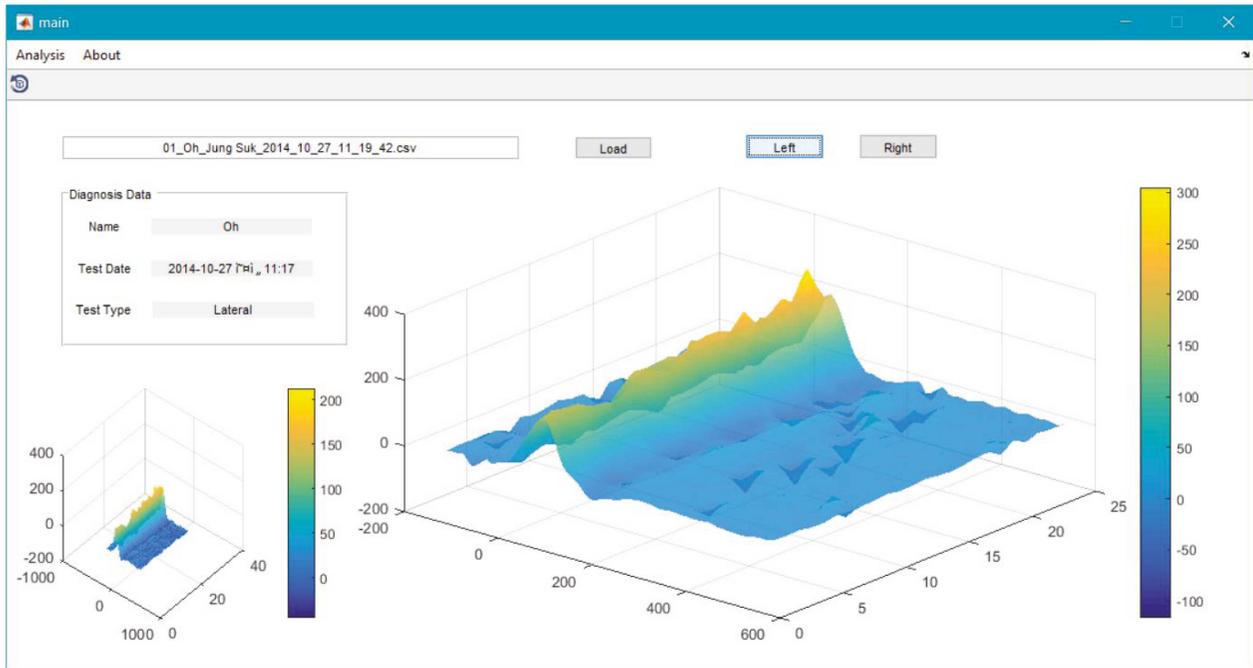


FIGURE 7: Main GUI of one side of one subject. The user can load the subject data on each side using “Load,” “Left,” and “Right” buttons. In this figure, the user can also find the metadata of the examination such as the subject’s name, test date, and test type. In addition, the small plot is representing the head impulse, while the large one is representing the corresponding eye response.

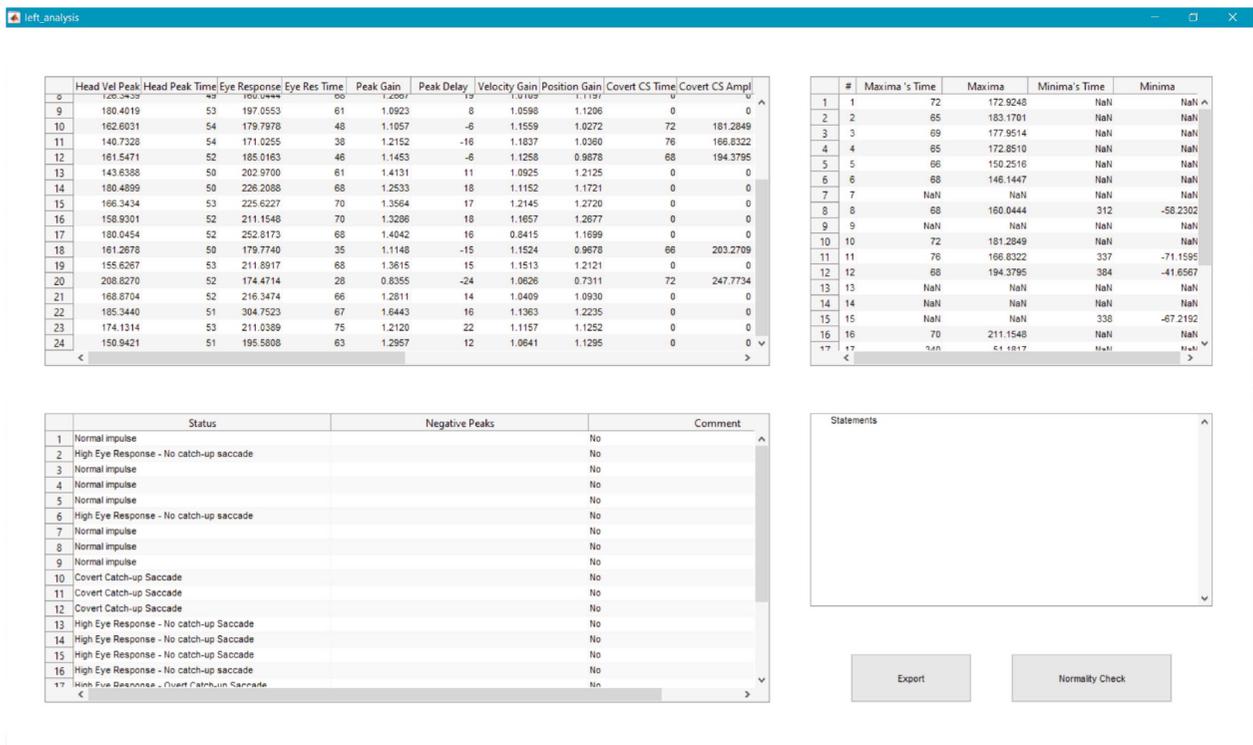


FIGURE 8: Statistical table of 14 parameters of one subject’s left side. These parameters include head velocity peak’s amplitude and time, eye response peak’s value and time, peak gain (the ratio of eye response’s peak to velocity impulse’s peak), peak delay (delay of eye response’s peak to head impulse’s peaks), velocity VOR gain, position VOR gain, CCS amplitude and time, OCS amplitude and time, and rebound peak’s amplitude and time. This figure also contains the optimal value table of all the significant minimum and maximum in the dataset. In addition, one descriptive table of status, which indicates that the response is normal, or contains catch-up saccade, is included. The user can note down statement and save for later use.

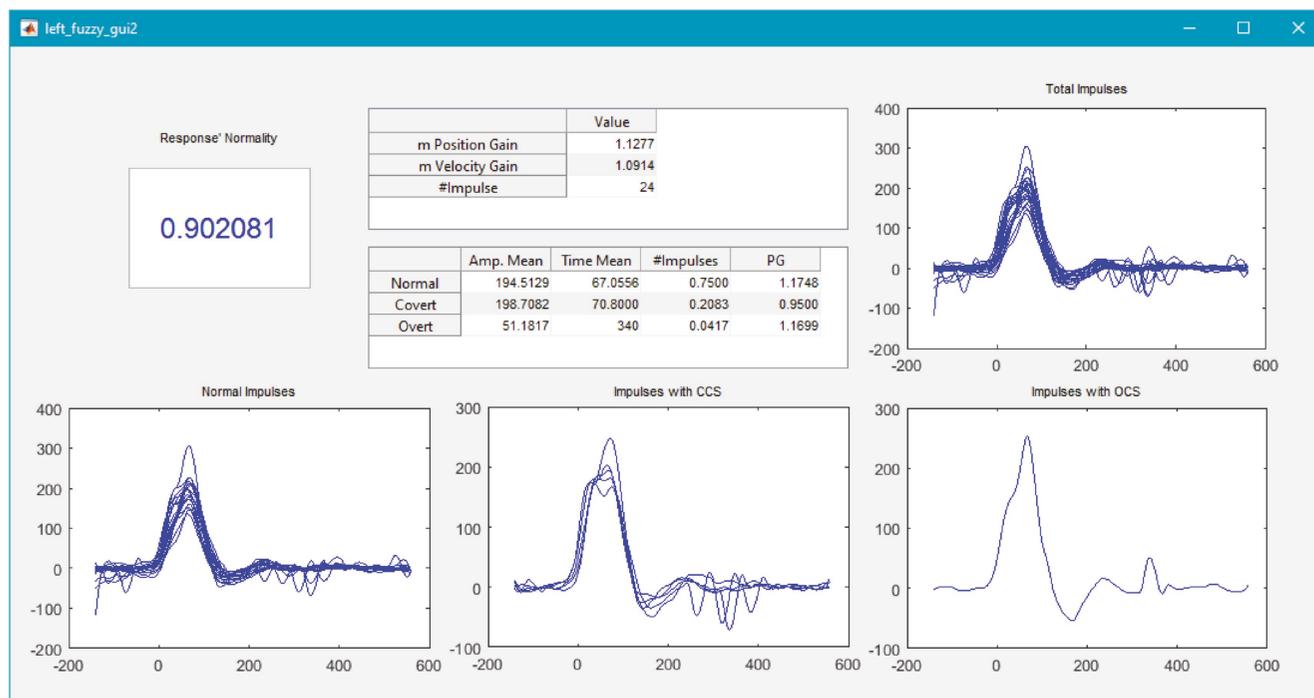


FIGURE 9: Normality and artifact index of the eye responses. This figure is evoked by clicking on the “Normality Check” button in the figure mentioned in Figure 8. In this figure, the user can find the normality, statistical analysis of gain, and catch-up saccades. This figure also includes four plots of total impulses, normal impulses only, impulses with CCS, and impulses with OCS.

reperform the test or adjust the normality of the dataset due to his/her own knowledge.

This is a robust system, which is the first one takes gain and CUS into account, to output not only the normality of the vHIT dataset, but also the artifacts. For future work, this system could be developed to work with any type of file output until it can get the head and eye movements with the right window. The current code works with ICS device only. We will provide the code as an open source. Furthermore, with sufficient data, this system can be highly developed with adaptive neural-network fuzzy inference system, for both normality and artifact. In addition, with clear understanding of the clustering of saccadic pattern as an input, this system can be developed further to apply in vestibular rehabilitation.

5. Conclusions

We successfully built the CDSS for vHIT VOR estimation using fuzzy inference system and evaluated the controls and VN dataset. This is a knowledge-based system that mimics the clinician’s reasoning to output the normality and artifact within the vHIT dataset.

The vHIT is interfered by several factors coming from real practice such as examination environment and patient condition. In addition, the evaluation of vestibular function with vHIT is only reliable when the artifact is low. Therefore, in order to effectively examine the vHIT dataset, this CDSS system produces two outputs, the normality and the artifact index. So if the artifact index is low, the clinician can rely on the normality. If not, he/she can review

the dataset and give her/his own opinion of the test. Therefore, the severe level is based on the normality and artifact. The recommended check protocol is firstly check for the artifact and the saccadic pattern, then evaluate and adjust the normality.

Conflicts of Interest

The authors declare that they have no conflict of interest.

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