# A Fuzzy Logic Based Parkinson's Disease Risk Predictor

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***Abstract*—With the world population aging rapidly, improving the quality of life for senior citizens has become an important societal issue. Parkinson's Disease (PD) is one of the most debilitating neuro-degenerative disorders that seriously affect the seniors' quality of life. In recent years, video games have been shown to be a viable way through which partial rehabilitation for PD can be carried out in a fun and low cost manner. Earlier research has shown that both patients' physical and mental conditions can be improved by playing video games. However, so far, the available games developed for PD are mostly intended for rehabilitation purposes. PD diagnosis still depends on the traditional neurological exams and experience of doctors, which require the patients to become self-aware of the symptoms and are usually too late for the patients to delay the progression of PD. To support the early detection of PD symptoms, we propose a fuzzy logic based PD risk predictor that has been implemented in a tablet game platform. The player's behavior data in the game environment are captured unobtrusively and analyzed in real-time. The player's current risk of developing PD is estimated using the proposed fuzzy logic based approach, which will help the player to be aware of high risk of having PD at an earlier stage. A pilot evaluation has been conducted to demonstrate the effectiveness of the proposed approach.**

## I. Introduction

Population aging has become a central issue in today's world. It is estimated that 22% of the entire global population will exceed 60 years of age by 2050 [1]. For the most serious example, the proportion of the elderly (people aged 65 or above) in Japan has increased from 12.0% to 23.3% of the population between 1990 and 2011. It is estimated that the elderly population in Japan will reach 38.8% by 2050 [2]. In Canada, 5.2% of the population has been aged above 65, and the number is forecast to more than double after 30 years. In 2010, the elderly proportion of the Singapore population reached 7.7%, and this number has since increased to 11.1% in 2012 [3]. With such a tremendously increasing population of the elderly, improving their quality of living has become an important societal issue.

Parkinson's Disease (PD) is one of the problems that seriously affect the elderly's quality of life. Patients suffer from the problems that affect their daily life, such as *akineisa* (difficulty in initiating movement), *bradykinesia* (reduced amplitude and speed of movement), abnormal facial expressions, and postural instability [4] [5]. There are around seven million people worldwide suffering from PD. Most cases occur after 60 although early onset of the disease also occurs [6]. The current standard treatment is L-3, 4-dihydroxyphenylalanine therapy. Physical therapy is adopted as an alternative means to slow down PD progression and delay the need for drug interventions due to the negative side effect of medication. As with other diseases, early detection of PD will remarkably delay the disease progression, and improve the patients' quality of life. However, PD diagnosis today still depends on the patients being self-aware of PD symptoms (e.g., shaking and rigidity) and consulting doctors, which usually results in missing the best opportunities for early treatment.

In recent years, video games have been developed for PD rehabilitation purposes [7] [8] [9] [10] [11] [12] [13] [14]. These games operate as an alternative for the traditional physical exercises. As the physical exercises need to be conducted intensively over a long period of time in order to be effective [15] [16], PD patients undergoing traditional rehabilitation tend to feel mentally bored and physically tired [7] [17] [18]. This reduces their motivations to persist as a result. The PD video games motivate the PD patients to exercise more [19]. However, as exiting games mostly focus on the purpose of PD rehabilitation, they often depend on the sophisticated devices or platforms (e.g., GestureTek and IREX) to capture and track players' motions, which are expensive and require professionals for system setup. In addition, most of the games need to be played with the presence of instructors, which make them unsuitable for independent home-based rehabilitation.

Therefore, to help the elderly detect the risk of having PD earlier, we propose a fuzzy logic based PD risk predictor which can be incorporated into tablet based games - the *Pumpkin Garden*. It takes a player's historical in-game finger movement and other behavior data as input, and calculates the player's risk of developing PD. The tablet device (e.g., iPad) is capable of being taken anywhere and installing applications easily. This will facilitate the elderly to play games anytime and anywhere without the need of professional help. The proposed game is incorporated with three tasks, which are specially tailored to measure the player's motion synchronization, task switching capability, and short-term memory, respectively. The player's behavior data during each game session are captured and uploaded to the game platform server. The player's in-game behaviors are analyzed in real-time with the proposed fuzzy logic [20] [21] based risk predictor to estimate his/her having PD risk. Suggestions are shown to the player and alert will be sent to the designated caregivers if a high level of risk has been identified. The data uploaded can be used for record keeping and contribute to possible future treatment and rehabilitation.

The proposed game and risk predictor made the following contributions: 1) the game provides a suitable environment for the player to exhibit actions related to possible PD symptoms for early PD detection; 2) the proposed fuzzy logic based risk predictor bridges the gap between the multiple PD related symptoms and a general risk of developing PD; 3) the player behavior data are captured and recorded in the database, which will contribute to treatment and rehabilitation, and future bench-marking for interactive media based research on PD.

The remainder of this paper is organized as follows. A review of related work is given in Section II. Section III presents the proposed tablet-based game platform and data analysis approaches. The proposed fuzzy logic based PD risk predictor is presented in Section IV. A pilot evaluation is introduced in Section V. Finally, Section VI concludes the paper.

## II. RELATED WORK

Till now, most existing PD video games focus on rehabilitation purposes. We review some representative works in this section.

Early studies regarding games as PD rehabilitation tools have been conducted in [8]. The authors tested the adaptation of PD patients in a virtual reality (VR) environment to explore whether VR can provide meaningful information to support clinical and neuropsychological PD treatment and rehabilitation. In the study, the players are tested in a VR environment that is related to their usual daily activities at home (e.g., eating or using the bathroom). Evaluations were conducted with 2 female PD patients and 10 control subjects. It is shown that VR contributes to improving the quality of life of PD patients through improved cognitive capabilities.

Some commercial training games and game devices such as Wii have been adopted to facilitate physical therapy for PD patients. In [13], the authors conducted a pilot study on the commercial games based on Wii fit with a balance board for PD rehabilitation. The study shows that the home-based training programme integrated with visual feedbacks could help to improve the PD patients' abilities of static and dynamic balance and mobility. However, the commercial games and devices are not specially tailored for PD rehabilitation. Therefore, they can be too challenging for PD patients, and may pose safety concerns during usage.

Some video games have been specially designed to fulfill the requirements of PD rehabilitation. In [9], a computational architecture based on the EyesWeb open software platform [22] was developed. Several modules are designed to be integrated in the architecture, such as analyzing and recognizing the PD patient gestures, generating real-time multimedia feedbacks, designing real-time therapeutic exercises adapted to the PD patients, and therapy progression evaluation. Some exercises (e.g., asking the player to paint using his or her body) were developed for evaluation purposes. A preliminary study was conducted on a male and a female PD patient. The study shows that the exercises are able to generate aesthetically resonant feedbacks in PD patients and encourage them to persist through further rehabilitation.

In [7], the authors developed an interactive multimedia system to facilitate PD rehabilitation based on two physical therapy techniques – multimodal sensory cuing [23] [24] and the BIG protocol [25]. It tries to fulfill the requirements from both the physical therapists in the area of being cost effective and space efficient. It focuses on the symptoms associated with *akinesia*. In the system, the patients are asked to complete movement related tasks by controlling their avatars, which are mapped in the screen through capturing the location of the patients' hands, feet, and torsos with a 10 near-infrared camera Motion Analysis System. Visual and auditory feedbacks are provided based on the accuracy and timing of the movements.

In [10], the authors proposed to develop a medical game system for PD diagnosis and management. The system aims to measure the patients' steadiness when traversing through the game environment and tremor at rest. The Novint Falcon Human Interface Device is used to record the players' movements. The system is designed to provide force feedbacks to guide the patients. However, due to the heavy requirement of Novint Falcon on hardware and other issues (e.g., accuracy measurement is difficult to achieve), the system implementation is rather difficult as stated by the authors.

In [11], the authors designed and implemented a collection of five mini-games (WuppDi!) to improve the memory and motion abilities of the PD patients. The games require a complicated setup. Assistance from healthy people is recommended to assure balance and stability of the patients. A field study was conducted with 13 PD patients to explore their experience in terms of game contents, game play, and motion. In [12], the authors improved WuppDi! by automatically personalizing game difficulty for each patient.

In [14], the authors developed an exercise game to study the influence of music on PD rehabilitation. In the game, the patient needs to repetitively grab a worm to feed the moles appearing from the holes. An evaluation conducted on 24 participants has shown that music has positive effects on the patients' performance, even without specific instructions provided to the players to follow the auditory cues.

It can be noticed that some thought-provoking works have been conducted on the aspects of game-based PD rehabilitation. However, there is almost no attempt of using games for early detection of PD. The high cost, complicated setup, specific requirement of the devices and particular design for rehabilitation also limit applicability of existing works in PD diagnosis. The commercial training games and devices are also not suitable for PD diagnosis as they do not meet the specific requirement of PD symptom detection. Therefore, to bridge these gaps, we design and implement a tablet based game tailored for PD diagnosis purposes and a corresponding risk predictor for early detection of PD symptoms.

## III. THE PUMPKIN GARDEN GAME PLATFORM

To achieve the purpose of PD symptom detection and risk prediction while motivating the player to persist over the long run, we have designed and implemented a tablet-based game – the *Pumpkin Garden*. It is a virtual farming game, and is integrated with three tasks specially designed to measure the player's three abilities related to PD symptoms. The three tasks are *weed clearing*, *animal herding* and *pumpkin harvesting*.

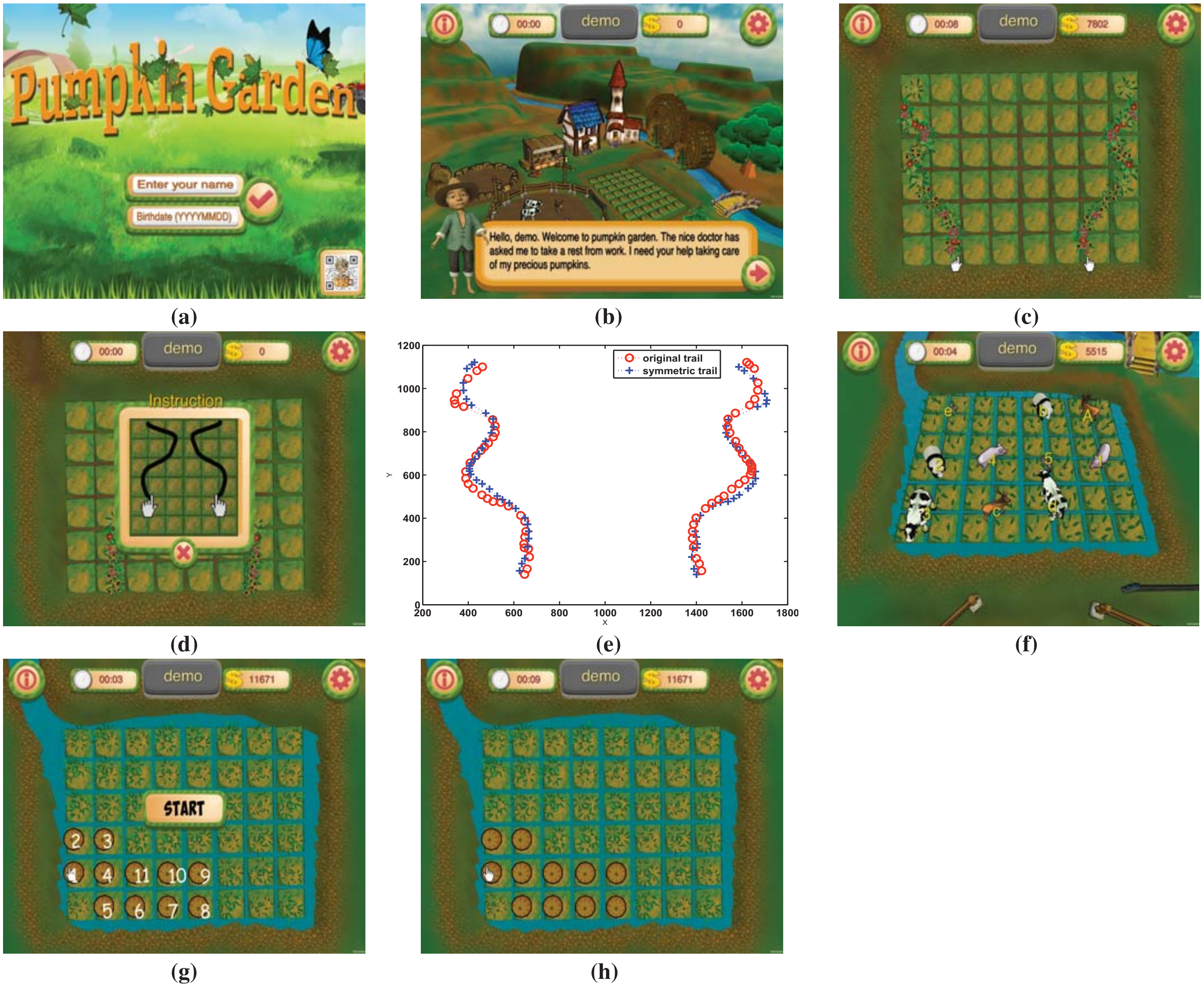



Fig. 1. The pumpkin garden game

The game is currently implemented on the iOS system. After a player logins to the game through the portal shown in Figure 1(a), the game interface is presented to the player as shown in Figure 1(b). The player's goal is to help taking care of the pumpkin garden by completing the three tasks in each game session. The player behavior data are captured and uploaded to the server for real-time data analysis and future record tracking.

### *A. The Weed Clearing Task*

After the player starts the game, the first task he is asked to complete is to clear the weeds on the farmland as shown in Figure 1(c). The weeds show up on the screen with randomly generated trails. The player needs to use two fingers from each hand to slide on the screen simultaneously following the weed trails in order to clear them. The trails for the left and right fingers are symmetrical with respect to the central vertical line of the screen. Virtual rewards will be given to the player based on his/her performance in the task (i.e., how many patches of weed are cleared). The task instruction can be activated by tapping the "i" button on the left-hand corner of the screen as shown in Figure 1(d) to help the player to understand how to complete the task. The weed clearing task is designed to measure the player's motion synchronization ability as poor motion synchronization is one of the possible PD symptoms.

The player behavior data, such as the finger positions and the task completion time, are captured unobtrusively. The synchronization ability can be measured through calculating the difference between the left and right finger movements. Figure 1(e) shows the example of the captured finger movement trails (the plotted curves with the circle sign) corresponding to the weed trails shown in Figure 1(c). The x-axis and y-axis are the pixel coordinates of the captured finger positions.

We use the difference between the left and right finger movement trails to measure the synchronization ability. More specifically, we first acquire the symmetry of the left (or right) trail with respect to the central vertical line of the screen. The symmetry trails are shown by the plotted curves with the "+" sign in Figure 1(e). Then we calculate the difference between the symmetry of the left (or right) trail and the captured original right (or left) trail. As the points are only captured when two fingers are in contact with the screen at the same time, the left and right trails will include the same number of points. Suppose each trail includes $N$ points. For a particular point $p_n$ ($1 \leq n \leq N$) whose coordinate is $< x_n, y_n >$, we can calculate the coordinate of its symmetric point $p'_n$, denoted as $< x'_n, y'_n >$. The coordinate of $p_n$'s actual corresponding point on the other captured trail is $< x''_n, y''_n >$. Then, the player's synchronization ability $s_1$ is measured by the average distance of the pair of points on the symmetric and captured trails:

$$s_1 = \frac{\sum_{n=1}^{N} \sqrt{(x''_n - x'_n)^2 + (y''_n - y'_n)^2}}{N}. \tag{1}$$

For example, for a point $p$ located at captured left finger movement trail (the plotted curve with circle sign on the left in Figure 1(e)), we first find the symmetric point $p'$ located at the symmetric curve (the plotted curve with the "+" sign on the right in Figure 1(e)) of the captured left finger movement trail. Then we find the corresponding point $p''$ located at the right finger movement trail (the plotted curve with circle sign on the right in Figure 1(e)) and captured with $p$ at the same time. We calculate the average distance of the all the pair of points $p'$ and $p''$ to measure the player's synchronization ability. For the trails shown in Figure 1(e), $s_1$ is calculated as 42.0693. A larger difference between two trails (i.e., a greater $s_1$ value) implies poorer synchronization ability.

### *B. The Animal Herding Task*

After completing the weed clearing task, animals will show on the farmland as shown in Figure 1(f). Each animal has a digit or an alphabet label. The player is asked to tap the animal one by one following the order of digit and alphabet alternatively in the correct sequence to herd the animals back to their fold before they destroy the crops. For example, the animals shown in Figure 1(f) are: a pig with 1, a deer with A, a panda with 2, a panda with b, a cow with 3, a deer with c, a pig with 4, a cow with d, a mouse with 5, and another mouse with e. In this case, the player needs to tap the animals one by one following the order: pig(1)→deer(A)→panda(2)→panda(b)→cow(3)→deer(c)→ pig(4)→cow(d)→mouse(5)→mouse(e). The animals will be back to their fold if they are tapped in the correct sequence. Otherwise, the player will be prompted to try again. This task is designed to measure a player's task switching ability as PD patients may have trouble switching between mental activities.

The original sequence of the animals showing up, the sequence of the player's tapping actions, and the task completion time are captured. We use the ratio of the necessary tappings to the tappings the player uses to complete the task to measure the player's task switching ability. Suppose the number of animals is $a$. Then the minimum number of tappings necessary for the player to complete the task will be $a$. Suppose the total number of tappings the player used to complete the task is $a'$. Then the player's task switching ability $s_2$ is measured as:

$$s_2 = \frac{a}{a'}. \tag{2}$$

If the player requires more tappings to complete the task (i.e., a larger $a'$ value and a smaller $s_2$ value as a result), it implies that the player's task switching ability is poorer.

### *C. The Pumpkin Harvesting Task*

After completing the animal herding task, the moment of harvesting finally comes. In the final task, pumpkins will show up on the screen one by one following a random sequence. Each pumpkin is labeled with a number as shown in Figure 1(g). The player needs to remember the sequence correctly. Once he taps the "START" button, the sequence numbers will disappear as shown in Figure 1(h). The player is then asked to tap the pumpkins following the sequence that he remembered in order to harvest them. This task is designed to assess the player's short-term memory since PD patient usually suffer from declines in short-term memory. Therefore, no matter whether the player taps correctly, the pumpkin will disappear for the purpose of not interrupting the player's memory.

The original pumpkin sequence, the player tapping sequence, and the task completion time are captured. We use the accurate rate of the player's tappings to assess his short-term memory. Suppose the length of the original pumpkin sequence is $l$. As no matter whether the tapping is correct or not, the pumpkin will disappear, the length of the player tapping is also $l$. But among these $l$ tapping actions, the number of correct tapping actions (i.e., the order of the pumpkin the player taps matches the position of the pumpkin in the original sequence) is $l'$. Then the player's short-term memory $s_3$ is measured as:

$$s_3 = \frac{l'}{l}. \tag{3}$$

A smaller $s_3$ value suggests poorer short-term memory as the number of correct tapping actions is few.

## IV. Fuzzy Logic based Risk Prediction

We have assessed the player's abilities in motion synchronization, task switching, and short-term memory. However, the individual measurement of these three abilities is not conclusive. They need to be combined together to reach a general indicative value as the risk prediction of the player developing PD. We propose to use fuzzy logic system to combine them together, as the fuzzy logic system has the advantage of bridging the gap between human experts (e.g., doctors and physiotherapists) and machines without a precise description of the real world, which is difficult to obtain in the case of PD diagnosis.

### *A. The Fuzzy Logic System*

A fuzzy logic system is a rule-based system [20]. For example, the following sentence describes a rule in the PD risk prediction scenario: *IF the synchronization ability is POOR AND the task switching ability is POOR AND the short-term memory is POOR, THEN the risk of the player having PD is VERY HIGH.*

Different types of fuzzy logic systems have been proposed. They include the pure fuzzy system, Takagi-Sugenor-Kang (TSK) fuzzy systems, and the fuzzy systems with fuzzifier and defuzzifier [20]. As the fuzzy systems with fuzzifier and defuzzifier have the advantage of providing a natural framework to represent human knowledge, we adopt this type of fuzzy systems in our current work. It operates as shown in Figure 2.

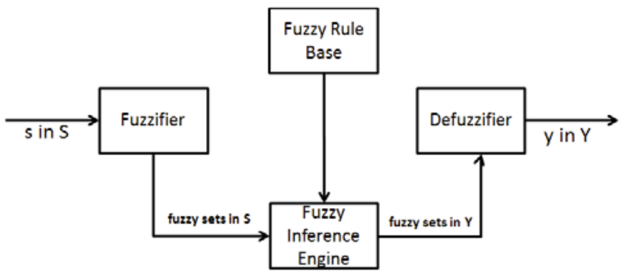



Fig. 2. A typical fuzzy logic system with fuzzifier and defuzzifier [20]

Firstly, a crisp point $s$ is transformed into fuzzy sets in $S$ through a fuzzifier. Then, according to some predefined rules, the fuzzy inference engine transforms the fuzzy sets in $S$ into fuzzy sets in $Y$, which are eventually transformed into a real-valued output $y$ through the defuzzifier.

We use the ability measurements from the three tasks of the game to derive the risk predictor for the player to develop PD. Therefore, the input for the fuzzy logic system is actually a 3-value tuple, denoted as $< s_1, s_2, s_3 >$, where $s_1$, $s_2$, and $s_3$ are the ability measurements from the tasks of weed clearing, animal herding, and pumpkin harvesting, respectively. For a fuzzy logic system to work, firstly, we need to define the fuzzy sets and the corresponding membership functions (MFs) which describe how much a real-value input belongs to a fuzzy set [20].

Currently, each $s_i$ ($i = 1, 2, 3$) is associated with three fuzzy sets: low (L), medium (M) and high (H). Correspondingly, three MFs are defined for each $s_i$ to characterize to what extent $s_i$ belongs to the particular fuzzy set associated with the MF. We currently use the Gaussian MF expressed as follows:

$$\mu_{S_i^d}(s_i) = e^{-(\frac{s_i - \overline{s}_i^d}{\sigma_i^d})}, \tag{4}$$

where $S_i^d$ ($i = 1, 2, 3$ and $d =$ L, M, H) is a fuzzy set, interpreted as $s_i$ is a member of the fuzzy set $d$ (e.g., $S_i^d$ is the fuzzy set of *low task switching ability measurement value* when $i = 2$ and $d = L$). $\overline{s}_i^d$ and $\sigma_i^d$ are the constant mean and standard deviation values for the corresponding Gaussian MF, respectively. The values are calculated according to the MF, and $\mu_{S_i^d}(s_i)$ describes to what extent $s_i$ belongs to $S_i^d$.

For the output $y$, we associate it with 5 fuzzy sets: very low (VL), low (L), medium (M), high (H), and very high (VH). The corresponding Gaussian MFs for the 5 fuzzy sets are:

$$\mu_{Y^d}(y) = e^{-(\frac{y - \overline{y}^d}{\sigma_y^d})}, \tag{5}$$

where $Y^d$ ($d =$ VL, L, M, H, VH) represents the fuzzy set $d$. $\overline{y}^d$ and $\sigma_y^d$ are the constant mean and standard deviation values for the Gaussian MF, respectively.

Secondly, we need to define the rules following which the fuzzy logic system works. We currently define the following 27 rules as shown in Table I.

TABLE I. RULES FOR THE FUZZY LOGIC SYSTEM

| Rule | $s_1$ | $s_2$ | $s_3$ | $y$ | Rule | $s_1$ | $s_2$ | $s_3$ | $y$ |
|---|---|---|---|---|---|---|---|---|---|
| 1 | H | L | L | VH | 2 | H | L | M | L |
| 3 | H | L | H | M | 4 | H | M | L | H |
| 5 | H | M | M | H | 6 | H | M | H | M |
| 7 | H | H | L | M | 8 | H | H | M | M |
| 9 | H | H | H | M | 10 | M | L | L | H |
| 11 | M | L | M | H | 12 | M | L | H | M |
| 13 | M | M | L | H | 14 | M | M | M | M |
| 15 | M | M | H | L | 16 | M | H | L | M |
| 17 | M | H | M | L | 18 | M | H | H | L |
| 19 | L | L | L | M | 20 | L | L | M | M |
| 21 | L | L | H | M | 22 | L | M | L | M |
| 23 | L | M | M | L | 24 | L | M | H | L |
| 25 | L | H | L | M | 26 | L | H | M | L |
| 27 | L | H | H | VL | - | - | - | - | - |

Each combination of $s_1, s_2, s_3, y$ in Table I is a rule. For example, the 1st rule is: *IF* $s_1$ *is* H, *and* $s_2$ *is* L, *and* $s_3$ *is* L, *THEN* $y$ *is* VH, which is actually the previous example rule mentioned at the beginning of this section.

With the fuzzy sets and rules defined, the proposed fuzzy logic system works as follows. Firstly, a real-valued point $s^* =< s_1^*, s_2^*, s_3^* >$ is mapped to the fuzzy set $S'$ through the Gaussian fuzzifier to suppress noise. The MF for $S'$ is as follows:

$$\mu_{S'}(s) = e^{-(\frac{s_1 - s_1^*}{a_1})^2} \times e^{-(\frac{s_2 - s_2^*}{a_2})^2} \times e^{-(\frac{s_3 - s_3^*}{a_3})^2}, \tag{6}$$

where $a_1$, $a_2$, and $a_3$ are constants satisfying the following condition to suppress noise:

$$a_i >> \sigma_i^d, \tag{7}$$

for all $d =$ L, M, H, where $i = 1, 2, 3$.

Then, the product fuzzy inference engine is equipped to infer the output fuzzy set $Y'$ according to $S'$ and the fuzzy rules, as follows:

$$\mu_{Y'}(y) = \max_{l=1}^{M}[\prod_{i=1}^{3} e^{(-\frac{s_{iP}^l - \overline{s}_i^l}{\sigma_i^l})^2} e^{(-\frac{s_{iP}^l - s_i^*}{a_i})^2} \mu_{Y^l}(y)], \tag{8}$$

where

$$s_{iP}^l = \frac{a_i^2 \overline{s}_i^l + (\sigma_i^l)^2 s_i^*}{a_i^2 + (\sigma_i^l)^2}, \tag{9}$$

for $i = 1, 2, 3$. $M$ is the number of rules. $\overline{s}_i^l$ and $\sigma_i^l$ are the mean and standard deviation values of the Gaussian MF corresponding to the fuzzy set of $s_i$ in the $l$th rule, respectively. $Y^l$ is the fuzzy set of $y$ in the $l$th rule. For example, if $l = 1$ (i.e., Rule 1 in Table I), then $\overline{s}_1^l$ and $\sigma_1^l$ are the mean and standard deviation values of the Gaussian MF corresponding to the fuzzy set H of $s_1$, respectively. $Y^l$ is the fuzzy set VH.

Then, the widely used center average defuzzifier is adopted to transform the output fuzzy set $Y'$ to a real value $y^*$ as follows:

$$y^* = \frac{\Sigma_{l=1}^{M} \omega_l \overline{y}^l}{\Sigma_{l=1}^{M} \omega_l}, \tag{10}$$

where $\overline{y}^l$ is the center [20] of the output fuzzy set in the $l$th rule, and $\omega_l$ is its height achieved from Eq.(8). The output $y^*$ is considered to be the risk predictor of the player developing PD.

It is worth of pointing out that the parameter settings for the Gaussian membership functions and fuzzifier, and the fuzzy rules, are not one-time decided. They need to be set through iterative experiment evaluations and suggestion from experts (e.g., doctors and physiotherapists). Though some work regarding automating parameter settings for fuzzy logic systems has been proposed [26] [27], suggestion from experts is still necessary.

### B. Example

We use an example to show how the fuzzy logic system works. The example data we use in this part are from our evaluation. Suppose after a player completed a game session, the ability measurements from the three tasks are: $s_1 = 87.6062$, $s_2 = 0.1471$, $s_3 = 0.0833$. The mean and standard deviation values for the Gaussian MFs associated with the input and output fuzzy sets are shown in Table II, and $a_i = 2\max\{\sigma_i^L, \sigma_i^M, \sigma_i^H\}$ for $i = 1, 2, 3$.

TABLE II. PARAMETER SETTINGS

| $d$ | VL | L | M | H | VH |
|---|---|---|---|---|---|
| $\overline{s}_1^d$ | - | 70 | 80 | 90 | - |
| $\sigma_1^d$ | - | 10 | 10 | 10 | - |
| $\overline{s}_2^d$ | - | 0.4 | 0.6 | 0.8 | - |
| $\sigma_2^d$ | - | 0.1 | 0.1 | 0.1 | - |
| $\overline{s}_3^d$ | - | 0.2 | 0.6 | 1 | - |
| $\sigma_3^d$ | - | 0.2 | 0.2 | 0.2 | - |
| $\overline{y}^d$ | 0 | 0.25 | 0.5 | 0.75 | 1 |
| $\sigma_y^d$ | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |

After the input values pass through the fuzzifier (Eq.(6)) and fuzzy inference engine (Eq.(8)), we will have:

$$\begin{aligned}\mu_{Y'}(y) = \max[&0.257 \times \mu_{VH}(y), 0.0724 \times \mu_L(y),\\ &0.0041 \times \mu_M(y), 0.0153 \times \mu_H(y),\\ &0.0043 \times \mu_H(y), 0.0002 \times \mu_M(y),\\ &0.0002 \times \mu_M(y), 0.0001 \times \mu_M(y),\\ &0 \times \mu_M(y), 0.2315 \times \mu_H(y),\\ &0.0652 \times \mu_H(y), 0.0037 \times \mu_M(y),\\ &0.0138 \times \mu_H(y), 0.0039 \times \mu_M(y),\\ &0.0002 \times \mu_L(y), 0.0002 \times \mu_M(y),\\ &0 \times \mu_L(y), 0 \times \mu_L(y),\\ &0.1398 \times \mu_M(y), 0.0394 \times \mu_M(y),\\ &0.0022 \times \mu_M(y), 0.0083 \times \mu_M(y),\\ &0.0023 \times \mu_L(y), 0.0001 \times \mu_L(y),\\ &0.0001 \times \mu_M(y), 0 \times \mu_L(y),\\ &0 \times \mu_{VL}(y)]\end{aligned} \tag{11}$$

After going through the defuzzifier (Eq.(10)), the risk predictor of the player having PD is calculated to be 0.7642.

## V. EVALUATION

As a pilot study, we conducted the evaluation of the proposed fuzzy logic based PD risk predictor with two groups of subjects. The first group includes 10 seniors, 5 of whom are over 70 years old, and the other 5 are between 60 and 70 years old. The second group is the control group including younger people between 20 to 35 years old. As the seniors are the group of people who are more likely to suffer from PD symptoms, the purpose of the evaluation is to study whether the seniors will exhibit higher risk predictor values compared to the control group. Each subject is evaluated over two full game sessions on two different days. We use the worst and average ability measurement results from each task to calculate the risk predictors of the person having PD, respectively. As an example, Figure 3 shows one senior subject playing the Pumpkin Garden game at home.

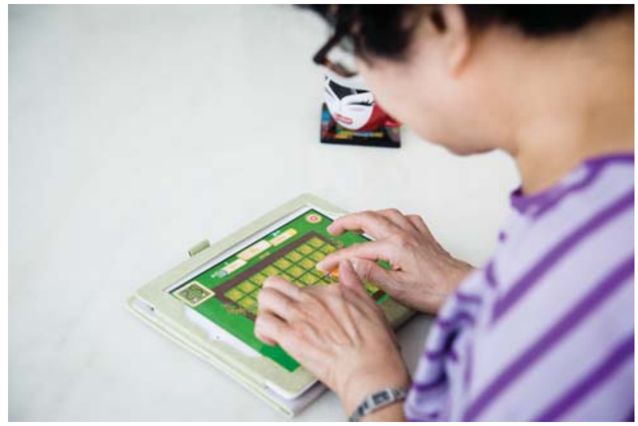


Fig. 3. One senior player playing game at home

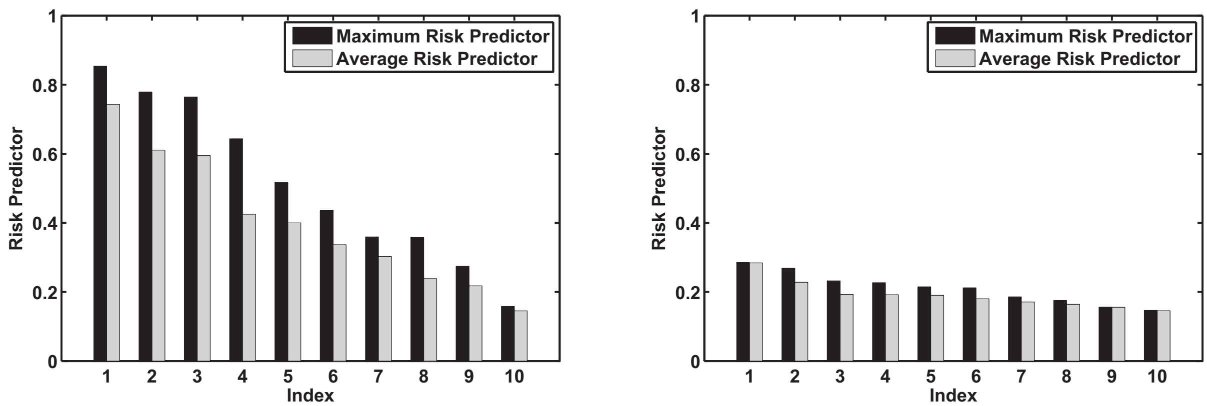
Table III shows the ability measurement values and the risk predictors (RP) calculated through the fuzzy logic system. The first five columns are the ability measurements and RP results for the senior subjects, and the other five columns are for the control subjects. There are two values in each cell. The upper value is the worst ability measurement result for each task corresponding to the subject and the maximum RP calculated based on the worst measurement results. The lower one is the average measurement result for each task and the average RP calculated accordingly. The results are shown in RP value descending order.

To display the RP results more clearly, Figure 4 shows the calculated maximum and average RPs for the senior and control subjects. In Figure 4(a) and (b), the 10 pairs of bars are the RP results for the senior and control subjects, respectively. The left and right bar of each pair are the maximum and average RP results, respectively. According to the results shown in Table III and Figure 4, most senior subjects achieve a RP value higher than 0.3, except the ones we highlight in **bold** in Table III. The RP results for the senior subjects are statistically higher than those of the control subjects with 95% confidence according to a 1-tailed t-test with $p$-value being 0.0014 and 0.0037 for the maximum and average RP results, respectively.

The maximum RP value for Senior 1 is higher compared to others because the abilities through the three tasks are all measured as poor. The trail difference (i.e., $s_1$) achieved in task 1 is over 100, which is only smaller than the trail difference result for Senior 2. His task switching ability and short-term memory are both measured as significantly worse than most of other senior subjects. One possible reason is that he is over 70 and the eldest one among all senior subjects. It can be seen that for the senior subjects over 70 (Senior 1, 2, 5, 6 and 8), three of their $s_1$ values are over 100, especially that Senior 2's $s_1$ value is over 200. The observation suggests that the motion synchronization ability of the senior over 70 is significantly

TABLE III. Ability Measurement and Risk Predictor Results

| Senior | $s_1$ | $s_2$ | $s_3$ | RP | Control | $s_1$ | $s_2$ | $s_3$ | RP |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 126.8623 | 0.2941 | 0.1818 | 0.8538 | 2 | 79.0741 | 1.0000 | 1.0000 | 0.2851 |
| | 106.7879 | 0.3394 | 0.4371 | 0.7429 | | 78.8902 | 1.0000 | 1.0000 | 0.2842 |
| 2 | 255.7041 | 0.4000 | 0.4545 | 0.7790 | 2 | 58.4835 | 0.7143 | 1.0000 | 0.2686 |
| | 174.3281 | 0.7000 | 0.5606 | 0.6105 | | 44.6683 | 0.8571 | 1.0000 | 0.1803 |
| 3 | 87.6062 | 0.1471 | 0.0833 | 0.7642 | 3 | 61.1725 | 0.8333 | 1.0000 | 0.2321 |
| | 60.9278 | 0.2241 | 0.4444 | 0.5948 | | 60.0334 | 0.8333 | 1.0000 | 0.2282 |
| 4 | 98.2885 | 0.6250 | 0.1667 | 0.6435 | 4 | 66.6807 | 1.0000 | 1.0000 | 0.2269 |
| | 70.0551 | 0.8125 | 0.4015 | 0.4251 | | 57.8038 | 1.0000 | 1.0000 | 0.1927 |
| 5 | 111.6229 | 0.5556 | 1.0000 | 0.5165 | 5 | 60.9307 | 0.9091 | 1.0000 | 0.2150 |
| | 96.2910 | 0.5556 | 1.0000 | 0.3999 | | 56.1191 | 0.9545 | 1.0000 | 0.1920 |
| 6 | 96.5121 | 0.6667 | 1.0000 | 0.4355 | 6 | 63.0932 | 1.0000 | 1.0000 | 0.2122 |
| | 85.0983 | 0.8333 | 1.0000 | 0.3369 | | 57.1279 | 1.0000 | 1.0000 | 0.1905 |
| 7 | 94.2737 | 1.0000 | 1.0000 | 0.3595 | 7 | 51.7061 | 0.9091 | 1.0000 | 0.1858 |
| | 82.0505 | 1.0000 | 1.0000 | 0.3000 | | 48.7901 | 0.9545 | 1.0000 | 0.1712 |
| 8 | 92.0825 | 0.9091 | 1.0000 | 0.3576 | 8 | 47.6047 | 0.9091 | 1.0000 | 0.1754 |
| | 66.9043 | 0.9091 | 1.0000 | **0.2384** | | 45.8487 | 0.9545 | 1.0000 | 0.1642 |
| 9 | 67.1207 | 0.7692 | 1.0000 | **0.2744** | 9 | 44.4146 | 1.0000 | 1.0000 | 0.1559 |
| | 60.4413 | 0.8846 | 1.0000 | **0.2177** | | 44.3441 | 1.0000 | 1.0000 | 0.1557 |
| 10 | 39.0553 | 0.9091 | 1.0000 | **0.1582** | 10 | 39.5931 | 1.0000 | 1.0000 | 0.1464 |
| | 35.5876 | 0.9545 | 1.0000 | **0.1453** | | 39.1595 | 1.0000 | 1.0000 | 0.1457 |




(a) Senior Subject Risk Predictor

(b) Control Subject Risk Predictor

Fig. 4. Risk Predictor Results

lower than others.

The maximum RP values for Senior 2 and 3 are also higher compared to most of other seniors as they both have two abilities measured as poor. For Senior 2, her $s_1$ value is extremely high, suggesting that her motion synchronization ability is quite poor. Her task switching ability is also not good as suggested by the $s_2$ value. For Senior 3, her task switching ability is not good, either. Her short-term memory ability is especially poor reflected by $s_3$. However, this result may be due to one-time error during game playing as Senior 1, 3 and 4 (whose worst short-term memory ability measurement values are obviously lower) have higher average short-term memory ability measurement results compared to their worst short-term memory ability measurement results. Senior 2's short-term memory ability measurement results are consistently lower regardless of worst or average measurement values.

Senior 5's synchronization ability is also measured as poor. Though Senior 5 is an expert in computer science, his maximum RP value is over 0.5, implying that possessing good computer game experience may have no positive impact on the performance of completing the tasks. Among all the senior subjects, Senior 10 achieves the lowest RP values, even lower than some control subjects. His synchronization ability is significantly better than other senior subjects as suggested by the lowest $s_1$ value among all senior subjects. This may be due to his past training as a pianist.

The maximum RP results for the control subjects are all lower than 0.3. Control 1 and 2's maximum RP results are a bit higher compared to others in the control group as they both have one ability measured a bit poor (i.e., the synchronization ability for Control 1 and the task switching ability for Control 2). It can be noticed that the control subjects all complete task 3 with good short-term memory ability ($s_3$ values for the control subjects are all 1). It implies that the control subjects have good short-term memory in general. Their $s_1$ values, except Control 1, are significantly smaller than most senior subjects. This suggests that the control subjects' synchronization ability is better. It can be noticed that most control subjects possess good task switching ability except Control 2 and 3. According to the observation during the game playing, it seems to be a bit difficult for them to tap the animals in the digit and alphabet alternative order. For example, after they tapped the animal with 3, they continued to tap the animal with 4 instead of the animal with c or C.

For the average RP results, most of the senior subjects (except Senior 8, 9 and 10) exhibit higher risk predicator values than the control subjects. Senior 10's average RP result is significantly lower than other senior subjects, possibly due to the same reason for his maximum RP result.

As a summary, the maximum and average RP results for most senior subjects are greater than those for the control subjects. And the fluctuation of the RP results of the senior subjects (with variance value of 0.0454 for the maximum RP results, and 0.0233 for the average RP results) is greater than that of the control subjects (with variance value of 0.0021 for the maximum RP results, and 0.0016 for the average RP results). The evaluation suggests that the senior person's risks of having PD is higher than younger persons according to the proposed PD risk predictor. Therefore, the proposed risk predictor calculated through the measurement of the players' motion synchronization, task switching, and short-term memory abilities is effective in reflecting the risks of the players having PD.

## VI. Conclusions

In this paper, we designed and implemented a farming-themed game – the Pumpkin Garden, which is specifically tailored for PD diagnosis. The player's abilities of motion synchronization, task switching, and short-term memory are measured according to the captured behavior data during game sessions. A risk predictor for the player having PD is calculated based on fuzzy logic system by combining the three ability measurements. The Pumpkin Garden game platform aims to facilitate the player to detect the risk of having PD earlier to allow the patients to reap the benefit of early treatment. The pilot evaluation conducted on 10 senior subjects and 10 control subjects shows that the proposed risk predictor can reflect the player's risk in having PD as most senior subjects in the evaluation have higher risk predictor values than the control subjects. In the future, we will continue the evaluation on diagnosed PD patients to study the effectiveness of the risk predictor and further refine the game design and the fuzzy logic system. More game tasks with personalized difficulty levels are also under development to measure the ability related to PD symptoms, such as tremor at rest and micrographia.

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