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Research Article

Gamification Assisted Language Learning for Japanese Language Using Expert Point Cloud Recognizer

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Starting from people limitations to understand Japanese, education and social life of those people in Japan can be hindered. Therefore, a game is needed that allows one to understand Japanese using Gamification Assisted Language Learning (GALL) method, involving the introduction of Japanese language implementation using expert point cloud ($EP) recognizer. This method is used to stimulate the sensory and motor nervous system and motivate students (players) to study harder. This can be evidenced by increase in players ability from 20% to 100%.

1. Introduction

Gamification emerged in the late 1960 [1]. Because researchers see the effectiveness of gamification use, it has become a major highlight since the early 2010 [2]. Gamification is a method to implement by which a boring activity is converted into a fun activity, to attract interest and attention and motivate and improve performance in certain activities. It is widely used in the fields of education, economics, social studies, culture, politics, health, business ecology, and many more related fields [3–8].

In general, gamification changes person's perception of nongame activity into games [9]. In this case, the game can also serve to stimulate different sensory and motor systems for each person [10], so as to enhance person's understanding and memory [11]. Then it can activate the brain cells as one of its functions can improve the ability of person language [12, 13]. Human intuitive theories explain the development of brain cells in the game because one can explain the world of the game, analyze some examples, and generate counterfactual thinking and produce effective plans [14].

On the other hand, some countries use language as one of the main conditions for continuing education and obtaining citizenship and residence [15]. In a study conducted by [16] on language education policy in China, Indonesia, Japan, the Philippines, and Vietnam, one of the countries that rejected internal linguistic diversity was Japan. It is governed by the myth of Japanese identity monoethnicity that is largely derived from the assimilation of Japanese norms that reinforce a monolingual as well as monoculture ideal of the Japanese state itself. Then at the Meiji restoration in 1868 began an educational revolution, where foreign language was the focus of education in Japan.

Currently, according to statistics from Japan Student Service Organization (JASSO) through articles written in Student Guide to Japan 2016/2017, the value of production per person (Gross Domestic Product) is the 3rd highest in the world, and Japan ranks the 7th in the world and number 1 in Asia because 24 Japanese nationals received Nobel prizes in 2016. These things make more and more people interested in continuing education in Japan, which can be seen from the data of 2011-2016: the number of international students is increasing (see Figure 1); then data as of May 1, 2016, explains that the number of international students continuing their education in Japan is 239287 people and that dominates from Asia, that is, 222627 people (see Figure 1) [17]. If viewed

Table 1: Number of International Students Based on Nations.

No.	Country/Region	Number of Students					
		2016	2015	2014	2013	2012	2011
1	China	98483	94111	94399	81884	86324	87533
2	Vietnam	53807	38882	26439	6290	4373	4033
3	Nepal	19471	16250	10448	3188	2451	2016
4	Republic of Korea	15457	15279	15777	15304	16651	17640
5	Taiwan	8330	7314	6231	4719	4617	4571
6	Indonesia	4630	3600	3188	2410	2276	2162
7	Sri Lanka	3976	2312	1412	794	670	737
8	Myanmar	3851	2755	1935	1193	1151	1118
9	Thailand	3842	3526	3250	2383	2167	2396
10	Malaysia	2734	2594	2475	2293	2319	2417
11	U.S.A.	2648	2423	2152	2083	2133	1456
12	Mongolia	2184	1843	1548	1138	1114	1170
13	Bangladesh	1979	1459	948	875	1052	1322
14	Philippines	1332	1028	753	507	497	498
15	France	1299	1122	957	793	740	530
16	Other	15264	13881	12243	42291	33313	34098
	Total	**239287**	**208379**	**184155**	**168145**	**161848**	**163697**

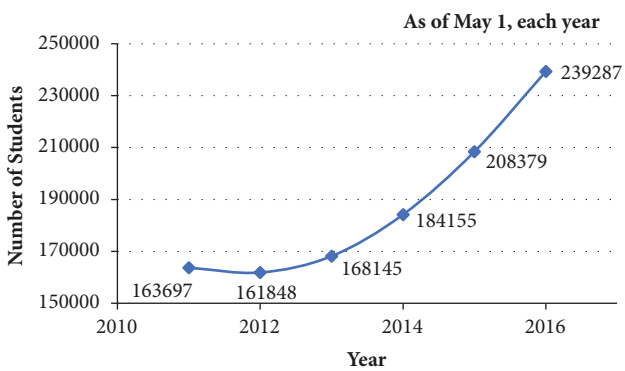

Figure 1: Movement of number of international students in Japan from 2011-2016.

statistically from a survey conducted by JASSO, by 2016 the number of Indonesian international students is ranked 6th after Taiwan (see Table 1) [18, 19].

Along with the increase of international students, Japan is also the 6th most popular country with many devotees to continue education. On the other hand, the increasing number of international students and the popularity of the country resulted in various problems and challenges that must be faced. According to [20], one of the factors which is a common problem often found against international students in Japan is the language skills. Of the 100 international students studying in Japan, 81% say that Japanese is hard to understand [20]. Based on these results, preferably before continuing education to Japan, prospective students must learn Japanese first, so as to facilitate life in Japan, and students who are interested in continuing education in Japan are easier to be accepted in schools or universities in destination (schools or universities that have the main terms of Japanese as a language of daily learning).

In the process of learning, Japanese has several elements that must be considered: the letters (*moji*), vocabulary (*goi*), and grammar (*bunpo*). One of the first elements to be learned in Japanese is to memorize letters such as hiragana, katakana, and kanji, because Japanese letters model is different from the alphabetic language in general [21]. In fact, it is quite difficult to memorize Japanese because of its form and complex writing. Therefore, many researchers are comparing several methods of learning Japanese language so that someone better understand the language.

One of the learning models is conventional or using textbooks. In general, conventional Japanese learning makes it difficult for a person to understand the material given [22]. Ref. [22] said that Japanese language learning methods that use multimedia elements can attract motivation and encourage someone to continue learning Japanese to understand the use of the grammar. Meanwhile, the problem when using multimedia elements is that the learner focuses more on the effects raised of the multimedia elements provided instead of focusing on Japanese content, such as graphics, animation, or other multimedia elements. Therefore, gamification is made using Japanese as the most important part of the game.

In its implementation, this educational game uses point cloud ($P) recognizer algorithm developed by [23], because the $P recognizer has fast computing and high accuracy. On the other hand, the weakness of the algorithm is that it can only detect the result of the pattern that has been made, so it cannot detect the process of making it. Then the algorithm is developed again into expert point cloud ($EP) recognizer for the player who can learn to write Japanese well and truly.

Table 2: Description of $-Family Recognizer Algorithm.

Symbol	Description
n	Number of sampled points
T	Number of training samples per gesture type
R	Number of iterations required
S	Number of strokes in a multistroke
$S!.2^s$	Number of different permutations of stroke ordering and direction

2. Related Work

2.1. Game Development Live Cycle (GDLC). The main stages in game development are design, prototype, production, and testing. Based on research conducted by [9, 24], GDLC has several processes, scilicet, initiation, preproduction, production, testing, beta, and release done iteratively to enable flexibility during the development process, resulting in good game quality. The quality can be measured from 5 criteria, namely, fun, functional, balanced, internally, and accessible.

2.2. Computer-Assisted Language Learning (CALL). CALL was born in the 1960s. Fundamentals of CALL framework are always doing mutual relationship between development, implementation, and evaluation so that CALL can always evolve [25]. Then in the evaluation several considerations are involved; that is,

(i) Can users understand what the application is doing?

(ii) What kind of content of the lesson that is created is compatible with current technological interactions? For example, in terms of reading, writing, or listening.

(iii) How well are the design elements with understanding of user?

According to [26] in general CALL is used audiolingually, where the students listen to a recording and then learner is asked to retell the recorded tape by saying or typing an answer that has been programmed by computer. Then in 2016 CALL was developed using game. The game has a Role-Playing Game Simulators gameplay (RPG Sims), where the inference gained by the game can be used to facilitate learning Japanese language, as it produces fairly good learning outcomes, and RPG Sims has a high potential to motivate learners too [27].

Once reviewed, game still adopts the conventional way of learning and then converts to digital. Things that become attraction or how to motivate learners to learn can be developed again by making the learning content as the main game content. Then according to [28], computer studies need to analyze linguistic input from learners to detect errors and provide corrective feedback and have contextual instructional guidance.

2.3. $-Family Recognizer. **Unistroke ($1) Recognizer** is a 2D gesture recognizer algorithm designed to read patterns quickly. As the name implies, $1 algorithm can only be used to read a single pattern (stroke) or it can be said to have 2 permutations [23, 29]. Characteristics of the $1 algorithm are rotation invariant and size invariant. Rotation invariant is a pattern formed by slope of angle created by user; if it is in accordance with the order of formation of the same pattern, it will produce same reading. Subsequently size invariant is a pattern formed with a certain size created by the user, where reading is done by adjusting the size of the data created, resulting in same reading. Here is the complexity algorithm of $1:

$$\$1 = O(n.T.R) \tag{1}$$

Multistroke ($N) Recognizer is an algorithm that reads more than one pattern (stroke) but uses a lot of memory resulting in a slow process, because of the permutation of each stroke [23]. Here is the complexity algorithm of $N:

$$\$N = O\left(n.S!.2^s.T\right) \tag{2}$$

Because this algorithm produces a slow process, the point cloud recognizer algorithm is developed.

Point Cloud ($P) Recognizer is to optimize the $N algorithm that reads a pattern based on a stroke made; then $P is based on the relationship between the points so it does not require permutation or the number of patterns does not affect the complexity level of the algorithm. This algorithm produces accuracy above 99% and the process is faster than $N [23].

Characteristics possessed by the $P algorithm are the size invariant and direction invariant. The size invariant of $P equals $1, while the direction invariant is a pattern formed in a different order that will produce the same reading, if pattern is formed according to existing datasets. Here is the complexity algorithm of $P:

$$\$P = O\left(n^{2.5}.T\right) \tag{3}$$

The explanation of the $-Family algorithm can be seen in Table 2.

2.4. Game Experience. Game experience is judged based on emotion, thought, reaction, and behavior from players because it is influenced by the functionality, content, service, player affinity, and value of the player, where there are some elements that become benchmarks, namely, user interface (UI), user experience (UX), gameplay experience (GX), and game balancing. That matter will be evaluated using game experience questionnaire.

The benchmark adopts research undertaken by. [30–38], specifically,

(i) User Interface (UI)

(1) Usability: UI can be said to be usable when all features work properly and have informative feedback.

(2) Consistent: UI can be said to be consistent when an event used is also used elsewhere with the same model, thereby reducing short-term memory.

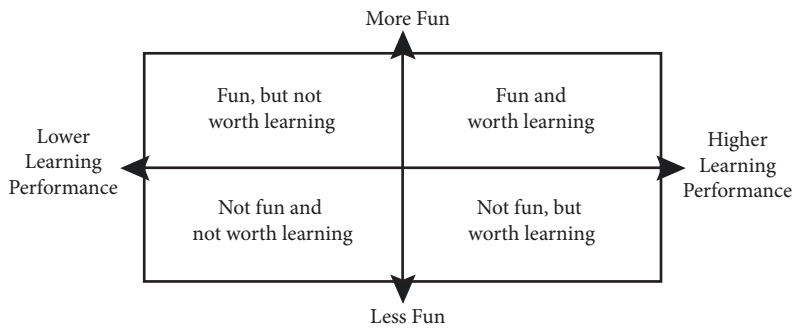

Figure 2: Gameplay Experience Evaluation for Learning Performance [30].

(ii) User Experience (UX)

(1) Useful: UX can be said to be useful if it can meet basic needs of player or game has benefits for player.
(2) Usable: UX can be said to be usable if it can be used efficiently and easily learned.
(3) Desirable: UX can be said to be desirable if it can contribute to user satisfaction by having a design with attractive aesthetic value.

(iii) Gameplay Experience (GX)

Based on research [35], there are 2 main factors that can be formed through cognitive and affective person, namely, beliefs and feelings, which are derived from a combination that is expected by someone to an object where it becomes something fun for player. Then besides fun, [30] adds a review for gamification where the content contained therein is worthy of studying (see Figure 2).

(iv) Game Balancing

(1) Game is fair: every action taken has an appropriate impact on the game. Any success and failure experienced by player can be understood rationally.
(2) Different skill levels: this is needed to determine the satisfaction of players, where there are challenges that have different levels of difficulty in every quest faced.

3. Propose Method

3.1. Gamification Assisted Language Learning (GALL). In general, the process of CALL is to change the learning of language conventionally to digital. When collaborated with gamifications, these high potentials can be maximized, since gamification has the following elements:

(i) Like games, the main requirement of gamification is to make a person feel happy and satisfied, and there are intrinsic elements of the contribution of knowledge in it.
(ii) Have goals to achieve.
(iii) Limiting game with the rules that apply to achieve the goal.
(iv) Provide information about progress of achievements that have been made to achieve the objectives.
(v) Have psychological elements to motivate players. Ref. [39] says there are 6 principal perspectives on motivation that closely relate to gamification, namely, trait perspective, behavioral learning perspective, cognitive perspective, perspective of self-determination, perspective of interest, and perspective of emotion.

Because Computer Assisted Language Learning (CALL) can be developed into Gamification Assisted Language Learning (GALL), GALL can maximize player interest to learn compared to CALL.

3.2. Datasets Japanese Language. Before recognizing Japanese writing required datasets are used as a measuring tool for the assessment standards of the games to be used as learning. These datasets are created by projecting the initial process of line formation to produce the final form of a point, where the datasets are stored in the xml format containing the position (x, y) of the writing. As seen in Figure 3, for example, this research has canvas of 5×5 and letter written is *Ku*. The letter is cut in accordance with the existing coordinates and then processed with the resample algorithm of $1 and $P where $1 each scratch generates 64 points with the same distance between points and $P each letter produces 32 points with the same distance between points. Visualization of datasets model made can be seen in Tables 3 and 4. The table describes the correct sequence of writing and the number of strokes contained in the Japanese language.

3.3. Expert Point Cloud ($EP). Generally, the $-Family Recognizer has a deficiency of reading a pattern based on the results that have been formed, not based on the manufacturing process. To learn Japanese, the process of writing the letter is very important, because the pattern of writing symbolizes the balance and neatness of writing someone; therefore a method is required that can read the process of making Japanese from beginning to end.

To accomplish this, the $P algorithm was developed again into an expert point cloud ($EP) recognizer, where the algorithm used is a combination and modification of expert

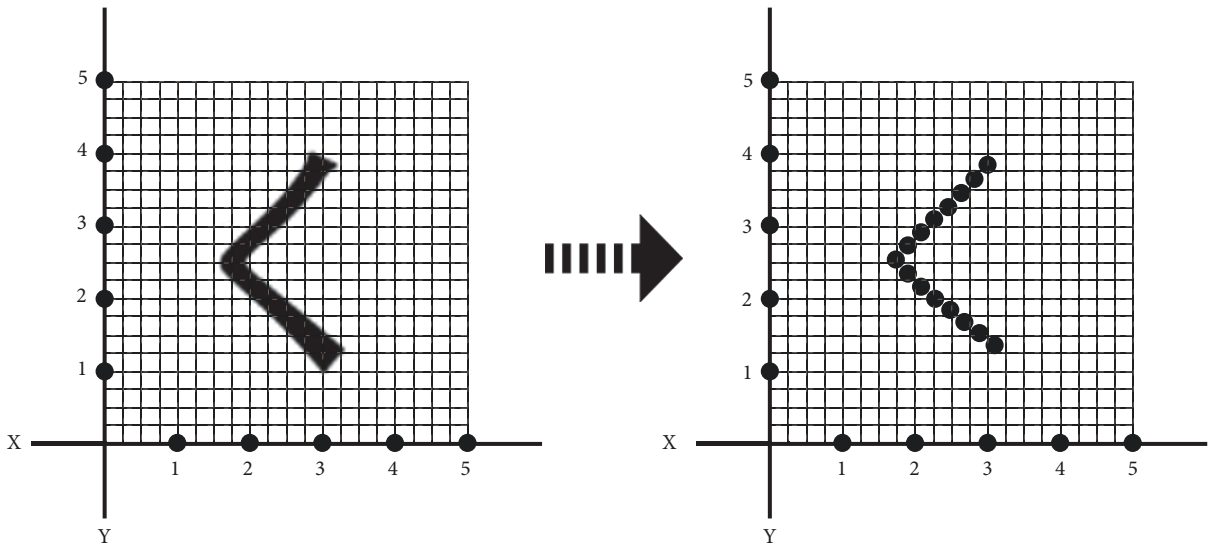

Figure 3: Example formation of dataset coordinates.

Table 3: Hiragana Letter.

	A	I	U	E	O
	あ	い	う	え	お
K	か	き	く	け	こ
S	さ	し	す	せ	そ
T	た	ち	つ	て	と
N	な	に	ぬ	ね	の
H	は	ひ	ふ	へ	ほ
M	ま	み	む	め	も
Y	や		ゆ		よ
R	ら	り	る	れ	ろ
W	わ				を
N	ん				

Table 4: Katakana Letter.

	A	I	U	E	O
	ア	イ	ウ	エ	オ
K	カ	キ	ク	ケ	コ
S	サ	シ	ス	セ	ソ
T	タ	チ	ツ	テ	ト
N	ナ	ニ	ヌ	ネ	ノ
H	ハ	ヒ	フ	ヘ	ホ
M	マ	ミ	ム	メ	モ
Y	ヤ		ユ		ヨ
R	ラ	リ	ル	レ	ロ
W	ワ				ヲ
N	ン				

system methods, unistroke ($1) recognizer from [29] and point cloud ($P) recognizer from [23].

Expert systems are used to make Japanese recognition systems sequentially, so that writing procedure from beginning to end can be properly written (see Tables 3 and 4). Subsequently, to detect every stroke (striation), $1 algorithm is used by doing resample, rotation, scale, and translation. After all strokes formed into letter, the $P algorithm is used to detect writing as a whole, by doing greedy cloud match, resample, scale, and translation. Examples of model illustrations of $1 and $P modified to form $EP can be seen in Figures 4–7 and explanation of the algorithm can be seen in Tables 5–11. Subsequently, overall algorithm flow can be seen in Figure 8.

3.3.1. Unistroke ($1) Recognizer Algorithm Model. The following are stages of $1 algorithm:

(1) Resample. Based on the illustration of Figure 4, step (a) describes the player being asked to create a Japanese letter; then systematically input from the player is processed to find out whether language is true or not. Letter processing starts from step (b); step (b) explains that the input made by player will change to N point in accordance with the coordinates of writing. After that at step (c) the calculation of the distance is done between the points until all points passed all and the results can be seen in step (d). Step (e) describes N-th distance divided into 64 points. Here is the formula used in the resample stages:

Table 5: Description of Formula Resample.

Symbol	Description
$\text{avg}\, D$	Average distance
d	Distance between starting points
D	d plus distance to the next point
p_i	Current point position
p_{i-1}	Position point to i minus 1
q_x	New coordinates of x-axis
q_y	New coordinates of y-axis

(a) Formula for calculating the average distance:

$$\text{avg}\, D = \sum_{i=1}^{n} \sqrt{(p_i - p_{i-1})^2 + (p_i - p_{i-1})^2} \tag{4}$$

(b) For each point, if $\text{avg}\, D \geq 1$ then the following equation is used:

$$d = p_i + p_{i-1} \tag{5}$$

Table 6: Description of Formula Rotation.

Symbol	Description
c_x	Coordinates of midpoint against the x-axis
c_y	Coordinates of midpoint against the y-axis
x_0	Starting point coordinates to x-axis
x_1	Coordinate 1st point of x-axis
x_n	Coordinates of n-point of x-axis
y_0	Starting point coordinates to y-axis
y_1	Coordinate 1st point of y-axis
y_n	Coordinates of n-th point of y-axis
k	Sum of all points
θ	Angle formed by θ
x'	Coordinate posts after rotation of x-axis
y'	Coordinate posts after rotation of y-axis

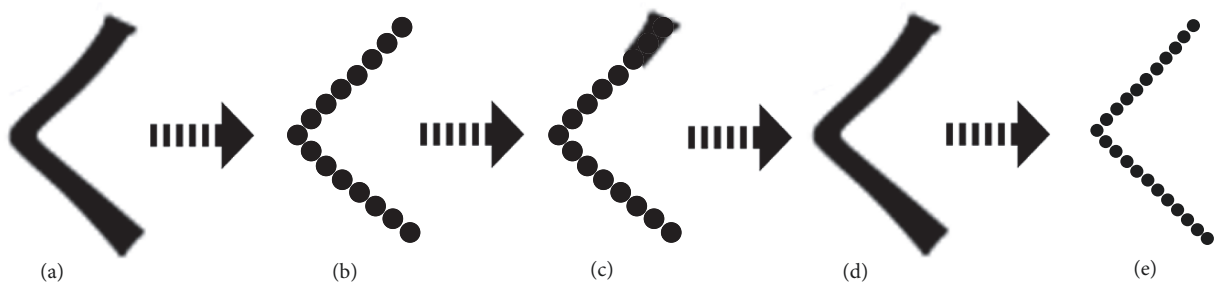

Figure 4: Resample Stages.

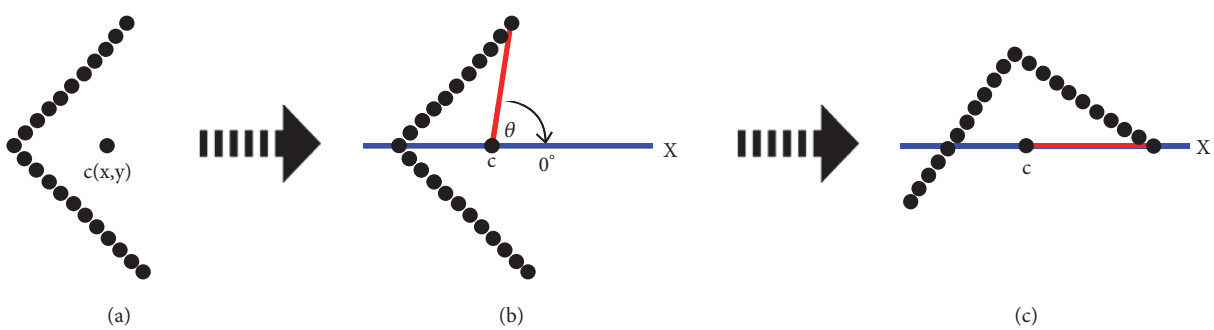

Figure 5: Rotation Stages.

Subsequently if $(D + d) \geq I$ then the following equation is used:

$$q_x = p_{i-1_x} + \left(\frac{\text{avg}\, D - D}{d}\right) \times \left(p_{i_x} - p_{i-1_x}\right) \quad (6)$$

$$q_y = p_{i-1_y} + \left(\frac{\text{avg}\, D - D}{d}\right) \times \left(p_{i_y} - p_{i-1\,y}\right) \quad (7)$$

If $(D + d) \leq I$ then the following equation is used:

$$D = D + d \quad (8)$$

(2) Rotation. In this step, Figure 5 describes step (a) where the midpoint of the writing is processed by resample. Then in step (b) withdrawal line is done from the midpoint to starting point of writing, after that the angle of θ is determined. In step (c) a rotation is performed on the x-axis until θ reaches angle of 0^0. This matter is done so that writing can still be detected even though writing canvas is upside down. Here is the formula used in the rotation stages:

(a) Formula to determine the midpoint:

$$c_x = \frac{x_0 + x_1 + \cdots + x_n}{k} \quad (9)$$

$$c_y = \frac{y_0 + y_1 + \cdots + y_n}{k} \quad (10)$$

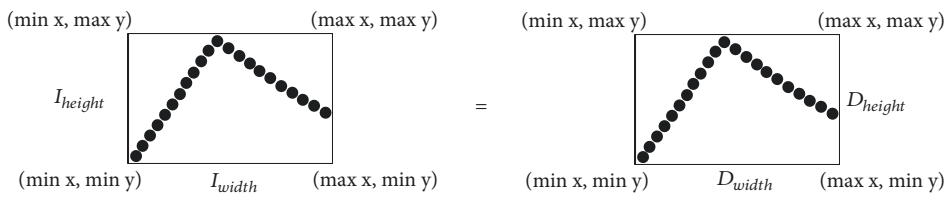

Figure 6: Scale Stages.

(b) Formula for determining angular tilt:

$$\theta = \operatorname{atan}\left(c_y - x_0, c_x - y_0\right) \quad \text{for } -\pi \le \theta \le \theta \tag{11}$$

(c) Formula for rotation:

$$x' = \left(x_n - c_x\right)\cos\theta - \left(y_n - c_y\right)\sin\theta + c_x \tag{12}$$

$$y' = \left(x_n - c_x\right)\sin\theta + \left(y_n - c_y\right)\cos\theta + c_x \tag{13}$$

(3) Scale. In this step, scaling is performed to determine the equalization of the large or small size of inputs made to existing datasets. Initially, there is formation of a bounding box by drawing line perpendicularly from the coordinates of min (x, y) and max (x, y) so as to form a box that has coordinates (min x, max y), (max x, max y), (minx, min y), and (max x, min y) (see Figure 6). Then, bounding box of player posts compared to datasets. If bounding box player is not the same as bounding box dataset, then calculation is done using the following formula:

$$q_x = p_x\left(\frac{I_{width}}{D_{width}}\right) \tag{14}$$

$$q_y = p_y\left(\frac{I_{height}}{D_{width}}\right) \tag{15}$$

(4) Translation. At this step is the determination of center point of writing player and datasets, so that center point of both writing models is in position $(0, 0)$. It means writing of player coincides with writing of datasets. Then look for all difference distance between point of player and dataset (see Figure 7). Here is formula used in the translation stages:

(a) Formula to determine center point of writing:

$$q_x = p_x - c_x \tag{16}$$

$$q_y = p_y - c_y \tag{17}$$

(b) Formula to determine average distance between points:

$$d_i = \frac{\sum_{k=1}^{N}\sqrt{\left(I[k]_x - D_i[k]_x\right)^2 + \left(I[k]_y - D_i[k]_y\right)^2}}{N} \tag{18}$$

Table 7: Description of Formula Scale.

Symbol	Description
q_x	New coordinates of x-axis
q_y	New coordinates of y-axis
p_x	current coordinates of x-axis
p_y	current coordinates of y-axis
I_{width}	length of bounding box of player input
I_{height}	Size of bounding box width of player input
D_{width}	length of bounding box of dataset
D_{width}	Size of bounding box width of dataset

Table 8: Description of Formula Translation.

Symbol	Description
q_x	Center point of x-axis
q_y	Center point of y-axis
p_x	Coordinate point input player against x-axis
p_y	Coordinate point input player against y-axis
c_x	Coordinate point datasets against x-axis
c_y	Coordinate point datasets against y-axis
d_i	Average distance
I	Input made by player
D_i	Dataset to i
k	Point to k
N	Total number of points

(5) Score. Calculation accuracy of ratio is calculated from 0 to 1 with the following formula:

$$s = 1 - \frac{d_i^*}{(1/2)\sqrt{{I_{height}}^2 + {I_{width}}^2}} \tag{19}$$

3.3.2. Point Cloud Recognizer ($P) Algorithm Model. In $P algorithm steps taken are not much different from $1; for the resample stage, the scale and translation remain the same as $1, which distinguishes it is the N-distance calculation which is divided into 32 points and calculated using greedy cloud match and $P algorithm does not have a rotation.

Greedy which is conducted by $P is looking for minimum distance that is compared between input player and datasets. In greedy usage there is distance calculation using cloud distance. Cloud distance uses variable weight to determine level of accuracy of a comparison. If a point in input player is paired to the nearest datasets point, then weight variable will

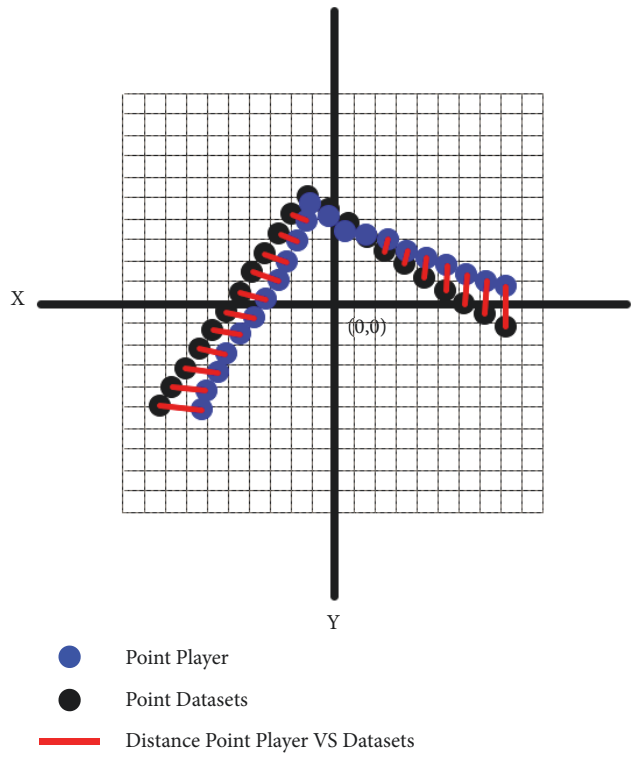

Figure 7: Translation Stages.

Table 9: Description of Formula Score.

Symbol	Description
s	Score
d_i^*	Distance to i
I_{height}	Size of bounding box width of player input
I_{width}	length of bounding box of player input

Table 10: Description of Formula Greedy Cloud Distance.

Symbol	Description
w	Weight
w_i	Weight to i
i	$1 \cdots n$
p_0	Coordinate starting point
n	Number of points already paired
I_i	Coordinate point input player to i
I_{i_x}	Coordinate point input player to i against x-axis
I_{i_y}	Coordinate point input player to i against y-axis
D_j	Coordinate point datasets to j
D_{j_x}	Coordinate point datasets to j against x-axis
D_{j_y}	Coordinate point datasets to j against y-axis

decrease. Here is the formula used for calculation of variable weight:

$$w = 1 - \frac{((i - p_0 + n) \bmod n)}{n} \tag{20}$$

Table 11: Description of Formula Score Final ($EP).

Symbol	Description
F	Score final
$s\$1$	Score $1
$s\$1_1$	Score $1 to 1
$s\$1_n$	Score $1 to n
$s\$P$	Score $P
n	Number of strokes plus overall stroke that make up the writing

In addition, within cloud distance there is an Euclidean distance that is used for distance calculation at point cloud. Here is formula used for calculating distance of point cloud:

$$\sum_{i=1}^{n} \left\| I_i - D_j \right\| = \sum_{i=1}^{n} \sqrt{\left(I_{i_x} - D_{j_x}\right)^2 + \left(I_{i_y} - D_{j_y}\right)^2} \tag{21}$$

$$\sum_i w_i \cdot \left\| I_i - D_j \right\| \tag{22}$$

3.3.3. Score Final Expert Point Cloud ($EP) Recognizer. For assessment of overall accuracy, the following formula is used.

If stroke = 1 then the following equation is used:

$$F = s\$1 \tag{23}$$

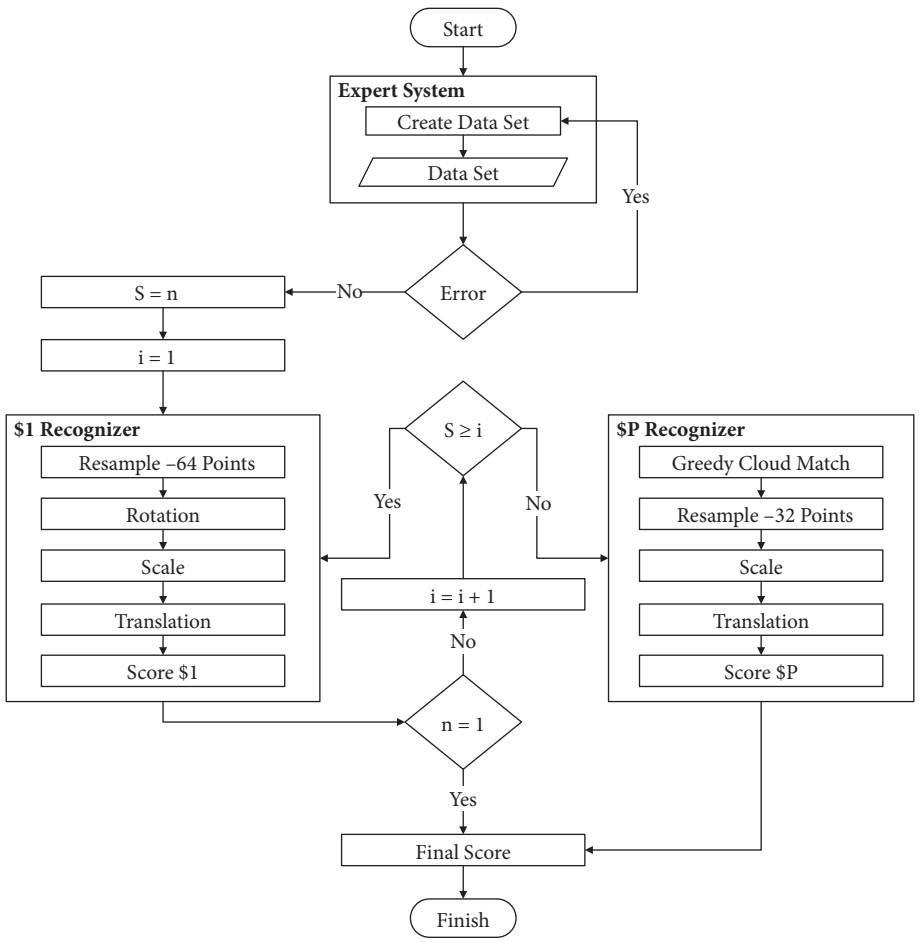

Figure 8: Expert Point Cloud Recognizer Algorithm.

If stroke > 1 then the following equation is used:

$$F = \frac{s\$1_1 + \cdots + s\$1_n + s\$P}{n} \tag{24}$$

$EP algorithm is used as the standardization of writing of language performed, since the input of the player will be compared with datasets that have been created, where it will affect accuracy of assessment.

4. Results and Discussion

In created RPG game, the battle system is lifted using turn based and has an active time battle (ATB), where, when the battle is done, the player and enemy alternately attack in accordance with the ATB that has been determined. Then to attack the player must write the Japanese language correctly, and damage is obtained by enemy in accordance with the accuracy of the writing.

In general, order of Japanese writing system can be seen in Figure 8. That figure explains the process of making datasets with algorithm process that runs up to get the accuracy of the writing player.

Then, after the game has been made, the game experience evaluation and pretest and posttest are given to 150 players to see players ability improvement, where there are 2 player categories: 46 players have learned Japanese and 104 player never learned Japanese. Test is done by asking player to make all the letters contained in Tables 3 and 4 along with the romaji.

On the other hand, to conduct game experience evaluation, a game experience questionnaire (GEQ) is made below:

(1) Are the features in this game is running well?

(a) Yes (100%)
(b) No (0%)

(2) Whether in-game display of buttons, portals, and all displays on each screen with the same model can make it easier to remember the function of interface used?

(a) Yes (100%)
(b) No (0%)

(3) Do tutorial and help feature can help you in playing?

(a) Yes (100%)
(b) No (0%)

(4) Is the system in the game easy to learn?

(a) Yes (100%)
(b) No (0%)

(5) How do you think about aesthetics are displayed in this game?

(a) Attractive (97%)
(b) Not attractive (3%)

(6) Does game you have played help you understand Japanese?

(a) Yes (100%)
(b) No (0%)

(7) How do you think difficulty level of the game after played?

(a) Appropriate (100%)
(b) Not appropriate (0%)

(8) Whether achievements and punishments provided matches the effort you are providing?

(a) Appropriate (100%)
(b) Not appropriate (0%)

(9) Is overall learning content provided worthy to be learn?

(a) Worth learning (100%)
(b) Not worth learning (0%)

(10) How do you think a game you have played?

(a) Fun (100%)
(b) Not fun (0%)

From GEQ it can be concluded that conditions found in the game experience have been met. For aesthetic problems, it is a matter of taste of player, because the developer cannot force someone to like aesthetics of the game made.

Before performing GEQ do pretest and posttest, where pretest is done before playing and posttest is done after playing, in which case player is asked to play for one week. Here are pretest results with 150 players: 10 players answered all questions correctly, 36 players answered with an average of 30%-50% wrong answers, and 104 players did not answer end answer but all wrong answers.

Subsequently, here are posttest results from the same person with pretest: there are 10 players who answered all the answers correctly (same player with pretest) and 134 people answered the correct average answer of 20%-100 %, while 6 players answered questions with all wrong answers.

5. Conclusions

Inference of this research is as follows:

(i) Japanese datasets are based on expert knowledge.

(ii) Currently $-Family has a new family of Expert Point Cloud Recognizer ($EP).

(iii) RPG game battle system using turn-based and ATB plus attack system using $EP can attract players to learn to write Japanese.

(iv) A game that is made already meets rules of game experience.

(v) Increased ability of a person is based on the capability of the person, because everyone has different capabilities. It can be said that the more diligent a person is to learn, the more science is absorbed.

(vi) A good game is a game that makes player feel happy to play it and unknowingly player can understand the science implicit in it.

(vii) Overall GALL in a matter of a week can increase players ability from 20% to 100%.

Data Availability

The data I sent is the same as in the paper.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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