# Prediction Scoring in Exergames for Rehabilitation Patients using K-Means Clustering

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***Abstract*— This paper highlighted a prediction scoring of difficulty modes in Medical Interactive Recovery Assistant (MIRA) exergames based on Kinect-based Rehabilitation Gaming System (RGS) for rehabilitation patients. The case study uses 19 rehabilitation patients with different lower limb limitations caused by stroke, traumatic brain injury (TBI) and spinal cord injury (SCI). MIRA exergames consists of three difficulty modes which are easy, medium and hard. Currently, physiotherapist will decide on difficulty mode based on the patients' improvement and most of the time they will used the default setting for every patient playing exergames. Thus, this study proposed a new prediction scoring using k-means clustering algorithm to help suggesting the difficulty mode of the game. K-means clustering also is used to find the benchmarks of the patients' history. The performance of the K-Mean algorithm is to make sure the patients are comfortable with their weakness side as suggested.**

***Keywords—rehabilitation, Kinect-based rehabilitation game system, machine learning***

## I. Introduction

Rehabilitation is a form of regulated exercises carried out daily for a certain period [1]. It was performed to improve a person physical and functional limitation caused by a various condition which includes disease (e.g. stroke) or injury (e.g. spinal cord injury, traumatic brain injury, musculoskeletal disorder). It also offers additional benefits, including improving psychological and cognitive functions, promoting social participation and increasing opportunities for returning to work. Rehabilitation or therapy system generally can be classified into three groups; conventional therapy (CT), robotic device therapy (RDT) and virtual reality therapy (VRT). The CT and RDT rely on physical intervention in performing the exercise. While VRT involves computer-assisted virtual intervention to perform the exercise. Through interactive video game-based experience, this does not only help the exercise session but also encourage and improve patient's motivation [2].

Kinect based Gaming System Rehabilitation (RGS) is one of the popular exergames platforms from VRT type. Studies reported its ability to significantly assist in the process of rehabilitation [3, 4, 5]. This system uses Kinect 360 Xbox sensors to capture patient movement while exercising. RGS based in Kinect shows the potential to create a pleasant setting for exercise. Studies have reported its capability to help significantly in the rehabilitation process [3, 4, 5]. Kinect-based RGS shows the potential to create an enjoyable exercise setting while at the same time collecting quantitative data related to rehabilitation [6, 7]. In addition, this system can provide adequate information on movement parameters for evaluation, entertain interactive exercise sessions and reduce the time required for performance assessment of patients [8]. Kinect-based RGS consists of tailored exercise video games in which the specific body part (upper limb or lower limb) was used to control the character in the game. In our study, we are using the Medical Interactive Rehabilitation Assistant (MIRA) system which a type of VRT system connected to Kinect 360 Xbox to collect the rehabilitation data of patients. It is a platform designed clinically to assist the doctor and physiotherapy. The patient or player can play game with three difficulty levels which are easy, medium and hard. Higher difficulty mode makes the game more challenging which requiring more involvement from the player.

However, it is difficult to define the mode of difficulty of the game for a patient. Most of the patients are playing the game with the default setting at MIRA which will reduce the performances of the patient whose cannot achieve the higher points [9]. The game session was pre-set by a therapist for each patient based on a fixed number of the session or when the patient has visibly performed well in the game [9]. Through this practice, a patient who does not actually improve in current difficulty has been shifted to a harder difficulty, possibly leading to deterioration in overall performance. Therefore, this study proposed a new scoring mechanism using k-means clustering to suggest the right time for a patient to shift the difficulty level of the game.

## II. Related Work

In the field of decision making, machine learning (ML) is the state-of-the-art technology which utilizes huge data set to discover patterns and reveal meaningful insight. It can be defined as "Artificial Generation of Knowledge from Experience" and is one of the fast growing fields in computer science and health informatics [10]. The application of ML methods in biomedicine and health has led to more evidence-based decision-making and help to go toward personalized medicine [11]. ML deals with the problem by extracting features from data to solve predictive tasks. The challenge is to discover relevant structural patterns and/or temporal

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patterns ("knowledge") in such data, which are often hidden and not accessible to a human expert [10]. There is rapidly growing interest in recent studies employing ML technique to facilitate the decision-making process in biomedicine and health domain.

Bayesian network is one of these methods increasingly developed in clinical epidemiology for the construction of disease model [12]. Training a Bayesian network involves the tasks of structure learning, identifying the graphical structure of the network, and parameter learning that estimates the conditional probability distributions. The prognostic reasoning is one of the characteristics in Bayesian networks for biomedicine and health-care amounts to making a prediction. The prediction for a specific patient is generally influenced by a sequence of treatments, which depends on the patient's information before the treatment is started. The result is also influenced by the progress of the underlying disease.

Another increasingly popular ML method in the medical domain is K-Nearest Neighbor (KNN). Zhu et al., compared the performance of KNN to the Clinical Assessment Protocol (CAP) in measuring the predictions of patients who had functional improvement or remained at home over a follow-up period of approximately one year [13]. The study highlighted the lack of comprehensive standardized assessments which often leads to inaccurate detection of healthcare needs, hence justifying the use of KNN because it is analogous to clinical reasoning. For example, a physician will likely recommend a particular treatment program to a new patient if the new patient's clinical profile matches those patients who have been successfully treated by the physician in the past with the same program. By using KNN, no means required to restrict themselves in a particular subset of covariates or a particular type of similarity measure. Moreover, when applying constraints, KNN algorithm would be made use of variables that had been identified clinically as relevant to rehabilitation potential. The study concluded that KNN was better than CAP in making a prediction. They extended this study by focusing on the rehabilitation using support vector machine (SVM) to classify whether there is a need for improvement in activity of daily living (ADL) functioning, or the patient can be discharged home. Both KNN and SVM achieved similarly improved performance compared to CAP. This study strengthens the conclusion that ML algorithms can achieve superior predictive capability than the current protocol. Despite ML results are less readily interpretable which can be used to guide the develop First, confirm that you have the correct template for your paper size.

## III. METHODOLOGY

The study involves the prediction on the scoring for the patients playing the exergames at MIRA system as the following work process shown in Fig. 1. Four important phases in the study which are data collection, clustering process using K-means, score computation and result. In the first phase, the data regarding the patients playing with MIRA will be collected at the PERKESO Tun Razak Rehabilitation Centre, Melaka. The second phase is the process of clustering using K-means algorithm. Typically, the K-means algorithm is simple and very fast clustering algorithm. The third phase is proposing the scoring value for each of the patient. Finally is the suggestion of difficulty in which the result of the scoring values will help the physiotherapy to define the appropriate level of patient difficulty.

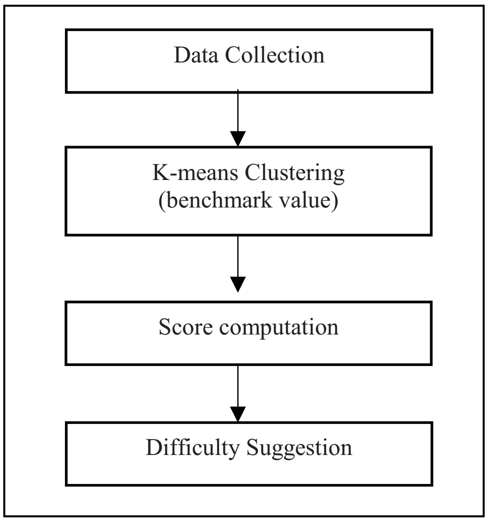


**Fig. 1.**The process flow of study

### A. Data Collection

In the first phase of the study, the data was collected on the patients who suffered with different lower limb limitations caused by stroke, traumatic brain injury (TBI) and spinal cord injury (SCI). Data on name, sex, age, diagnosis and weak side was extracted from the MIRA database. This study involved 19 patients at the age between 18 to 50. It is found that 16% of the patients are having left side weakness, 58% of the patients are having right side weakness while 26% of them suffering both side weaknesses. Weak side of patient's injury was defined according to their affected side of limb injury and recorded by physiotherapist before begins the rehabilitation process. Every patient was instructed to play games related with movement with a minimum of five sessions for both weak side (injured) and non-weak side (healthy) of body parts at the easy, medium and hard level of difficulties. For each mode of difficulty, the player must complete at least 3 sessions with a maximum of 9 sessions.

In MIRA games, 'Izzy the Bee' and 'Atlantis' have been selected to be played by patients for the data collection. The range of motion (ROM) value will be collected throughout the games. In 'Izzy the Bee' game, the patient will play a role as a bee, which will collect the pollens from flowers and deposit them in their hive while trying to avoid incoming obstacles as shown in Fig. 2. While in the 'Atlantis' game, the patient will play a role as an archaeologist maneuvering a submarine with the objective to inspect all artifacts while avoiding undersea mines along its path.

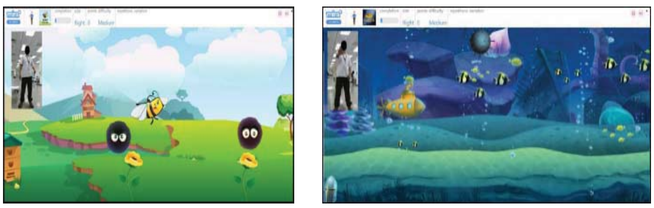

**Fig. 2.**Screenshots of example MIRA exergames: Izzy the Bee (left), Atlantis (right).

The patient's limb is set as the source of movement to control the in-game character while playing a game. At the end of each session, recorded game statistics are stored as raw data in the database and can be extracted for analysis purpose in portable document format (PDF) file type. It has been found that 16% of patients playing the games with left side, 58% of patients playing the games with right side while 26% playing with both sides.

### *B. K-Means Clustering*

Fig. 3 shows the K-Means clustering framework in finding the suggestion output.

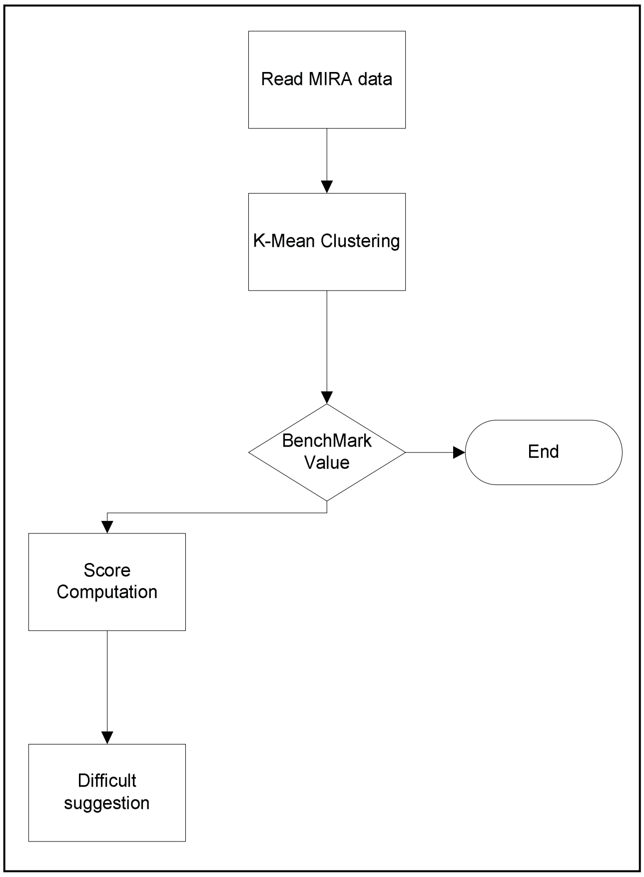


**Fig. 3.** The K-means clustering framework

K-Means clustering algorithm was developed by MacQueen in 1976. K-means algorithm is a well-known clustering partitioning method and a classic clustering algorithm that partitioning a data collection into a k number group of data. It has two main phases in which initialization is the first phase in which the k centroids are defined. It consists of two main phases where is the first phase is to define the k number of centroids and the second phase is to cluster each point that belongs to the given data set and associate it with the nearest centroid [14]. Euclidean distance is considered as to determine the distance of the data points and the centroids. Then, we need to recalculate new k cluster centers after all the objects are distributed. Once we find the k new centroids, a new binding between the same data points and the nearest new centroid will be created, which will generate a loop [15]. The algorithm then tries to improve these centroids choices iteratively until no further improvement can be made [16]. The pseudo code of the k-means clustering algorithm is listed as in Fig. 4 [15].

*Input:*
*$D=\{d_1, d_2, \ldots, d_n\}$ //set of n data items*
*k //number of desired clusters*

*Output:*
*A set of k clusters*

*Steps:*
1. *Arbitrarily choose k data items from D as initial centroids;*
2. *Repeat*

*Assign each item d1 to the cluster which has the nearest centroids;*
*Calculate new mean for each cluster;*

*Until convergence criteria is met.*

**Fig. 4.** The K-Means clustering algorithm

According to the MIRA system, 26 attributes of data are generated depending on the game and movement. However, the analysis of the data found that only five attributes generated from 'Izzy the Bee' and 'Atlantis' games. These attributes are average acceleration ($A_{cc}$), average percentage ($A_p$), distance ($D$), points ($P$) and repetitions ($R_e$). Thus, we considered only these five attributes in the clustering since they are related to the range of motion (ROM). The description of five attributes are listed in Table I. The number of the cluster was set to 3, in correspond to three difficulty level.

TABLE I. DESCRIPTION OF VARIABLES

| **Variables** | **Descriptions** |
|---|---|
| Average acceleration | The change of speed when performing a specific movement. |
| Average percentage | The percentage of movement (e.g. for knee flexion, the maximum would be 90°). Also known as Range of Motion (ROM). |
| Distance | The total distance of the limb during performing specific movement. |
| Points | Score of the game. |
| Repetitions | Number of count when performing a correct movement. |

The result from k-mean clustering will be considered as the benchmark for average acceleration, average percentage, distance, point and repetitions. The general idea is to compare the current value with the benchmark and compute the score. The score will determine whether the player is eligible to move to higher difficulty level, stay with current difficulty level, or go back to lower difficulty level.

### *C. Score Computation*

Score computation is a process to calculate the scoring with the set of rules; 0 or 1 for each patient. It begins with a patient playing the game with all recorded variable values in easy level of difficulty. The patient will play the game using their weak side and the algorithm will proceed with the calculation of the weak side scoring. The patients input from five attributes values will be compared with the k-means clustering benchmark values by returning a binary output (0 or 1). The rules is if the new value is lower than the benchmark value, it will return to 0 as an output. Otherwise it will return to 1. Then, the binary output will be used to compute the score for weight as show in Table II. The weight based in Equation (1) required to determine whether the patient could move to another level of game difficulty or not. Note that more weight is given to $A_p$ and $R_e$. The reason behind this is that the physiotherapist believes that their routine evaluation of rehabilitation depends largely on these two variables [8].

Considering  as the total score, the scoring system can be defined as following calculation:

$$T_s = (0.1 \times A_{cc}) + (0.35 \times A_p) + (0.1 \times D) + (0.1 \times P) + (0.1 \times R_e) \tag{1}$$

Where $A_{cc}$ is the average acceleration in , $A_p$ is the average percentage in %, $D$ is distance in m, P is point (score of the game), and $R_e$ is repetitions value.

TABLE II. SCORING TABLE

| Variables | $A_{cc}$ | $A_p$ | $D$ | $P$ | $R_e$ | $T_s$ |
|---|---|---|---|---|---|---|
| | 0 | 0 | 0 | 0 | 1 | 0.35 |
| | 0 | 0 | 0 | 1 | 0 | 0.1 |
| | 0 | 0 | 0 | 1 | 1 | 0.45 |
| | 0 | 0 | 1 | 0 | 0 | 0.1 |
| | 0 | 0 | 1 | 0 | 1 | 0.45 |
| | 0 | 0 | 1 | 1 | 0 | 0.2 |
| | 0 | 0 | 1 | 1 | 1 | 0.55 |
| | 0 | 1 | 0 | 0 | 0 | 0.35 |
| | 0 | 1 | 0 | 0 | 1 | 0.7 |
| | 0 | 1 | 0 | 1 | 0 | 0.45 |
| | 0 | 1 | 0 | 1 | 1 | 0.8 |
| | 0 | 1 | 1 | 0 | 0 | 0.45 |
| | 0 | 1 | 1 | 0 | 1 | 0.8 |
| | 0 | 1 | 1 | 1 | 0 | 0.55 |
| | 0 | 1 | 1 | 1 | 1 | 0.9 |
| | 1 | 0 | 0 | 0 | 0 | 0.1 |
| | 1 | 1 | 0 | 0 | 0 | 0.45 |
| | 1 | 1 | 0 | 0 | 1 | 0.8 |
| | 1 | 1 | 0 | 1 | 0 | 0.55 |
| | 1 | 1 | 0 | 1 | 1 | 0.9 |
| | 1 | 1 | 1 | 0 | 0 | 0.55 |
| | 1 | 1 | 1 | 0 | 1 | 0.9 |
| | 1 | 1 | 1 | 1 | 0 | 0.65 |
| | 1 | 1 | 1 | 1 | 1 | 1 |
| **Weight** | **0.1** | **0.35** | **0.1** | **0.1** | **0.1** | |

### D. *Difficulty Suggestion*

The last phase of the study is the difficulty suggestion. In the difficult mode is advising the patients for his/her current status. It consists of seven suggestions for the patients as show in Table III.

TABLE III. DESCRIPTION OF OUTPUT SUGGESTION

| **Output Suggestion** |
|---|
| 1. Stay in easy mode. |
| 2. Proceed to medium. |
| 3. Stay in medium. |
| 4. Return to easy mode. |
| 5. Proceed to hard mode. |
| 6. Return to medium mode. |
| 7. Session ended in hard mode. |

For example, if a patient is currently playing in medium difficulty, for a score of 0.1, the algorithm will suggest the player to return to an easy difficulty. If the patient scores 0.45, the patient must play again in medium difficulty. The patient can only advance to the hard difficulty if they can score at least 0.55 or above. Fig. 5 shows the steps involve in determining the output suggestion to patient.

```
Perform Difficult Suggestion Algorithm
If Session < 3
          Continue Games Level
EndIf
If Game = Easy and 9 <= Session >= 3
          If Score < 0.55
              Continue Easy
          Else
             Continue Medium
Endif
If Game = Medium and 9 <= Session >= 3
          If 0.55 < Score < 0.35
              Continue Medium
          Else
             Continue Hard
EndIf
If Game = Hard and 3 <= Session
              Continue Hard
Endif
End
     Output Scoring Table
```

**Fig. 5.** Difficult suggestion algorithm

## IV. RESULTS AND DISCUSSIONS

### A. *K-Means Clustering*

K-Means Clustering clustered the variables for the games based on the three difficulty levels; easy, medium and hard. The values for all difficulty are lower than for the non-weak side for average acceleration, distance and points. However, the values for the weak side were higher for average percentage and repetitions than those for the non-weak side. Both average percentage and repetitions involve the direct physical movement of the limb. Support from the non–weak side plays an important role in helping the weak side achieve high ROM and perform proper movement while maintaining stability when performing a movement using the weak side. On the other hand, poor support from weak side during movement using non-weak side contributed to poor physical capability in terms of ROM and number of repetitions. Table IV shows the results of the clustering using k-means for both weak and non-weak sides.

TABLE IV. RESULTS FROM K-MEANS CLUSTERING FOR WEAK AND NON-WEAK SIDE

| Weakside | Variables | Easy | Medium | Hard |
|---|---|---|---|---|
| Yes | Average Acceleration | 000.6616 | 000.7027 | 000.73382 |
| | Average Percentage | 033.0823 | 039.0630 | 038.2898 |
| | Distance | 011.3345 | 011.9270 | 010.9091 |
| | Points | 107.1576 | 170.7372 | 138.5705 |
| | Repetitions | 008.3473 | 011.4872 | 008.8971 |
| No | Average Acceleration | 000.6945 | 000.7559 | 000.7840 |
| | Average Percentage | 028.0264 | 031.3088 | 037.0447 |
| | Distance | 014.0419 | 016.2632 | 012.0165 |
| | Points | 113.5419 | 175.3889 | 139.0995 |
| | Repetitions | 008.2867 | 009.1667 | 008.6138 |

### B. *Difficulty Suggestion*

The computed score will be referred to the scoring table for difficulty shift suggestion. The difficulty suggestion based on the seven output suggestions (referred to Table III) and the results show in Table IV. For instance, the patient who was currently in medium level of difficulty was suggested to return to the easy difficulty. If the patient scores 0.45, they have to play again in the medium difficulty. The player can only advance to hard difficulty only if they can score at least 0.55 or above. The maximum session allowed for each level of difficulty is 9, which mean that if the player is still stuck at easy difficulty by the 9th session, the algorithm will be ended indicating that the patient capability is limited at easy difficulty. The difficulty suggestion based on the seven output suggestions and the results show in Table V.

TABLE V. THE RESULTS FOR HYPOTHETICAL SCENARIO TESTING

| Scene | Weakside | Difficulty Mode | $A_{cc}$ | $A_D$ | $D$ | $P$ | $R_e$ | Algorithm output |
|---|---|---|---|---|---|---|---|---|
| 1 | Yes | Easy | 0.5684 | 23.89 | 08.432 | 147 | 17 | Stay in easy mode. |
| 2 | Yes | Easy | 0.7684 | 22.59 | 09.213 | 111 | 12 | Proceed to medium |
| 3 | No | Medium | 0.7995 | 58.59 | 10.44 | 165 | 4 | Stay in medium |
| 4 | No | Medium | 0.9129 | 25.67 | 14.234 | 148 | 3 | Return to easy mode. |
| 5 | Yes | Medium | 0.9376 | 48.51 | 14.113 | 169 | 12 | Proceed to hard mode. |
| 6 | No | Hard | 0.6784 | 37.58 | 10.43 | 126 | 7 | Return to medium mode. |
| 7 | Yes | Hard | 0.6528 | 45.45 | 07.730 | 154 | 11 | Session ended in hard mode. |

## V. CONCLUSIONS

A methodology which incorporates the k-means algorithm has been proposed to a developed scoring mechanism for prediction difficulty in exergames, specifically for knee flexion movement. The result from the k-means algorithm has been used as the benchmark value for each correspondent variables. Then, the total score is computed based on the comparison between new and benchmark value. Finally, suggestion on difficulty mode will be returned by the algorithm based on the total score. Seven scenarios (output suggestions) have been used to test the algorithm successfully. As for the future research, we will perform other methods for comparison with K-Means clustering.


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