The Accuracy of the k-Nearest Neighbors and k-Means Algorithms in Gesture Identification

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***Abstract*—In today's digital era, human-computer interaction interfaces evolve and increase together with the needs of the users. However, the existing technologies have their limitations, which can hinder the efficiency of modern input devices like the Kinect sensor or other similar sensors. In this paper we improved our previous algorithm by extending it with two algorithms that aim to help telerehabilitation for individuals with movement disabilities. These two algorithms are based on the k-Nearest Neighbors, the k-Means algorithms. The algorithms are designed to accommodate the needs of the patients by adapting to their gestures based on their previous three. Using these gestures, the algorithms create multiple gesture acceptance domains around each coordinate of the gesture. Consequently, they decide whether the next user-input gesture can be considered the same movement. The accuracy of these algorithms was evaluated in three acceptance domains by comparing gesture descriptors with either the Euclidean or the Manhattan distance calculation methods. The results show that k-Nearest Neighbors algorithm yields better results in larger acceptance domains, while the k-Means algorithm can provide a better gesture acceptance rate in the smaller ones. The results show that both algorithms can be used in the telerehabilitation process, although the k-Means algorithm is more accurate than the k-Nearest Neighbors algorithm.**

***Index Terms*—cognitive aspects of virtual reality, cognitive infocommunications, human-computer interaction, Kinect, motivation, real-time gesture recognition, rehabilitation**

I. Introduction

In a virtual reality (VR) system, the human plays a crucial role as a key element [1]. The interaction, usability, and comfort between the human and the machine are essential factors to consider. These aspects are addressed in the field of Human-Computer Interaction (HCI), which is a multidisciplinary research area focused on studying and addressing such questions [2]. The fields of Cognitive Aspects of Virtual Reality (cVR) and Cognitive InfoCommunications (CogInfoCom) both address HCI, and one of their main focuses is human cognition. They both focus on showcasing the latest advancements in information and communication technologies (ICT) that facilitate the interaction between humans and machines [3–8]. Their objective is to enhance, restore, or even develop new cognitive abilities in users by utilizing ICT engineering tools and model-based approaches. Not to mention, CogInfoCom and cVR are also closely related [9].

Fortunately, both fields also focus on human-machine blended interaction, particularly in the context of evaluating gestures and movements [10–18]. This opens up new ways for analyzing several human factors using novel cognitive IT approaches. These fields of research also delve into various areas including eye-tracking [19], brain-computer interfaces (BCIs) [20, 21], VR systems [22, 23], virtual laboratories [24, 25], gamification [26], sentiment analysis [27], and other educational environments [28, 29]. The findings from these studies hold significant value in fields such as education, development, and rehabilitation.

Motion rehabilitation stands out as a crucial and significant application area, particularly in the field of healthcare information technology. This area of research is quite important since many people suffer from physical disabilities. One of their causes is stroke, which is a frequent disease in modern society, and has a great impact on the human population. Research studies have shown that 48% of individuals who have survived brain-to-asthma disease suffer from half-side paralysis [30, 31]. Additionally, cognitive decline can be detected in over 60% of cases. Aphasia, a language impairment, affects approximately 12-18% of stroke patients. Furthermore, 24-53% of individuals with stroke become partially or completely dependent on others for their daily activities. Given these challenges, it is imperative to incorporate modern technology to address the needs of these patients [32, 33].

Therefore, rehabilitation for patients can be made more interesting by incorporating engaging and modern environments for exercises or gesture tracking. Many computer-aided solutions are already available that assist with traditional therapy. However, these solutions often require direct interaction with a computer, such as pressing keys or using a mouse, which can pose challenges for some patients. Bruno et al. explored the potential of using commercial video games in rehabilitation. They examined 4,728 relevant articles

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yield results that are comparable to conventional rehabilitation methods [34, 35]. Still, it is argued by Ghazarian and Noorhosseini that exercise games may not meet the needs of patients if the application relies solely on pre-calibrated settings or predetermined correction values [36].

Extracting motion descriptors from the sensors that are used as the input interface is a crucial aspect of controlling applications with motion. Our previous work aimed to retrieve, process, analyze, and improve the motion descriptors that were obtained from the Microsoft Kinect sensor [17, 18]. In the previously referenced studies, we presented multiple algorithms that are easy to use in a home environment as a part of telerehabilitation. Certain gestures can be recommended by the therapist to the patients and they can exercise in their homes. This way, they can also receive help from their families if needed. Based on the results of the exercises, it can be decided whether the patient made any progress during the physical rehabilitation process. Low-cost sensors, such as the Microsoft Kinect, are also commonly used in the telerehabilitation process [37].

As can be observed, our goal is to support telerehabilitation. Thus, this study aims to provide another set of algorithms and methods to the existing ones, thus increasing the number of algorithms to choose from for gesture recognition. For this goal, we have expanded our previous work with the k-Nearest Neighbors (k-NN) and k-Means algorithms [38, 39]. These algorithms are evaluated in this study to see how well they support gesture identification.

Therefore, this study is structured as follows. Section II provides an insight into problems regarding gesture recognition with the Microsoft Kinect as well as into our previous work. Section III presents the materials and methods used in this study. The results and discussion are detailed in section IV, while the limitations and future plans regarding this research can be observed in section V. Conclusions are drawn in section VI.

II. Problem Identification and Previous Solution

Nowadays, hospitals are overcrowded, but this issue can be alleviated by telerehabilitation. Among others, the Microsoft Kinect sensor offers a cost-effective alternative to more expensive sensors. This makes this sensor accessible for people with movement disabilities to do physical rehabilitation exercises at their homes [37]. However, to achieve this, an easy-to-use application with algorithms that are specifically designed for the Kinect is necessary.

With the Software Development Kit (SDK) developed by Microsoft, the Kinect sensor can provide real-time x, y, z coordinates for various body joints of the user. It uses a built-in coordinate system for this process. However, the following two problems arise when the Kinect sensor creates these coordinates.

The first problem concerns the position of users, and thereby of gestures. The Kinect sensor assigns different coordinate values to the same gesture when the user stands in a different position in front of it. This also happens when the Kinect is placed in a different position. Therefore, algorithms that can sense various positions need to be developed.

The second problem concerns the speed of movement of users. The mentioned speed is measured in frames per second. Naturally, slower gestures have more frames, while faster movements have fewer frames. Similarly to the first problem, the various numbers of frames make it challenging to recognize the same gestures as the corresponding movement descriptors can be on another frame. This means that depending on the speed of the gesture, the same movement can have different number of frames. Therefore, some normalization method is required to address the varying number of frames.

To solve these problems, we originally proposed the Asynchronous Prediction-Based Movement Recognition (APBMR) algorithm in a previous study [18]. The algorithm does not require extensive computational power, supports low-cost sensors like the Microsoft Kinect, can be used during telemedicine, and provides more precise adaptation to the needs of the patients. The APBMR algorithm utilizes prediction techniques to anticipate the user's next gesture based on the preceding three movements. It then determines whether the forthcoming gesture corresponds to the same movement, with the aim of keeping the motivation of patients. For this, it creates three acceptance domains at ±0.05 m, ±0.10 m, and ±0.15 m of each coordinate of a gesture. The goal of the user is to stay inside these acceptance domains in each frame. Since all frames are evaluated, a gesture can be considered accepted if its coordinates are at least 50% inside in these acceptance domains. If one is accepted inside the strictest acceptance domain, that would mean that the APMBR algorithm can accurately predict and classify the gesture of the user based on the previous three gestures. Additionally, it monitors the patient's position and the gesture's speed.

III. Materials and Methods

Both the implemented k-NN and k-Means algorithms use the same principle as the previously mentioned APBMR algorithm. In fact, its source code and graphical user interface (GUI) were modified, and these new algorithms were integrated into them. Both of the GUIs were created in WPF using C#. The modified GUI can be observed in Fig. 1.

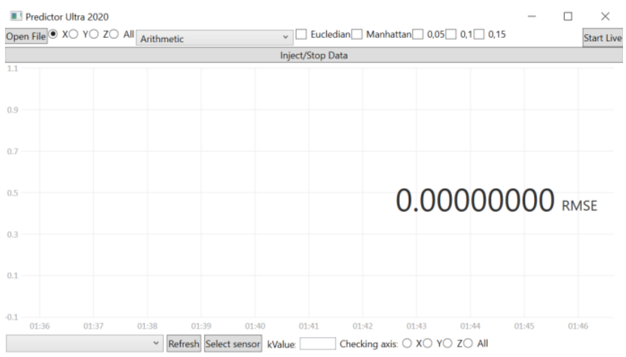

Fig. 1. The GUI of the application that is used in this study.

More checkboxes and radio buttons can be found in the newer version of the GUI. Compared to the older one, the acceptance domains of the gestures can be selected as can be seen in upper right corner in Fig 1. These are ±0.05 cm, ±0.10 cm, and ±0.15 cm. Originally, the APBMR algorithm evaluated the gestures in all three, but here, it is possible to evaluate them separately. Also, in the original version, Euclidean distances were compared between the older gestures and the forthcoming ones. Now it is possible to compare Manhattan distances as well. There is also a new option: The gestures can now be displayed on certain axes. Any axis can be chosen by itself, and there is an option to display the gesture descriptors on all axes simultaneously.

As was mentioned, the application was extended with the k-NN and k-Means algorithms. These algorithms can only work when all three axes are investigated. This means that they cannot handle coordinates separately for each axis. These implemented algorithms require a new parameter called k. This can be chosen by the user, but it must be an integer. Based on empirical testing, the value of k should be between 1 and 10. These algorithms are elaborated on in the following subsections.

Similarly to the APBMR algorithm, the gesture recognition process with both the k-NN and k-Means algorithms used the previous three movements of the user to create acceptance domains for the next gesture. This was done so that the algorithm could easily adapt to any change in the user's next movement. If we increased or decreased the number of used gestures, the algorithms became less accurate. Changing the value of k did not affect the adaptability of the algorithms. However, by increasing the value of k the computational time was also increased.

Both algorithms were evaluated using three different gestures (triangle, infinity symbol, waving) that were repeated ten times. The movement descriptors of these gestures were imported from a file that contained recorded coordinates of these gestures. We used a recording that was created in 2019 with 48 students. 33 were male and 15 were female. They were 22.3 years old on average with a standard deviation of 2.8 years. Their average height was 178.1 cm with a standard deviation of 10.2 cm. There were no selection criteria to join the research, thus every person who was willing could help with the measurements. Each movement was done 10 times by one participant and they were asked to slowly change position during the process while repeating the gestures. However, they always had to face the Microsoft Kinect sensor which captured each frame of the gestures and gave them x, y, z coordinates in its own coordinate system.

The accuracy of these two algorithms was evaluated in all three acceptance domains (±0.05 cm, ±0.10 cm, and ±0.15 cm) with two distance calculation methods (Euclidean and Manhattan). A gesture was considered acceptable if at least 50% of it was in the chosen acceptance domain.

A. *The k-NN algorithm*

Essentially, this algorithm assumes that other coordinates are located in close proximity to the coordinate that is investigated at a moment. Once the value of k is determined, it looks for the k nearest neighbors to the coordinate that is investigated. The average of these distances provides an approximate estimation. The steps of the algorithm are the following in the application.

1. The data to be examined have to be loaded.
2. A value for integer k has to be chosen.
3. Iterates through all elements in the loaded dataset.
4. Calculates the distances or differences between each coordinate and the one that is investigated at the moment.
5. Sorts the calculated distances in ascending order.
6. Selects the k smallest distances after sorting.
7. Calculates the averages of these k distances.

As can be seen, no significant modifications were made to this algorithm, and its basic principle remained largely intact. However, there are some differences in the implementation.

Since the estimation of a forthcoming gesture is based on the previous three, the entire dataset did not have to be considered. Instead, the coordinates of the three gestures were taken into account. Additionally, the coordinates of each axis were split into separate parts. When considering all three axes together, the results were not satisfactory. Therefore, the calculation of distances between the investigated gesture descriptors is performed on the same respective axis.

The value of k cannot be too large since there is an upper limit on the number of coordinates for each gesture. Therefore, the value of k must be smaller than the number of distances calculated for estimating a single gesture.

The obtained k distances do not explicitly indicate which coordinate they were calculated for, and no indices were saved during the examination process. Therefore, the coordinate represented by the given distance was determined based on the examined value, the obtained distance, and other data. This retrieval process uses the same distance calculation method as the one used for calculating the distances.

We also had to ensure that the distances are never zero since the algorithm iterates through all coordinates of the three gestures and calculates the distance relative to the examined gesture. It is possible for the distance to be zero at least once because it may occur between the coordinates of the three gestures. However, a zero value is not acceptable in this case because the distances are examined and the k smallest distances are selected. Thus, one or more zero values can significantly affect the estimations.

B. *The k-Means algorithm*

The k-Means algorithm is primarily used for solving clustering problems. Its principle is to analyze a dataset and approximate one or more centroids that represent the groups or clusters of data points. Contrary to the k-NN algorithm, more modifications were made to this algorithm. Its steps are the following in the application:

1. The data to be examined have to be loaded.
2. The value of integer k has to be determined.
3. Randomly selects k data points from the dataset as initial centroids.
4. Assigns each data point to the cluster whose centroid is closest to it.
5. Calculates the distances between each data point and the centroids.
6. Groups the data points into clusters based on the distances (assigns each data point to the cluster whose centroid is closest to it).
7. Calculates the new centroids by computing the average of data points within each cluster.
8. Repeats steps 5-7 until the values of centroids do not change or converge.

If the value of k is now known in advance, the algorithm should be run with different k values and an optimal solution should be found.

During the implementation process, there were cases where, due to random selection, the centroid values were the same. This more likely occurs when a certain gesture consists of fewer frames. Therefore, if a new coordinate estimation occurs and the randomly selected values are the same for multiple centroids, the random selection will continue until all of them receive different values.

Once the clusters and the points within the clusters are found, the algorithm examines the clusters to see if they actually contain points. Since the differences between the coordinates are very small, it is possible that a cluster might not contain any points. If it does contain points, the analysis continues. The three closest coordinates from the clusters compared to the examined coordinates are selected, separately for each axis. Additionally, the algorithm finds the three closest coordinates for each axis. This way, a total of 27 coordinates are chosen from the cluster. Then, once the first closest coordinate is found, its value is modified to avoid selecting it as the second closest value as well.

In the case of having nine coordinates from a cluster, the average of the three closest coordinates is calculated for each axis separately. These steps are performed for the other clusters as well until the new estimated points are yielded. The new estimated points and their coordinates are examined separately for each axis to check if they are suitable. However, the most important criterion is that the difference between the estimated coordinate of a given axis and the corresponding investigated coordinate should be smaller or equal to 0.05. This number was chosen because it represents the smallest magnitude of the acceptance domain. Due to this, the gesture will only be accepted if it is genuinely accurate.

If any of the estimated coordinates of the clusters are not suitable, the values of the coordinates that do meet the criteria will be determined as the values of the corresponding centroids, and the cycle starts again.

Considering that the initial approximation of the result is often incorrect due to random selection and averaging, we used a selected value for k in this algorithm. This value is completely independent and can be decided by the user in each case. There is also no maximum restriction on it, except that it should not be excessively large and unnecessary. The value of k is responsible for determining how many times the cycle, i.e., the approximation and estimation process, is executed. This is necessary because there may be cases where the values of the estimated coordinates do not meet the 0.05 criterion even after multiple approximation attempts.

Empirical testing shows that the larger the value of k is, the more accurate the estimated results will be. However, if k is drastically too large, there will be no noticeable improvement in the results, but it will not affect negatively the accuracy of the results either.

IV. Results and Discussion

This section is split into three subsections. In the first one, the results regarding the k-NN algorithm are shown. The results of the k-Means algorithm are presented in the second subsection, while the application of the algorithms is presented in the third.

A. Results of the k-NN algorithm

The results regarding the k-NN algorithm can be observed in Table I. The median of accepted gestures regarding the ten repeating gestures is shown in it in each acceptance domain. Every three lines correspond to a certain gesture. The first three are the triangle, the second three are the waving, and the third three are the infinity-shaped gesture.

TABLE I
The median of the accepted number of gestures with the k-NN algorithm.

k	Euclidean			Manhattan		
	±0.05	±0.10	±0.15	±0.05	±0.10	±0.15
1	0	4	10	0	4	10
5	0	4	10	0	4	10
10	0	4	10	0	4	10
1	10	10	10	10	10	10
5	10	10	10	10	10	10
10	10	10	10	10	10	10
1	2	10	10	1	10	10
5	2	10	10	2	10	10
10	5	10	10	5	10	10

As can be observed in Table I, the triangle gestures produced the worst gesture acceptance numbers. While the infinity-shaped gestures yielded better numbers, the waving gestures proved to be most easily recognizable. The median of accepted gestures is also quite similar between the two distance calculation methods. Fig. 2 shows how the waving gesture was predicted by the k-NN algorithm. The value of integer k was 10. The blue line represents the gesture prediction, while the orange one is the actual gesture.

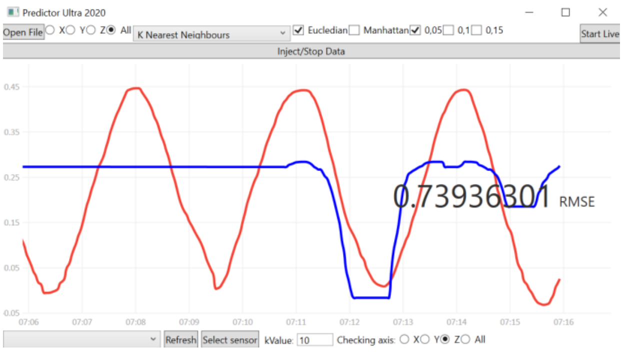

Fig. 2. Gesture prediction with the k-NN algorithm.

B. *Results of the k-Means algorithm*

Next, the results of the k-Means algorithm were investigated in a similar way. The results can be found in Table II.

TABLE II
THE MEDIAN OF THE ACCEPTED NUMBER OF GESTURES WITH THE K-MEANS ALGORITHM.

k	Euclidean			Manhattan		
	±0.05	±0.10	±0.15	±0.05	±0.10	±0.15
1	7	10	10	5	10	10
5	10	10	10	10	10	10
10	10	10	10	10	10	10
1	10	10	10	10	10	10
5	10	10	10	10	10	10
10	10	10	10	10	10	10
1	7	10	10	5	10	10
5	10	10	10	10	10	10
10	10	10	10	10	10	10

The k-Means algorithm yields better results can the k-NN algorithm. As can be seen in the case of the k-Means algorithm, the worst median of accepted gestures is five out of ten. Naturally, it is also possible to increase the number of k above 10 to enhance accuracy. However, the also increases the prediction time. Fig. 3 shows how the waving gesture was predicted by the k-Means algorithm. The parameters were the same as in Fig. 2.

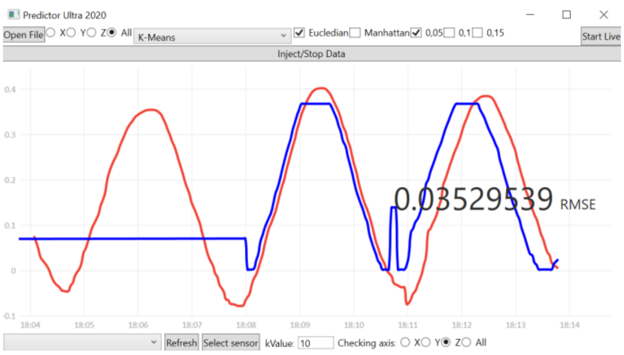

Fig. 3. Gesture prediction with the k-Means algorithm.

C. *Application of the algorithms*

The results show that both algorithms are easy-to-use and viable in recognizing the gestures of the users. Additionally, these algorithms can adapt to the current capabilities of the users provided that the best options are used. Consequently, telerehabilitation can be an option using these algorithms. Therefore, the presence of a therapist is only required during a consultation. Thus, the rehabilitation process of people with movement disabilities could be made more convenient and safer in their homes.

V. Limitations and Future Plans

As in most cases, the current application can also be improved in various ways. It may be useful to implement other algorithms (even in real-time) to provide new methods for gesture recognition. The implemented algorithms could also be run in a parallel manner, thus all of them could evaluate gestures at the same time. This would simplify the selection of the most suitable algorithm for a certain gesture. The results of the application could be stored in a database, ensuring that previous estimation results are not lost. New types of checks can also be designed to classify gestures and coordinates, resulting in multiple acceptance criteria. By further examining these results, additional conclusions could be drawn. Automating the application is also possible, thereby providing an easier-to-use user interface. In addition to the current user interface, a 3D coordinate system could be implemented. This could provide better visibility of the analyzed movements and the shape and deviations of the estimated movements.

VI. Conclusion

In this paper, an existing application was extended with two algorithms: the k-NN, and the k-Means algorithms. They were evaluated in three acceptance domains by calculating distances between gesture descriptors with either the Euclidean or the Manhattan method.

The evaluations of the algorithms clearly indicate that while the k-Means algorithm operates in a more complex manner, it is capable of providing more accurate predictions of forthcoming gestures in most cases. However, the k-NN algorithm can also prove to be more appropriate for certain gestures. In conclusion, these algorithms could be used at home, the rehabilitation process can be made easier for both the therapist and patient if they choose these methods. Based on the results however, the k-Means algorithm is more suitable for gesture recognition than the k-NN algorithm.

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