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Improving Rehabilitation Practices: A Real-Time Method for Assessing the Reproduction Quality of a Given Recovery Exercise Executed by a Patient

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Abstract— ***In this paper, we introduce a new real-time method for assessing the reproduction movements of a patient compared to expected movements during rehabilitation exercises. A global analysis is also conducted to evaluate the quality of execution. The method relies on human key point detection and the use of the Fréchet distance metric. This method enables the application to alert the patient when their movement deviates from the expected one: the intended movement and an error message are visually displayed. The advantage of our method lies in its dynamic capability and the precise percentage accuracy of the patient's performance provided at the end of the rehabilitation exercise.***

Index Terms— ***Exoskeleton, Movement Evaluation, Rehabilitation, Simulation.***

I. INTRODUCTION

In recent years, the use of collaborative robots has increased. Numerous applications exist, including medicine [1][2], education [3], army [4], etc. Collaborative robots are designed to work with humans. They are considered as assistive technologies to help in daily life whether at work, at school, or at home.

A medical exoskeleton is an example of a collaborative complex electro-mechanical robot. Also known as a wearable system. It is also called a wearable system, it is worn by a human and matches their body [5]. In medical applications, exoskeletons are used for paraplegic patients, stroke patients, disabled/amputated patients, and for daily compensation [6].

An increasing number of rehabilitation institutions are adopting exoskeleton rehabilitation robots for treatments, leading to rapid growth in the medical exoskeleton market. This growth is driven by the increasing demand for effective rehabilitation approaches for a growing number of patients.

However, a significant challenge remains: the digital evaluation of the quality of the movement performed by the patient during exercises, whether in real-time or globally.

In response to this challenge, this paper introduces a method capable of assessing the quality of the patient's upper limb movements in real-time during a rehabilitation exercise.

In the absence of a physical rehabilitation exoskeleton, we have developed an application that animates an expected movement and compares it with the patient's movement. The patient must observe and try to replicate the expected movement in real-time. The application can alert the patient in real-time if the movement deviates and will provide a global similarity score at the end of the exercise. Therefore, the method developed focuses on comparing the movement of patients with the expected movements within a 2D environment.

This paper is structured as follows. A state-of-the-art overview is presented in the next section (Section II). Subsequently, the global scenario used for this work is presented in Section III. The methodology that leads to the final evaluation method is described in Section IV. The results obtained from the proposed method are presented in Section V, followed by the conclusion in Section VI.

II. STATE OF THE ART

The evaluation of human movements holds significant importance in various fields, especially in the context of rehabilitation.

In [7], a patient undergoes home-based rehabilitation exercises. Using the PoseNet model, body key points are identified. Distances and angles between left and right elbows, as well as left and right knees, are calculated. These data are stored for remote access by the doctor to assess

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Volume 11 Issue 7 July 2024

exercise accuracy based on angular measurements, allowing for timely corrective instructions.

In [8], the study evaluated the reliability and validity of using Mediapipe in rehabilitation sessions. While the technique was validated for calculating movement amplitudes, precise validation of anatomical key points was lacking. Our goal is to analyze upper body movements using anatomical key point 2D coordinates.

A movement comparison study was conducted using a 3D space, as referenced in [9]. Patients replicated Tai Chi movements. Movements comparison was achieved by calculating Euclidean distances from normalized 3D coordinates of anatomical reference points. The method was successfully tested on two patients to assess system efficacy, accurately determining if movements between virtual teachers and real students were identical. However, the depicted body trajectory suggests certain anatomical points, notably the elbow, were not precisely identified.

Authors in [10] used real-time 2D Fréchet distance on Bézier curves, created from anatomical key point coordinates over time, to compare movement similarity between real and virtual humans. They obtained key points coordinates using the OpenPose AI model. To address missing coordinate gaps, existing coordinates were used to generate necessary intermediate points for Fréchet distance calculation. However, this method's reliance on random generation of intermediate points introduces potential inherent imprecision to compare movement similarity.

Our proposed method will be based on an AI model capable of capturing all data without any loss during exercises. Movement comparison will rely on the Fréchet distance metric, based on the coordinates of each human key point collected. Moreover, the literature insufficiently addresses the calculation of success scores, specifically based on results obtained with the Fréchet Distance metric.

III. SCENARIO

The real-time method for assessing patient movement compared to the expected movement was established through a general scenario as shown in Fig. 1:

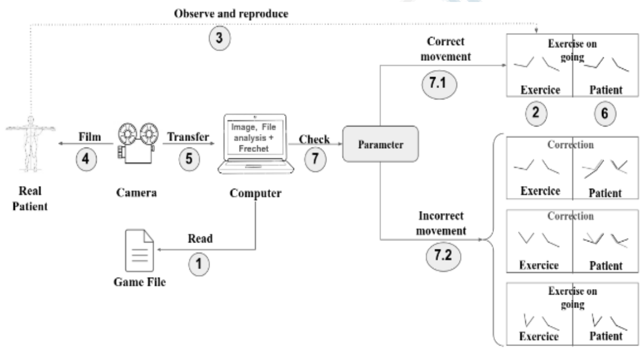

Fig. 1. Scenario representing our method of movement evaluation.

This scenario can be described with the following steps:

1) The computer reads an exercise file.
2) The computer animates the virtual exercise file.
3) The patient observes and tries to reproduce the virtual exercise.
4) A camera films the patient's movements.
5) The computer reads and analyzes images from the camera. Then patient key point coordinates are compared to these in the exercise file with a metric.
6) The patient's movements are represented by a virtual patient.
7) In accordance with a defined parameter that manages the display, we can have two options:
   a) If the reproduction is correct, the" Exercise on going" message appears.
   b) If the reproduction deviates from what is expected, a visual alert occurs (the intended movement is displayed, and an alert message is shown on the animation).

In all steps, we use frames T that represent the x or y coordinates of each point of the upper limbs: wrist (w), elbow (e), and shoulder (s), on both the right (r) and left (l) sides as represented by Fig. 2 and the following formula (1).

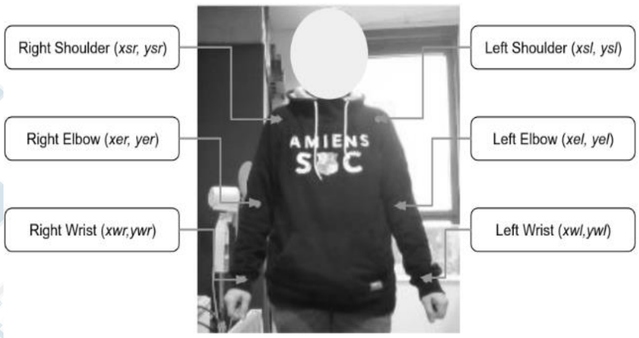

Fig. 2. Patient's upper limb key points.

$$T = (xwl, ywl), (xwr, ywr), (xel, yel), (xer, yer), (xsl, ysl), (xsr, ysr) \quad (1)$$

A movement m is formed by a succession of frames i, as characterized by the formula (2):

$$m = (xwl_i, ywl_i), (xwr_i, ywr_i), (xel_i, yel_i), (xer_i, yer_i), (xsl_i, ysl_i), (xsr_i, ysr_i) \quad (2)$$

The AI model for human pose recognition, needed to exhibit high performance and avoid data loss to ensure smooth graphical reproduction of human movements. After experimenting with and reviewing scientific literature on several AI models, including MoveNet, PoseNet, and Open-Pose [11], [12], in a well-lit environment: the MoveNet AI model meets these criteria for this work. We've applied this model in our proposed method.

Game files are used to animate the expected movement (steps 1 to 2). These files included frames T used to simulate movement. With the aid of dedicated software, these files facilitated the dynamic animation of the movement. The animation synchronization between the animated exercise and the patient's real movement was achieved through the implementation of a parallel programming methodology. Each frame captured by the camera corresponded to the reading of a line within the game file. Data used for the expected movement (steps 1 to 2) and the patient's movement (steps 3 to 6) are formatted identically for the movement analysis.

The main challenge in this paper lies in steps 5 to 7. Step 5 aims to devise a methodology for comparing the movements of the patient with those of the expected movement. Meanwhile, steps 6 and 7, seek to implement real-time alerts to notify the patient when their movements deviate. Finally, a performance score is generated after each exercise.

IV. METHODOLOGY

In this section, we present our methodology that leads to the final evaluation method: comparing movements in real-time and notifying the patient when their movements differ from what is expected.

A. Curves of movement

To explain the methodology, we only talk about the x-coordinate of the right wrist during the first steps. The curve of the movement performed by the patient and the expected movement, are first generated separately (Fig. 3).

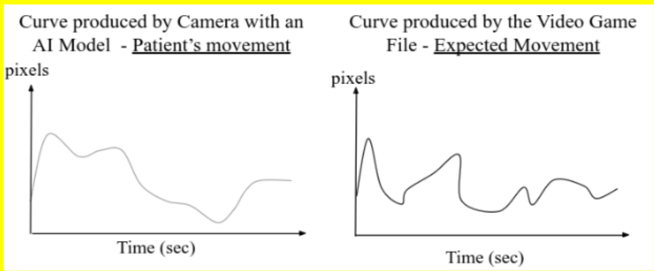

Fig. 3. Curves representing the evolution of one coordinate of one key point for patient and expected movements.

The two curves will be placed on the same graph (Fig. 4).

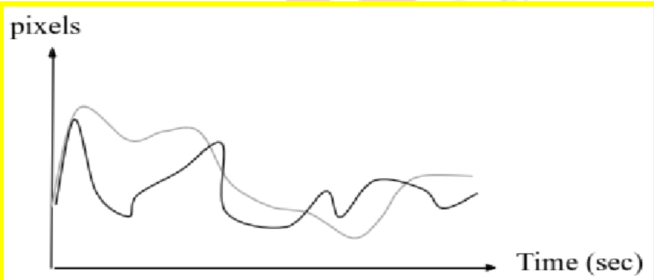

Fig. 4. Patient's and expected movements we want to compare.

The curves' similarity will be analyzed with a metric. A similarity means the patient's movement is correct but if there are deviations, this means the patient's movement isn't correct.

B. Fréchet Distance

The Fréchet Distance metric df was selected according to the state of the art. This metric compares the similarity between two curves. To calculate the Fréchet Distance value, several steps are involved. Firstly, we use the coordinates of two curves ($L1$ and $L2$) to compute Euclidean distance and get a Distance Matrix MD. $L1_i$ corresponds to value number i on the first curve, and $L2_j$ corresponds to value number j on the second curve (3):

$$MD_{i,j} = d(L1_i, L2_j) \quad (3)$$

Then we use the Distance Matrix to establish the Fréchet Distance Matrix MF with the following recursive formula:

$$MF_{i,j} = max(MD_{i,j}, (MF_{i-1,j}, MF_{i,j-1}, MF_{i-1,j-1})) \quad (4)$$

In our study, we apply the Fréchet distance to compare the expected movement m_{ex} curves and the patient's movement m_p curves (5):

$$df = f(m_{ex}, m_p) \quad (5)$$

C. Curve Sampling

According to the literature, the Fréchet distance metric is rarely applied in a real-time application. To achieve real-time movement analysis, a sample analysis was conducted. The expected movement files are known, and a general sampling was performed based on these files, as shown in Fig. 5.

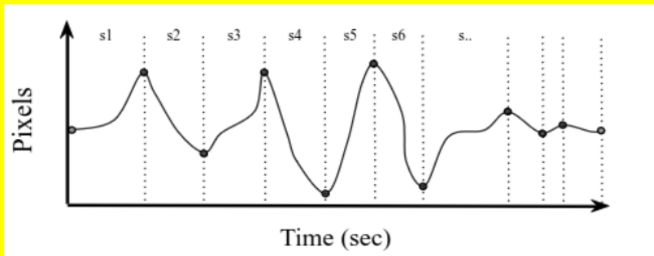

Fig. 5. Example of sampling on a curve representing the evolution of the x or y coordinate of a human anatomical key point.

Each sequence s_i represents either a positive or negative slope. Therefore, during real-time analysis, we examine the two curves sequence by sequence (6).

$$\forall i \in [1, n], df = f(m_{ex}[s_i], m_p[s_i]) \quad (6)$$

D. General application for movement comparison

Up to now, we've only discussed work conducted on the x-coordinate of the right wrist. However, the Fréchet distance also applies to all other coordinates of each reference anatomical point, denoted by the variable a, ranging from 1 to 12 as shown in Fig. 6.

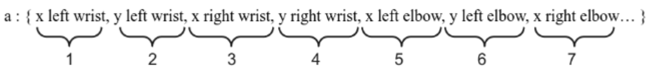

Fig. 6. Variable a representing all coordinates in our study

Due to the sampling conducted on the curves representing the evolution of the x or y coordinates of human anatomical key points, Fréchet distance calculations will be performed

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Volume 11 Issue 7 July 2024

on the lengths of these determined sequences according to the coordinates point n_a in (7):

$$\forall a \in [1,12], \forall i \in [1, n_a], df = f\left(m_{ex}[a][s_i], m_p[a][s_i]\right) \quad (6)$$

E. Notifying the patient in real-time

We've established a real-time movement comparison method between the patient's and expected movements. We need to identify when the patient's movement deviates from the expected one.

Whenever such a deviation occurs, the patient receives two graphical notifications: a corrective message and a graphical representation indicating the ideal position the patient should adopt, as illustrated in Fig. 1.

To address this, we have introduced a parameter known as the tolerance threshold st. Generally, a tolerance threshold is a predefined value used to determine the acceptable range of deviations in results or data. This parameter will be applied to the Fréchet Distance results curve obtained during movement analysis, as represented in Fig. 7.

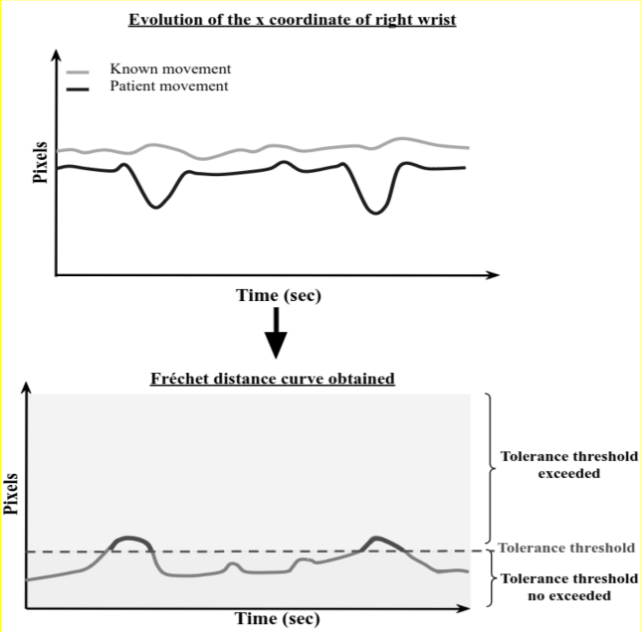

Fig. 7. Fréchet distance result curve obtained for the x coordinate of the right wrist between the patient's movement and the expected movement.

We can observe from the Fréchet distance results that the curve exceeds the tolerance threshold twice, indicating that the patient's movement differs from the expected movement.

Our objective is to determine an optimal value for the tolerance threshold. We need to test several values of st.

Therefore, an initial range of these values must be defined.

This range can be determined based on the size of the images, as shown in Fig. 8.

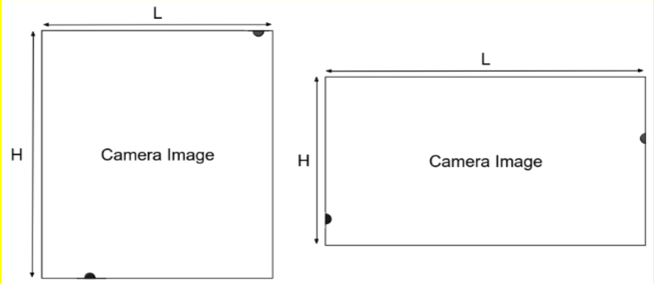

Fig. 8. st range of values based on image size.

Let's consider that on the left or the right representation, one point represents one of the key points belonging to the patient, and another key point belongs to the expected movement. These points represent the same key points (wrist, elbow, or shoulder, left or right) with a distance between them. In the left representation, the maximum value will be H pixels, while in the right representation, the maximum value will be L pixels. From now on, the minimum and maximum values of the possible interval st are determined in a generalized manner (8).

$$st \in [0, (H, L)] \quad (8)$$

Our objective is to conduct an analysis within this interval in order to get as close as possible to the optimal value of the tolerance threshold.

In Artificial Intelligence, the Mean Squared Error (MSE) is commonly used to assess the accuracy of prediction models, particularly in regression. A lower MSE indicates better model accuracy.

In the quest for the optimal tolerance threshold value, the utilization of the MSE is contemplated to assess the agreement between known scores denoted as $score_k$ and estimated scores, denoted as $score_{est}$ (9).

$$MSE = \frac{1}{n}\sum_{i+1}^{n} (score_k, score_{est})^2 \quad (9)$$

To search for the optimal tolerance value, we initially examined various tolerance values to ensure that the known and estimated scores were both verified. Subsequently, we calculated the MSE values for each of these tolerance values as demonstrated in Fig. 9.

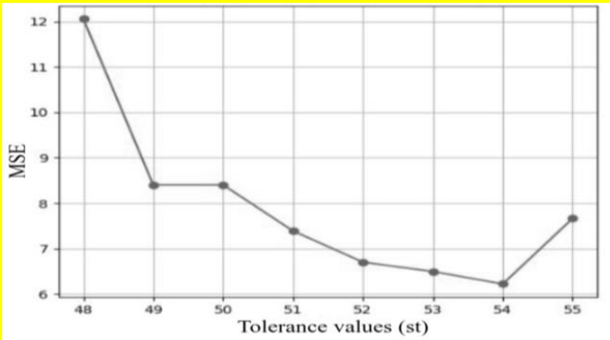

Fig. 9. Evolution of the MSE values according to tolerances values tested.

The optimal value of tolerance threshold (st_{opt}) is the objective (10):

$$st_{opt} = (MSE)\ (10)$$

According to results obtained from the Fig. 9, the MSE minimum value is obtained when the tolerance value is set to 54. The figure 10 represents $MSE = f(st)$ when st is set to 54 (11).

$$y = st_{opt}\ \times x\ \ (11)$$

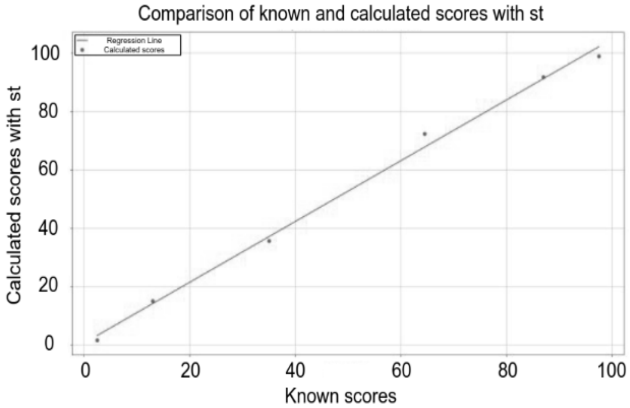

Fig. 10. MSE curve obtained with a tolerance value defined to 54.

F. Exercise global score

For each exercise e performed by the patient, a success score$score_p$, representing the similarity between the expected and the patient movements, is generated as an exercise conclusion. However, the score established depends on the tolerance threshold and the exercise (12).

$$score_p = f(st, e)\ \ (12)$$

The score based on the tolerance threshold value is calculated using the following formula, where n represents the frame number from the exoskeleton movement file read during the exercise (13):

$$score_p = 100 - \left(\frac{\left(\sum_{j=0}^{n} \left(\sum_{a=1}^{12} df_j[a] > st\right)\right)}{a\ \times n} \times\ 100\ \right)(13)$$

At the end of the exercise, the physiotherapist obtains a score. It's compared with previous scores obtained by the same patient to determine if there is any progress.

G. The strengths of the method

By employing human key point detection and the Fréchet distance metric in real-time, our approach enables continuous movement quality assessment. It provides visual feedback to alert patients when deviations from the expected gesture occur.

The objective of this study was to demonstrate the feasibility and effectiveness of our proposed method for enhancing rehabilitation outcomes by promoting movement accuracy and consistency.

Additionally, we aim to showcase the utility of our approach in calculating a similarity score between patient movements and expected movements, thus providing clinicians/doctors with a quantitative measure of performance.

V. RESULTS

This section presents results obtained when our method is applied to a good or a poor movement. The analysis is focused on the coordinates x and y of the right wrist in all cases.

A. Analyze of a good movement

The patient has well executed the exercise proposed. There are some minor variations on the evolution of x and y coordinates compared to the expected one as presented in Fig. 11.

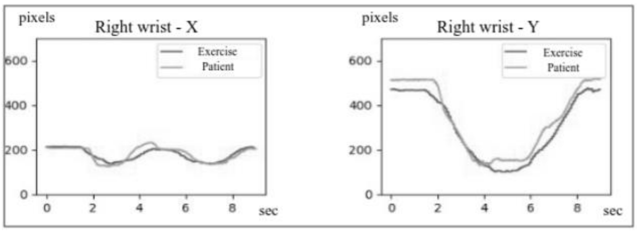

Fig. 11. Evolution of x and y coordinate of the right wrist during a good movement.

When a movement is executed perfectly, the Fréchet distance curves appear normal with only minor variations as on Fig. 12. The tolerance threshold value has not been exceeded during the exercise. This indicates that the patient's movements were correct throughout the entire execution.

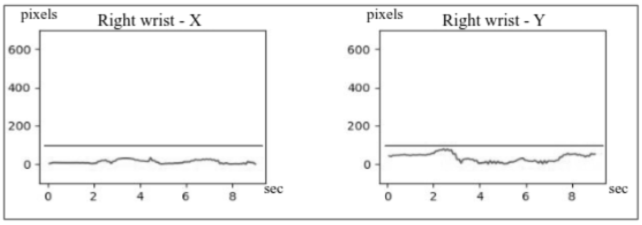

Fig. 12. Fréchet Distance curve obtained from the Fig. 11

The global similarity score of this exercise is: 100%.

B. Analyze of a poor movement

However, in the case of imperfect movement, the curves are different (Fig. 13). We observe a significant gap in the y coordinate of the right wrist between 2.5 seconds and 8 seconds.

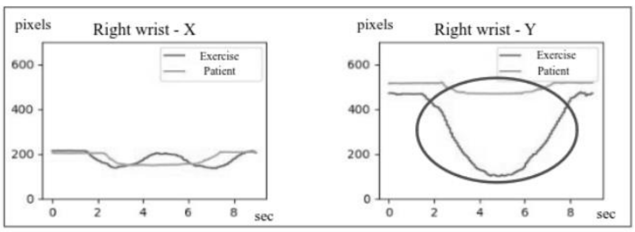

Fig. 13. Evolution of x and y coordinate of the right wrist during a poor movement.

When we applied the Fréchet distance, results are

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Volume 11 Issue 7 July 2024

presented by Fig. 14.

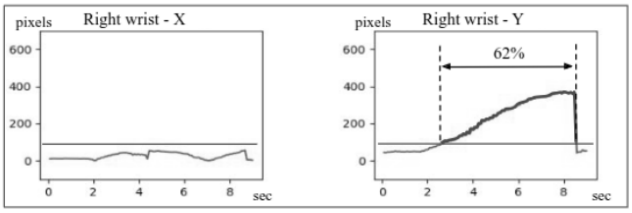

Fig. 14. Fréchet Distance curve obtained from the Fig. 13

The tolerance threshold has been exceeded during 62% of the exercise. This indicates the patient's movements were incorrect. The global similarity score for this exercise is 100-62 = 38%.

VI. CONCLUSION

We propose a practical and precise tool for physiotherapists and patients. Thanks to real-time notifications and the robust selection of the AI model for detecting human anatomical key points, patients can correct their movement when deviations from expected movements occur in a 2D environment. Additionally, the global similarity score displayed at the end of each exercise allows medical professionals to observe the progression of one or more patients more accurately. Physiotherapists can also adjust future rehabilitation sessions accordingly**.**

Looking ahead, there is potential to extend the proposed method into a 3D coordinate system for further evaluation. A new step can be added to the scenario presented in Fig. 1 when the patient's movement deviates too much, a physical exoskeleton can take control and assist the patient in correcting their movement.

Beyond medical applications, this method holds promise for broader use, such as in video games where players replicate on-screen dances, eliminating the need for costly equipment or sensors. Importantly, our method offers the advantage of real-time movement recording without requiring additional equipment on the person being monitored.

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