Real-Time Evaluation of Hands Position at Sport Training Machine

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***Abstract*—The digitalization of sport training machines enables sensor-based applications for recognition of human movement at exercise performing. In this demo, we continue our development of the mobile application that uses evaluation of athlete's hands position in real-time. We show more effective solution (in terms of the position accuracy) than we demonstrated at the previous FRUCT conferences. Our previous solution is based on an accelerometer as a sensor for input data. Our successor solution combines an accelerometer and a gyroscope based on Kalman filter. This combination reduces the influence of acceleration on evaluating the angle of the lever of sport training machine relative to the vertical axis (the "Bench Press" exercise is used as a demo use case). The accurate measurement of hands position supports estimation of the total distance passed by hands (with given weight). This metric is important for training as well as for new class of sport competitions.**

I. Introduction

A digital referee, in the realm of sports and fitness, is an innovative tool designed to bridge the gap between technology and physical training. This advancement emerges from the increasing need to provide athletes with precise and instant feedback, ensuring that their training is both effective and safe. We continue our development of the mobile application that uses evaluation of athlete's hands position in real-time [1], [2].

The mobile application being developed taps into the potential of modern technology, combining sensors, complicated algorithms, and user interface design to monitor the performance of exercises on sport training machines crucial for an athlete. To work with this application, training machines must be based on technology that uses a lever design.

One of the primary features of the app is its capability to measure the amplitude of repetitions. Amplitude, in this context, refers to the range of motion during a particular exercise. For instance, in a squat, the amplitude would refer to the depth the athlete reaches. Ensuring the correct amplitude is vital for two reasons:

- **Muscle Activation:** Achieving the right amplitude ensures that the targeted muscle groups are activated adequately. This is essential for muscle growth, strength, and endurance.
- **Injury Prevention:** Incorrect amplitude can lead to strain and potential injury. For example, a half-squat might put undue pressure on the knees.

If an athlete nails the amplitude, the application sends a notification, confirming that the repetition was done correctly. Conversely, if the repetition lacks the necessary amplitude, it cannot be counted, ensuring that the athlete is always striving for perfect form.

In essence, the digital referee application is more than just a tool. Such applications transform the world of sports training. The digitalization embodies the perfect synergy between technology and fitness, ensuring athletes can push their limits while remaining safe and informed [3].

The rest of this paper is organized as follows. Section II introduces the evaluation problem of hands position. Section III considers the accuracy problem in evaluation of hands position (the 1st version of our mobile application). Section V shows experiments with the new version of our algorithm for the evaluation of hands position. Section VI summarizes the key findings of our study that demonstrates the efficiency of the successor algorithm for the evaluation of hands position.

II. Evaluation of Hands Position

The prototype consists of an Android OS mobile application designed for a smartphone with the corresponding OS, and capable of receiving data from the sensor for further processing.

The algorithm for assessing the correctness of execution is implemented based on the use of calculating the moving average according to a graph with a given window size in real time. To calculate the correctness of the exercise, a sensor must be used - an accelerometer built into the phone. The input data of the algorithm is the activation of the accelerometer - an increase in acceleration along three axes: a_X, a_Y and a_Z, which are converted into the current angle between training machine lever axis and vertical axis. The following problem arises: the signals received from sensors usually have noise due to various conditions. So, to eliminate small irregularities and fluctuations in the signal, we use a simple low-pass filter (LPF) with window size of 2 and the smooth parameters k_1 and k_2.

$$p(T) = k_1 p_i + k_2 p_{i-1},$$

where $0 \leq k_1$, $k_2 \leq 1$, $k_1 + k_2 = 1$, $i = 0, 1 \ldots N$, and $i \in T$. The coefficient k_1 determines the degree of filter smoothing. The higher this ratio, the more filtering will be applied to the signal. Based on the experimental results, the values $k_1 = 0.95$ and $k_2 = 0.05$ were accepted.

To carry out the operating mode, it is necessary to calibrate, i.e., to determine the limiting positions of the hand (training machine lever), as well as the amount of movement of the athlete without working weight. The initial and final positions of the athlete's hand are recorded for further calculation of the average calibration value (the etalon). To ensure correct repetition of measurements, the etalon records are compared with the measured value during the working set.

III. The Accuracy Problem

Accurately determining the position of an athlete's hands during exercises is crucial for assessing the correctness of the movement, ensuring the desired muscle activation, and preventing potential injuries. With the advent of digital fitness and training solutions, there is an increasing demand for precise motion tracking. However, this task is riddled with challenges:

The Problem with Linear Acceleration: Linear acceleration, which represents the rate of change in velocity of the athlete's hands without considering the direction, can lead to misleading readings:

- Rapid changes in linear acceleration, especially during explosive exercises or when changing direction swiftly, can introduce noise into the data.

The Issue of Extraneous Vibrations: Vibrations that are not part of the exercise, possibly arising from external sources or even the internal mechanics of the training machine, further complicate the tracking:

- External Factors: These could be vibrations from nearby machinery, ground movements, or even other athletes working out in close proximity.
- Internal Factors: The training machine itself might introduce vibrations due to its mechanical operations, wear and tear, or if it's not perfectly balanced or stabilized.

The Implications: Inaccurate hand position data can lead to misguided feedback, which might result in ineffective training or even promote incorrect techniques and also it makes it impossible to use this application as an instrument to estimate the correctness of the working amplitude.

IV. The Proposed Solution

Basically, smartphone provides this types of sensors: **Accelerometer and Gyroscope:**

- **Accelerometer:** It measures linear acceleration forces on the device. By removing the effect of gravity, it can provide information about the device's movement in terms of direction and magnitude of acceleration.
- **Gyroscope:** It measures the angular rotational velocity around the device's X, Y, and Z axes. In simple terms, it can tell how fast and in which direction the device is rotating by each axis.

The Need for Sensor Fusion: Both sensors have their advantages and limitations:

- **Accelerometer:** While it can provide orientation relative to the Earth's gravitational pull (like determining if the device is face-up or face-down), it's susceptible to error when the device is in motion. Any sudden movement can create "spikes" in data.
- **Gyroscope:** It provides smooth and accurate rotational data but has no sense of absolute orientation. Over time, the gyroscope has a "zero–drift", leading to cumulative errors in orientation estimation.

In this paper we provide to combine these two sensors to receive more accurate data without disadvantages, described before. By fusing the data from both sensors, we can leverage their strengths and compensate for their weaknesses, resulting in more accurate and stable orientation readings.

Kalman Filter: The Kalman filter is an optimal recursive estimation algorithm that takes multiple sensor inputs to produce a more accurate combined output. In the context of combining accelerometer and gyroscope data:

1) **Prediction:** The filter starts with a prediction phase, where it uses the previous state (e.g., the last known orientation) and the gyroscope data to predict the device's new orientation.
2) **Update:** In the update phase, the filter refines this prediction using the accelerometer data. It computes the difference between the predicted orientation and the orientation as indicated by the accelerometer. This difference, known as the "Kalman gain", is then used to correct the prediction and produce a final combined orientation estimate.
3) **Iterative Process:** The beauty of the Kalman filter lies in its recursive nature. It continually adjusts its predictions based on new sensor readings and the differences from previous predictions, leading to refined and accurate results over time.

Benefits:

- **Accuracy:** By combining the relative accuracy of the gyroscope with the absolute orientation data from the accelerometer, the Kalman filter can produce highly accurate orientation estimates.
- **Stability:** The Kalman filter smooths out the noise from both sensors, resulting in stable readings even during sudden movements or vibrations.
- **Drift Compensation:** The filter compensates for the gyroscope's tendency to drift over time by continually referencing the accelerometer's absolute orientation data.

In conclusion, using a Kalman filter to combine accelerometer and gyroscope data allows for highly accurate, stable, and drift-free orientation estimations, making it a favored technique in various applications like drone stabilization, mobile device orientation detection, and virtual reality.

V. Experiments

To estimate the viability of the proposed approach with combining data from accelerate and gyroscope by a Kalman filter we conduct an experiment. This experiment shows difference between two approaches: data from accelerometer with LPF against data from accelerometer and gyroscope. For this experiment we developed the new algorithm and tested it with the previous one developed (accelerometer with LPF), on the exercise machine of the company ”MB Barbell” of the ”Bench press” type with adjustable weight, showed in Fig. V. Additionally, for the demonstration, MB Barbell lever-type street machines were used to perform exercises: “bench press”, “squat”, “deadlift”, and “overhead press”.

A pair of smartphones with pre-installed smartphone software is fixed on the macine with a two latches in a certain position. The latches are placed on both sides of lever mechanism with the same distance from the axis of lever rotation point. The attachment point of the latch is located at a pre-measured distance from the axis of rotation of the frame of the training machine.

Fig. 1. Training machine for our experiments.

Fig. 2. Training machine for our experiments. The smartphone holders are installed on both sides on the movable frame (lever).

The purpose of the experiment:

- Evaluate performance, accuracy of the proposed solution.
- Evaluate data stability of the proposed solution in different conditions, like vibrations from the training machine itself.
- Check if this proposed algorithm solve the problem with linear acceleration, that influence the received data.

Experimental setup:

- MB Barbell street machine “Bench Press” with the two installed latches (smartphone holders);
- The smartphone with application that collects data only from accelerometer and smartphone with application that collects data from accelerometer and gyroscope with Kalman filter. Smartphones are installed to the latches on both sides of the lever.
- The application for the smartphone was programmed for the experiment this way: the program starts collecting data from sensors (accelerometer and (or) gyroscope) and convert it to the training machine lever angle. The data collecting stops when the total distance passed by hands obtained by application get 2.5 meters for the application with the proposed approach and 5 meters for application that use only accelerometer data. This happened due to long experiment time: integration error in distance calculation made application stop collecting data with linear acceleration problem earlier.
- The volunteer used to perform exercises on this training machine until both smartphones stop collecting data — total passed distance by hands exceeds real 2.5 meters.

Results: The experimental result graph showed in Fig. V. Non-scaled measurements are showed in Fig. V

- Red line presents angle computations by application from accelerometer with filtration;
- Blue line presents angle computation with the approach algorithm;
- Y-axis presents lever angle during experiment in degrees;
- X-axis presents samples, obtained by algorithm: 700 samples in total.

To combine data from two smartphones, to each data sample from accelerometer and gyroscope added value 5 in order to make them on the one level. This issued due to different angles of installed latches. Furthermore, the ”blue” line (data from accelerometer only) was cut to red one, due to long experiment time: integration error in distance calculation made application stop collecting data earlier.

The experimental facts depicted in Fig. V show the main disadvantage of the obtaining lever angles only with accelerometer: the low-pass filter can’t smooth the data properly because of fluctuations of the accelerometer-only based data. Red line on scaled graph shows, that the proposed approach with data fuse (accelerometer and gyroscope) with Kalman filter, reduces liner acceleration problem.

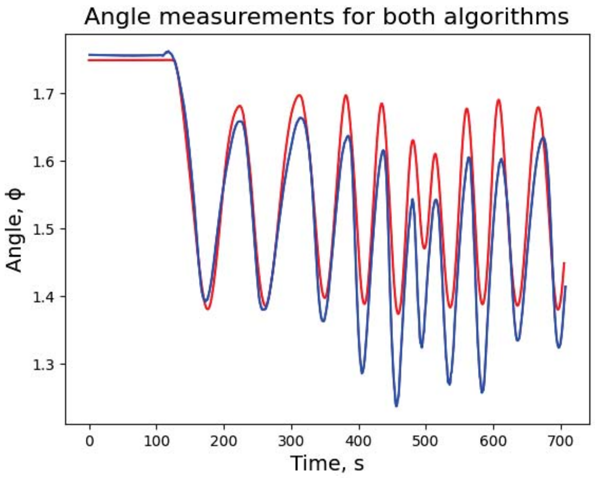

Fig. 3. Scaled visualized processed data from two smartphones. Red line present angle computations from accelerometer with filtration. Blue line present angle computation with the approach algorithm.

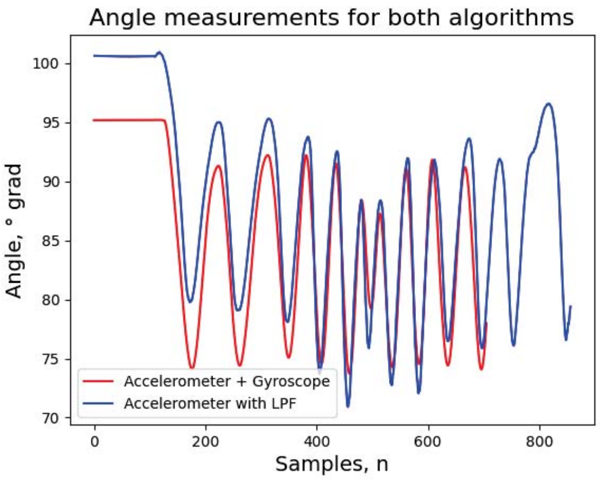

Fig. 4. Non-scaled visualized data from two smartphones. Red line present angle computations from accelerometer with filtration. Blue line present angle computation with the approach algorithm.

VI. Conclusion

The demonstrated solution shows a significant improvement in accuracy and data structure. To confirm the improvement, experiments were conducted with two smartphones simultaneously installed in to the latches. This option makes possible to achieve the most objective comparison of results. Testing was carried out on volunteer with athletic anthropocentric data. The new algorithm avoids the occurrence of linear accelerations and reduces the influence of vibrations on the measurement results. Further research will be aimed at improving the speed of the new algorithm due to the increased

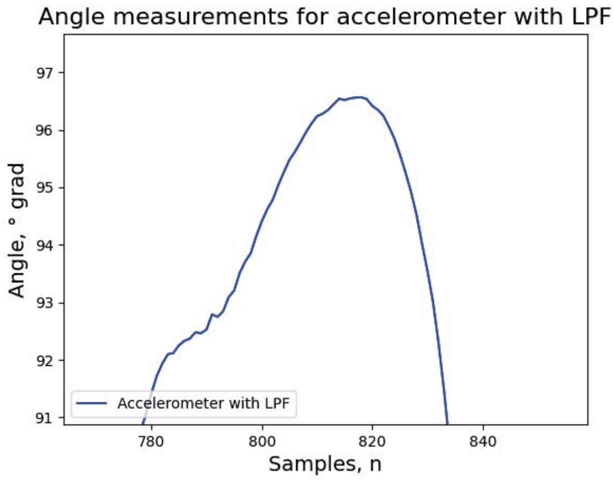

Fig. 5. Zoomed-in the last repeat of the experiment by volunteer.

number of data processing stages.

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