Motion Analysis with Wearable 3D Kinematic Sensors

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Abstract— **Wearable motion sensors provide data that directly reflect the motion of individual body parts and that can enable the development of advanced tracking and analysis procedures. Today widely available light and small size sensors make a wide range of practical measurements feasible. As these sensors are somewhat inaccurate, they are primarily suitable for monitoring motion dynamics. A number of studies conducted so far show that these sensors can be efficiently used for motion pattern identification and classification enabling general motion analysis and evaluation. To make full advantage of the feasibility and widespread use of these sensors, it is necessary to provide for, in terms of lifetime and computational complexity, efficient calibration and data analysis procedures.**

I. Introduction

Natural human motion is a complex process that involves the entire psychophysical system. Motion analysis can contribute to a better and more comprehensive understanding of specific activities and of behavior in general. We can ascertain that motion evaluation is an important part of recreation, rehabilitation, injury prevention, and the objective determination of the level of functional ability of individuals.

In the context of motion analysis, we strive for detection and recognition of different motion patterns. Essentially, motion pattern recognition is based on the capture and analysis of motion data of different motion-involved body segments.

In modern methods for motion tracking, the relevant data are the starting point for a comprehensive motion analysis. Wearable wireless motion sensors [1-16] provide data that directly reflect the motion of individual body parts and that can enable the development of advanced tracking and analysis procedures. Today available kinematic sensors that are based on Microelectromechanical systems (MEMS) are small, light, widely affordable, and come with their own battery supply. These sensors cause minimal physical obstacles for motion performance and can provide simple, repeatable, and collectible motion data indoors. Moreover, because of their low energy consumption, MEMS sensors are a promising tool for tracking motion outdoors.

II. Sensor Data Interpretation

A. *The general 3D sensor model*

A 3D sensor is a device that measures a physical quantity in the three-dimensional space. As shown in Figure 1, values measured with a 3D sensor represent the projections of the measured quantity on three, mutually perpendicular, sensitivity axes of the device. These axes form the sensors coordinate system.

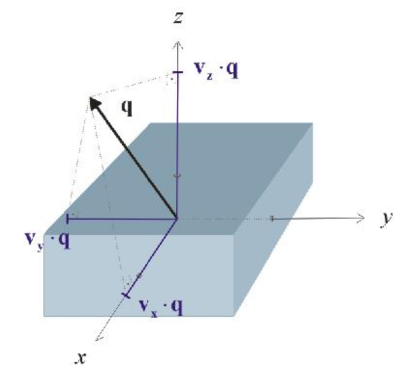

Figure 1. The illustration of the projections of the measured quantity vector **q** on the sensor sensitivity axes given with directions of $\mathbf{v}_x$, $\mathbf{v}_y$ and $\mathbf{v}_z$. If the orientation of the sensor sensitivity axes is error free, these axes coincide with the coordinate system axes *x*, *y* and *z*.

Providing measurements along the sensitivity axes, 3D accelerometers, gyroscopes and magnetometers enable complete motion capture, including the change in position as in orientation.

A number of available sensors enable data capture with high sample frequencies. This is a great benefit when capturing data of rapid movements.

B. *3D accelerometer*

A 3D accelerometer enables measurements of acceleration caused by gravity and self-accelerated motion along the three orthogonal sensitivity axes. As such, accelerometers have a number of applications in several fields.

The result of sensitivity to gravity is that when at rest, the accelerometer shows 1 g of acceleration directed upwards along the axis of sensitivity oriented along the direction normal to the horizontal surface. This makes it easy to determine the orientation with respect to the direction of the vector of gravitational acceleration in the accelerometer coordinate system. It is a necessary condition that the accelerometer is stationary or moving with negligible acceleration in relation to the gravitational acceleration.

Although the MEMS sensor technology is improving rapidly, MEMS accelerometers do not enable the estimation of the exact sensor position. When trying to estimate the orientation of an inaccurate sensor during its accelerated movement, the specific problems of correct gravitational acceleration estimation appear. Improperly deducted gravitational acceleration is reflected in an incorrectly determined motion direction of the accelerated sensor. Since the position data is obtained with double integration of acceleration, even small errors in the estimated direction of acceleration can cause a significant deviation of the calculated sensor position form its true position. Therefore, based on the measured acceleration, it is extremely difficult, if not impossible, to determine the exact position of a moving body.

Widely available low-cost and somewhat inaccurate MEMS accelerometers are hence primarily suitable for monitoring motion dynamics. Rather than determining the absolute values of the motion, when capturing motion dynamics we dedicate are attention to the relative changes, trying to create an effective framework for motion pattern identification.

C. 3D gyroscope

3D gyroscopes measure angular velocity in an inertial space and as accelerometers have a number of applications in many fields.

By providing angular velocity measurements, 3D gyroscopes are also used to determine orientation. In general, the orientation is treated as the position of the coordinate system of a rigid body observed relative to a reference coordinate system with the same origin. Orientation can be described using rotations needed to bring the coordinate system of a rigid body, initially aligned with the reference coordinate system, into its new position. In gyroscope measurements, the gyroscope is considered as the rigid body and inertial space coordinate system as the reference system. The measured angular velocity determines the rotation of the sensor to its new position.

Because the measured angular velocities represent simultaneous rotations, it is not appropriate to consider them sequentially. Rotations in general are not commutative, and each possible rotational sequence has a different resulting angular orientation. Three simultaneous angular velocities, measured with the gyroscope can hence not be considered to be sequential. There are six possible different sequences of rotations around three axes. Each of these six sequences determines a different angular orientation, none of which corresponds to the three simultaneous rotations result.

Angular velocities can be represented as vectors that are oriented along the direction of the axis of rotation, and their size corresponds to the size of the angular velocity. However, these vectors cannot be unreservedly treated in the same manner as normal vectors. In general, the sum of two angular velocity vectors in 3D space does not correspond to their rotational sum. For this reason, the angular velocity vectors cannot be regarded as Euclidean vectors. Hence, when analyzing data obtained with a 3D gyroscope it is necessary to provide for the correct interpretation of the obtained angular velocity data.

To obtain the correct angular orientation, it is appropriate to consider that every angular orientation can be represented by a single rotation. Vector SORA (Simultaneous Orthogonal Rotations Angle) [17, 18] is a rotation vector which has components that are equal to the angles of the three simultaneous rotations around the coordinate system axes. The orientation and magnitude of this vector are equal to the equivalent single rotation axis and angle, respectively. As long as the orientation of the actual rotation axis is constant, given the SORA, the angular orientation of a rigid body can be calculated in a single step, thus making it possible to avoid computing the iterative infinitesimal rotation approximation.

SORA is simple and well-suited for use in the real-time calculation of angular orientation based on angular velocity measurements derived using a gyroscope. Moreover, because of its simplicity, SORA can also be used in general angular orientation notation. Using the vector SORA provides for the correct interpretation of the values measured with the gyroscope. The measured values are equal to the projections of the measured angular velocity on the sensitivity axis of the gyroscope. This interpretation allows the applying of the general 3D sensor model to the 3D gyroscope.

D. 3D magnetometer

A 3D magnetometer provides for magnetic field measurements. As such, the 3D magnetometer can be a useful tool for determining orientation relative to the Earth’s magnetic field. However, due to disturbances in the magnetic field and the influence of motion on measurement error, 3D magnetometers are mostly used for intermediate motion phases when the sensor is at rest and not for capturing motion itself.

III. SENSOR CALIBRATION

When analyzing motion dynamics, just as in the case of absolute motion values estimation, accurate data are the basis for an effective and a comprehensive analysis. The accuracy of the captured data is essential for relevant and comparable results. The first step in motion data capture and analysis is hence sensor calibration.

According to the generally adapted model, the accuracy of the values measured with a 3D sensor is influenced by the accuracy of the sensor axis sensitivity, zero level offset and orientation. The sensitivity of the sensor is called the ratio of the measured change in value and the real change, assuming that the sensor characteristic is full-scale linear. Zero level offset is the sensor measurement output when the real measured value is equal to zero. For a 3D sensor, considering sensitivities and zero level offsets gives 6 calibration parameters.

Further on, because of the imprecise manufacturing, the orientation of the sensor sensitivity axis may deviate from the sensor coordinate axes. The orientation of the 3D sensor sensitivity axes in the sensor coordinate system is fully defined with 6 parameters.

The aim of different calibration procedures is to compensate for the measurement errors that arise because of the enlisted inaccuracies. According to the presented model, a total of 12 parameters are needed to be estimated. If the enlisted inaccuracies are time-invariant, the calibration parameters are constant and the calibration procedure is said to provide for static compensation. On the other hand, if the enlisted inaccuracies are time dependant, dynamic procedures have to be implemented and the calibration parameters are functions of time.

Because of their small dimensions, low weight and affordability, MEMS sensors allow a wide range of practical measurements that can be conducted by individuals who do not have any prior special training. Time, computation and cost consuming calibration diminish the feasibility of the widespread use of these sensors to some extent. Accounting for the above-mentioned considerations, it is necessary to provide for, in terms of lifetime and computational complexity, an efficient calibration procedure that does not require any additional expensive equipment and is suitable for everyday practical use.

For calibrating a 3D sensor a number of measurements are perform. The calibration parameters are estimated based on the known values and the measured values.

Most procedures for calibrating the 3D accelerometer exploit the fact that the value of the measured acceleration at rest is constant and equal to gravity acceleration. Measured data are obtained during different orientations of the sensor on a level surface.

For calibrating a 3D gyroscope, the sensor is usually rotated with known angular velocities around know axes. As the rotation axis remains constant, considering vector SORA, the measured angular velocity can be obtained by averaging the non-constant measured values during each calibration rotation. Considering this, it is possible to perform sensor calibration without the usage of special equipment that provide for constant rotation of the device.

To determine the zero level offset of the 3D gyroscope it is sufficient to carry out a single measurement while the gyroscope is at rest.

In the present general 3D sensor model, the influence of sensor noise is neglected. In practice present sensor noise causes errors in the estimated calibration parameters. It should be noted that for both sensors, the accelerometer and the gyroscope, the measured values can be obtained by averaging a large number of samples. When averaging, the power of noise declines with the number of samples. With a sufficient number of samples it is thus possible to achieve that the noise affecting the calibration is substantially less than the noise affecting each individual measurement. During accelerometer calibration, the sensor can be at rest an arbitrary long time. For a given value of the gyroscope calibration angular velocity, a greater number of samples results in a higher rotation angle.

IV. MOTION DATA SEGMENTATION

Measurements consisting noise are typical for the affordable kinematic sensors is use today. It is therefore necessary to implement an adequate filtering technique to reduce the influence of noise in the obtained raw data. Sensors supporting high sampling frequencies are advantageous for this purpose.

The obtained filtered and re-sampled data are the basis for motion segmentation, pattern recognition, classification and clustering. Procedures used for this purpose are the ones used for general matching and similarity determination in the field of time series analysis. A quality tutorial on this topic can be found in [19].

Motion segmentation refers to the process of identifying motion sequences in the collected time series data. It is achieved considering some similarity measure that is applied to the target and the query sequence.

Due to its simplicity and efficiency, the Euclidian distance is the most popular and common time series similarity measure. However, it requires that both sequences are of the same length. The measure itself is sensitive to distortions. In some time series, different subsequences can have different significance; a part of the series can be shifted or scaled in time; a part of the time series can be a subject to amplitude scaling. For this reason, the Euclidian distance is not always the optimal distance measure.

In general time series similarity determination, elastic distance measures like Dynamic Time Warping (DTW) and its derivates [19, 20], the Longest Common Subsequence (LCSS) [19, 21], and the Minimal Variance Matching (MVM) [21] can be implemented to solve the problem of time scaling.

DTW searches for the best alignment between two time series, attempting to minimize the distance between them [19]. DTW allows for dips and peaks alignment with their corresponding points from the other time series. DTW requires that each point of the query sequence is matched to each element of the target sequence.

LCSS finds subsequences of two time series that best correspond to each other. When used for time-series analysis, it finds a match between two observations whenever the difference between them is below a given threshold. LCSS allows skipping elements of both the query and the target sequence and as such solves the problem of outliers.

The MVM algorithm [21] computes the distance value between two time series directly based on the distances of corresponding elements. While LCSS optimizes over the length of the longest common subsequence, MVM directly optimizes the sum of distances of corresponding elements and does not require any distance threshold. MVM can skip some elements of the target series and is so used when the matching of the entire query sequence is of interest.

Elastic measures are in general more robust than the Euclidian distance but are computationally more intensive. Adaptations of DTW exist that upon implementation of certain constraints make the execution of the DTW and the Euclidian distance comparable.

Elastic measures adapt well when parts of the comparing time series have different time scale. However, their efficiency and reasonableness of their deployment for motion pattern recognition is yet to be fully investigated.

V. MOTION EVALUATION

A number of studies conducted so far have been focused on identifying motion patterns and enabling motion evaluation based on the analysis of individual motion parameters obtained using wearable motion sensors [8, 10-14]. Most studies aimed to identify different body postures are based on collecting data from sensors attached to the body and making distinction between standing, sitting and lying down. In such stationary examples, the gravitational acceleration projections on the sensors coordinate axes are relatively easy to identify. Recognition of walking periods and transitions between different body postures using a kinetic sensor attached to the chest [11] is intended for the ambulatory monitoring of physical activity in the elderly population. The kinematic sensor here combines a gyroscope and two accelerometers. The analysis is based on the wavelet transform.

A sensor including only a single gyroscope is shown to be efficient for measuring transitions between the sitting position standing [8]. Such a sensor is designed to assess the risk of falling in the elderly population.

A system for pedestrian navigation in [9] is based on the use of the gyroscope to identify the intervals of rest.

In a study [14] a comparative analysis of different techniques of classification human leg movement using individual parameters of the signals obtained with a pair of gyroscopes has been presented. The authors compare the results of different classification methods including Bayesian decision-making, decision trees, the least squares method, the k-nearest neighbors, Dynamic Time Warping, Support Vector Machines, and neural networks. The comparison is based on the parameters of the relationship distinction, data processing cost and the self-study requirement.

A comparative analysis of different human activities classification using sensors mounted on a moving body is presented in [10]. Human activities are classified using five sensor units mounted on the chest, shoulders and legs. Each sensor unit consists of a gyroscope, accelerometer and magnetometer. Characterizing parameters are excluded from the raw data using Principal Component Analysis (PCA).

Different studies also deal with the possibilities of the usage of wearable sensor devices for identification motion patterns in sports. In [15] authors investigate motion during the golf swing. The purpose of this study is to determine the repeatability of the kinematics of the chest and pelvis during the backswing for different swing recurrences, between different players, days and locations (open and closed driving range). The results of the analysis indicate a high degree of repeatability in different conditions.

In [16] a simple and practical detection of improper motion during the golf swing is presented. Here, individual swing motion is explored. Acceptable deviations, (i.e., those not having an effect on swing accuracy and consistency) from those leading to unsuccessful shots are differentiated using PCA. This enables the detection of an improper swing motion as illustrated in Figure 2. To accomplish this task, multiple swing motion data were captured using a single wearable motion sensor consisting of a 3D accelerometer and a 3D gyroscope. The analysis itself can be performed using an arbitrary component of the measured kinematic data, e.g. acceleration or angular velocity. Each swing observation is labeled according to its performance. Along with objective outcome evaluations, subjective marks provided by the golfer are also considered for the overall performance evaluation. Reflecting the overall feeling and easiness of swing motion, the subjective marks are very valuable when considering the player's individual swing characteristics.

The proposed method refers to a specific player, for his specific swing and with a specific club. According to this method, any portion of the golf swing (e.g., only the backswing) can be analyzed, which enables the detection of an improper motion in the early phases of the swing. With early improper motion detection, focus is given to the problem itself and not to the subsequent reactions.

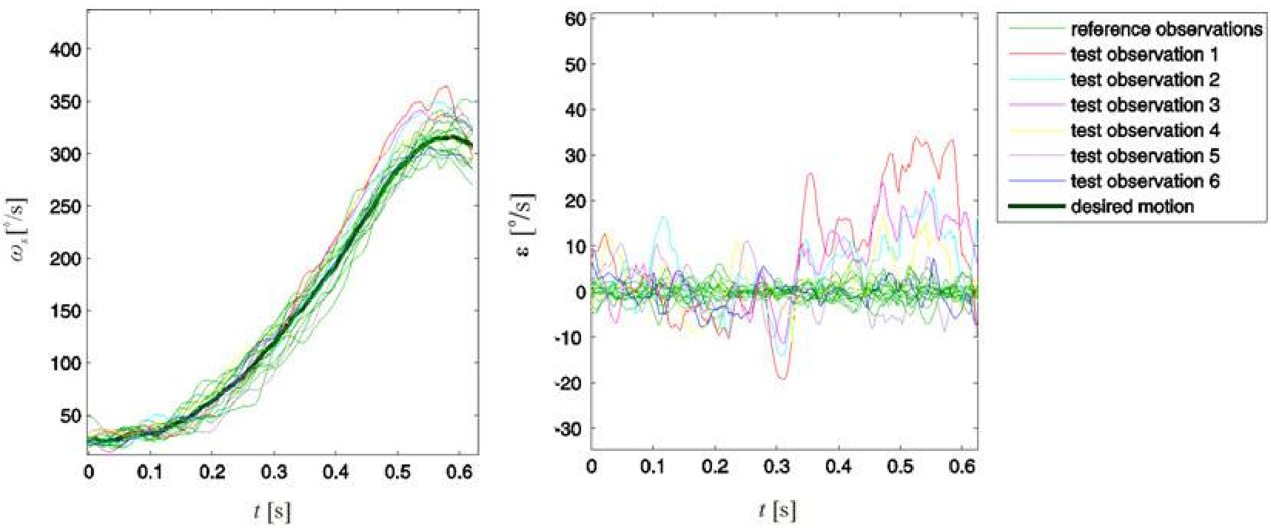

Figure 2. A demonstrative example of the efficiency of wearable motion sensors together with suitable analysis techniques for motion analysis: improper motion detection during the golf swing. The left panel shows different observations of the golfer's leading arm rotation around its intrinsic longitudinal axis during the first 0.625 s of the backswing. All reference observations refer to properly performed swings and are used to establish the acceptable deviations from the desired motion. The desired motion is obtained as the mean of the reference observations. Test observations 1-5 refer to an improperly performed swing, and 6 refers to a properly performed swing. Note that not all improper swing motions could be detected by directly comparing the test and reference observations. Test observations 1, 2, and 3 could eventually be detected. However, test observations 4 and 5, although referring to improperly performed swings, could not be distinguished from the reference observations. By showing the acceptable and test observation residual deviations in time domain, obtained using the PCA based procedure [16], the right side indicates errors in the performed swings. Acceptable deviations residuals represent deviations in properly performed swings attributed to noise and/or different artefacts. The deviation residuals for test observations 1-5, for which improper motion was detected, considerably exceed acceptable deviations residuals. Consistently positive values in the second half of the considered swing interval for test observations 1-4 indicate a typical improper motion in the associated swings.

VI. CONCLUSION

Wearable kinematic sensors cause minimal physical obstacles for motion performance. Together with proper data analysis techniques, these sensors provide for simple and practical motion analysis and evaluation.

It is possible to evaluate motion and detect improper motion in the early phases of its performance. This is essential for the offline improvement process.

Exploring the possibilities of developing biofeedback applications relying on early-phase improper motion detection for real-time motion supervision and training can motivate further study. If upgraded with sufficient processing power, wearable motion sensors can be used to perform well-designed real-time analysis of the collected data. If further equipped with adequate small and light hardware (for example, audio speakers), useful feedback applications could be enabled. Instantaneously providing feedback information and bringing it to consciousness could help to improve shot accuracy and consistency in real time. Providing efficient swing analysis and performance evaluation in real time and offering immediate information on the likely outcome of the performing motion could potentially transform the approach to instruction and practice.

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