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Abstract

This paper proposes a series of methods for representing changes in human motion during injury rehabilitation using Micro-Electro-Mechanical Systems (MEMS) inertial sensors. Tracking the changes over a recovery period requires methods for evaluating the similarity of movement in an impaired state against a non-impaired state. We investigate the use of motion analyses such as the centre of mass (COM) tipping distance, the variance of joint velocity eigenvalues and the cumulative state changes of Gaussian mixture models (GMM) for monitoring the symmetry between the left and right sides of body during rehabilitation exercises. The methods are tested on an injured athlete over 4 months of recovery from an ankle operation and validated by comparing the observed improvement to the variation among a group of uninjured subjects. The results indicate that gradual changes are detected in the motion symmetry, thus providing quantitative measures to aid clinical decisions.

Keywords

motor, human, rehabilitation, sensing, injury, inertial, symmetry, control

Disciplines

Engineering | Science and Technology Studies

Publication Details

M. Field, D. Stirling, M. Ros, Z. Stephen. Pan & F. Naghdy, "Inertial sensing for human motor control symmetry in injury rehabilitation," in 2013 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM), 2013, pp. 1470-1475.

Inertial Sensing for Human Motor Control Symmetry in Injury Rehabilitation

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Abstract—This paper proposes a series of methods for representing changes in human motion during injury rehabilitation using Micro-Electro-Mechanical Systems (MEMS) inertial sensors. Tracking the changes over a recovery period requires methods for evaluating the similarity of movement in an impaired state against a non-impaired state. We investigate the use of motion analyses such as the centre of mass (COM) tipping distance, the variance of joint velocity eigenvalues and the cumulative state changes of Gaussian mixture models (GMM) for monitoring the symmetry between the left and right sides of body during rehabilitation exercises. The methods are tested on an injured athlete over 4 months of recovery from an ankle operation and validated by comparing the observed improvement to the variation among a group of uninjured subjects. The results indicate that gradual changes are detected in the motion symmetry, thus providing quantitative measures to aid clinical decisions.

I. INTRODUCTION

Human movement assessments are a common practice in the physiotherapy of injured workers and athletes. Apart from the human-observer based posture analysis for prescribed exercises, associated clinicians such as physiotherapists are in need of quantitative measurement techniques to supplement their assessments. This is particularly important for insurance physicians who pass judgements on the physical work capability of long-term disability claimants. Variance among these assessments affects the recommended work activities for their clients, which in turn, affects the risk of further debilitating injuries, threatening workplace safety [1]. Similarly, sport related injuries are assessed before athletes may return to competition. The crucial decision to return is balancing the risk of aggravating the prior injury, hence, periodic assessments are conducted to judge an appropriate time to resume competitive sport. Recently, there has been increased interest in the use of sensors, such as MEMS accelerometers and gyroscopes, and computational methods to automate motion analysis, especially for repetitive exercises normally associated with rehabilitation.

We propose a system to objectively measure the similarity of human movements over a sequence of repetitive trials using inertial motion data. By representing the motion as a sequence of discrete postures, or motion primitives, from a Gaussian Mixture Model (GMM) the characteristic changes

in movement between trials can be quantified by variations in the sequence. Therefore a gradual change can not only be identified but also explained by examining the exchanged postures between iterations. Since the rehabilitation of leg injuries is often tested with repeated symmetrical challenges over the period of recovery, we correlate the condition of the injury with the ratio between accumulated motion primitive state changes in tests associated with each leg. Additionally, we compare this approach to an analysis of the centre of mass (COM) in relation to the ground contact polygon bounded by the position of the supporting foot and to the variance of the joint velocities in successive trials.

This paper outlines a pilot study testing the proposed methods to track an elite athlete during the rehabilitation phase after an ankle operation. The significance of the detected changes in movement throughout the recovery is evaluated by the typical variation in a control group. After establishing a set of exercises and features to monitor throughout the rehabilitation period an athlete and their trainer will be more informed on their progress with respect to the pre-injured state by wearing a set of inertial sensors.

The remainder of this section summarizes the related literature, Section II explains the methods of analysis and Section III describes the procedure and apparatus in the experiment. Section IV presents the results and analysis whereas Section V provides a discussion of the significance of the results and potential future improvements, while Section VI outlines the conclusions of the paper.

A. RELATED WORK

Rehabilitation studies and movement assessments are designed to estimate the physical limitations of a candidate or patient. The range of exercises prescribed for these tests depends on the location of an injury and the level of functional capability under assessment. Standardized tests have been proposed in physical work capability assessments involving a lifting evaluation [2] and in postural stability such as the Star Excursion Balance Test (SEBT) [3]. Despite the inherent problems of observer-based evaluations, direct investigations into the standardization of these evaluations have rarely employed an extensive use of motion sensors [4], [5].

Research into the quantification of rehabilitation progress from stroke or injury is widely studied with localized positioning of motion sensors [6]. Sensor systems have typically concentrated on high frequency optical tracking for precision

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and have had achieved success in measuring important health conditions such as cerebral palsy and Parkinsons disease [7], [8]. Increasingly, there has been interest in the use of MEMS accelerometers, as opposed to optical, due to a greater potential for the portability and deployment of data capture. As a consequence, a number of studies have measured the correspondence between optical and inertial sensing of posture to quantify any reduction in motion fidelity which may affect subsequent research with inertial sensors in the field [9], [10]. The classification of falls risk in the elderly is a highly active research area, in which MEMS accelerometers are often adopted to assess postural stability [11] due to the need for a pervasive sensing technology. Similarly, they are useful for the circumstances addressed in this paper, since clinicians will not be restricted to a specialized laboratory and can interact with a patient in a location of their choice with minimal interference with the sensors.

The representation dynamic human movement with multiple sensors is central to assessing the gradual change of motion over a repeated rehabilitation exercise. Although this has been extensively studied in the areas of computer animation, machine vision and human-robot interaction [12], it has been seldom extended into the analysis of rehabilitation. The closest investigations to those presented here also involve analyzing mixture models over multiple full-body motion capture recordings. In [13] a Factorial Hidden Markov Model (FHMM) was used on optical recordings of an athlete training for a marathon. The Kullback-Leibler divergence between a recorded motion and all previous training sessions was calculated to show a gradual change in the movement over the training period. In our previous work, a standard functional capacity assessment involving a multi-stage lifting task was analysed using the pattern of GMM state changes over the course of the test [5]. In this paper we show that gradual changes can be identified in a variety of ways and collect additional data from a group of control subjects to provide validation for the significance of the change.

II. EXPERIMENTAL SETUP

A. Procedure

A group of 14 subjects (10 male and 4 female) participated in the study, four of whom were athletes. Two of the athletes were nursing an injury, one of which was monitored with a series of exercises every 4 weeks during a 12 week period of rehabilitation and training after surgery on the right ankle, and the other was observed once at the beginning of their rehabilitation. The motion recorded for this subject included walking for 40 metres with eyes closed and balancing on a single leg for 20 second periods alternating between each leg and between keeping eyes open and closed. Each unique task was repeated up to 3 times per recording session.

In order to assess the significance of the change in motion across rehabilitation sessions two uninjured subjects were recorded performing the balance test in three sessions spaced over a similar time period. This estimates the typical variation between recordings for an average person. Finally,

the remaining 10 subjects performed one session of each balance test.

B. Apparatus

The data was recorded using a motion capture suit, MVN, from Xsens Technologies, which comprises a set of 17 MEMS inertial sensors to measure body posture [14]. Each sensor employs an Extended Kalman Filter to accurately estimate orientation of a body segment to within 2° degrees RMS [15] and are connected in a chain to a pair of Bluetooth 2.4GHz transmitters attached to the lower back of the subject as depicted in Figure 1a. The data is sampled at 120Hz by wireless receivers on a workstation within 50 metres of the transmitters and resolved into a 23 segment kinematic model of the body.

C. Motion Features

The motion features associated with the kinematics of the 23 segment body are summarized in Figure 1b, where a visualization of the 3D articulated body illustrates the location of the joints and the notation for describing the position and orientation of each body segment. The joint positions, x , are relative to a reference frame attached to the pelvis/L5-Sacrum, $\{1\}$, but the angular velocity, ω , is relative to previous body coordinate frame and expressed in pelvis frame. Each set of joint angles, θ , is also expressed with respect to the previous coordinate frame according to the hierarchy of connected joints.

For the analyses, joint angles are used to calculate the COM position, x_{c_i} , of the i^{th} body through forward kinematics and the velocity vectors, $\dot{x}$, were used to evaluate the variation in postures which ensures that a comparison of balance tests is independent of the specific posture a participant held.

Fig. 1. (a) The inertial sensor MTx (left) [14] and positioning of the sensors and wireless transmitters on the body (right) (b) Visualization of the motion capture features used in the analysis. The subject is undertaking single leg balance test.

III. METHODOLOGY

The approaches presented here for analyzing the change in motion during a rehabilitation period focus on exercises assessing balance and symmetrical movements.

A. Centre of Mass Tipping Distance

The stability of a multi-joint mechanical body depends on the location the COM and centre of pressure (COP) in relation to the ground supporting surface area. An approximation of the COM position can be made by calculating joint positions through forward kinematics and utilizing standardized measurements of body mass parameters, m_i , obtained from anthropometric data [16]. The position is given by,

$$x_{com} = \frac{\sum_i m_i x_{c_i}}{M}, \quad (1)$$

where x_{c_i} and m_i are the position in the global frame and mass of the i^{th} body segment respectively and M is the total mass of the body. Since the position and orientation of the foot in relation to the body is measured, a set of points (fixed in the foot body frame) encompassing the surface area of the foot define the boundary of the ground support area. In the absence of pressure sensors to detect the ground contact, the kinematic model uses foot accelerations to detect foot falls. Consequently a threshold on the height of the foot points determines which subset of points are in contact with the ground in the event of a foot being raised.

The convex hull of the contact points is referred to as the ground support polygon, as shown in Figure 2, enclosed by a set of normal vectors a_i . If concatenated as,

$$A = [a_1 \quad \cdots \quad a_j]^T, \quad (2)$$

the region is expressed as the set of points,

$$\{x | Ax \preceq b\}. \quad (3)$$

The body is statically stable if the centre of mass is located within this region. Therefore the minimum distance between the centre of mass, x_{com} , and an edge of the ground support, x^* , is indicative of risk of instability and can be expressed as a linear program,

$$\begin{aligned} &\text{minimize} \quad \|x_{com} - x\|, \\ &\text{subject to} \quad Ax \preceq b, \\ &\quad \quad \quad a_i x = b_i, \end{aligned} \quad (4)$$

where the second constraint requires equality for at least one of j polygon boundaries, $i \in \{1 \dots j\}$, and b is a set of j linear bias terms. The resultant distance is denoted $d = \|x_{com} - x^*\|$ and when x_{com} resides outside the polygon the sign is reversed.

Indeed for dynamic motion the condition that d remains positive is insufficient for stability. It has been shown that a dynamic stability condition can be ensured with the COP or the zero moment point (ZMP) and is extensively researched in legged robot locomotion [17].

Fig. 2. Illustration of the centre of mass tipping distance (black line) as the distance from the x_{com} (green) to the nearest edge (black) of the support polygon (grey region). The convex hull of all foot marker positions is shown by the dashed line and indicates how the ground support may change if the elevated foot (red points) was lowered. In this case the left foot (blue points) is contact with the ground.

B. Probability Density Variability

The objective of static balance tests may be considered as the minimizing the velocity of the joints especially those of the supporting leg. The variance of a particular feature would therefore indicate the relative success of a balance trial. A probability density function for x was estimated via,

$$f(x) = \frac{1}{N} \sum_{n=1}^N \frac{1}{(2\pi h^2)^{1/2}} \exp - \frac{\|x - x_n\|^2}{2h^2}, \quad (5)$$

where the heuristic $h = (\frac{4\sigma^5}{3N})^{1/5}$ determines the bandwidth of the function with the assumption of an underlying Gaussian distribution [18]. Although this estimation reveals a consistent change during rehabilitation in Figure 3 it is limited to the univariate case of the sagittal-axis at the knee joint. To compare this variability independent of the recruitment of different balance adjustments across recordings we selected joint velocities in the horizontal plane for the supporting leg, where $\dot{X}_L = [\dot{x}_{20} \quad \dot{x}_{21} \quad \dot{x}_{22}]$ are the joints for the left leg. The largest eigenvalue associated with $\dot{X}$ indicates the magnitude of the direction in which the largest adjustments are made. The symmetry of the balance test was thereby evaluated with the ratio of eigenvalues from the left and right leg tests.

C. Gaussian Mixture Model Cumulative Change

An extension to estimating the variance in velocity as a Gaussian distribution is to propose a Gaussian mixture approach. A GMM is used to estimate the probability density from T data points as a combination of a discrete set of K Gaussian distributions indexed by a latent binary matrix $z \in \{0, 1\}^{T \times K}$. The prior probability of component k is $p(z_k = 1) = \pi_k$ such that the probability of a data point x is given by

$$p(\mathbf{x}) = \sum_{k=1}^K \pi_k \mathcal{N}(x_t | \mu_k, \Sigma_k), \quad (6)$$

Fig. 3. Comparison of the joint probability density function using Eqn 5 in left and right foot balance for the Y-axis knee velocity over four sessions with the rehabilitating athlete.

where $\mathcal{N}(x|\mu, \Sigma)$ is a multivariate Gaussian distribution of mean μ and variance Σ . μ and Σ is estimated by the iterative Expectation Maximization algorithm. The number of clusters (K), however, is estimated by incorporating the Minimum Message Length (MML) criterion into a search algorithm which is based on a variation of the AutoClass algorithm [19].

After training a GMM the sequence of state transitions associated with a particular motion task may be estimated via posterior probabilities as

$$\tilde{z}_t = \underset{k}{\operatorname{argmax}} p(z_{tk} | x_t, \mu_k, \Sigma_k). \quad (7)$$

The resulting state vector summarizes the likely underlying sequence of Gaussian distributions. An example of $\tilde{z}$ is shown in Figure 4a of a walking motion where the repeated sequence of cluster activations represent key stages of a gait cycle, and 4b displays the message length for the search algorithm terminating at $K = 7$.

For this experiment, the joint linear velocities of the supporting leg were used to train a GMM. The resultant model is thereby composed of several Gaussian clusters that together explain all of the captured motions, and each cluster represents a postural state of the subject undergoing the set task. The cumulative sum of the state changes per exercise is indicative of the amount of work done by the motion and is used here to evaluate the quality of the balancing motion.

IV. RESULTS

A. Centre of Mass Tipping Distance

The COM tipping distance was applied to a walking motion of the recovering subject at the beginning of rehabilitation and at the end. Figure 5 displays the distance over time for each recording. The first session is clearly below zero less frequently than in the last session, which means x_{com} was outside the ground support polygon for a shorter duration in each gait cycle. Figure 6 shows the walking cycles of each session in greater detail. Immediate decreases in d correspond to the foot lift phase while an increase indicates

Fig. 4. (a) Maximum probability assignment of binary latent variables z for each time sample of a gait. A clear gait pattern is apparent in the sequence of activated mixture components. (b) Example minimum message length search result for selection of K .

the transition to a double support phase. The final session is marked by confident strides since x_{com} consistently resides further from the ground support at the extremities of the single leg phase whereas the first session suggests a safer gait.

Fig. 5. Centre of mass distance to ground support polygon, d , during a walking motion for session 1 (red) and session 4 (black) with the recovering athlete. The grey region indicates period shown in Figure 6.

Fig. 6. Centre of mass distance to ground supporting polygon for two walking cycles in sessions 1 (red) and 4 (black) with the recovering subject. Illustrations above each graph show the phase of gait and highlight the significance of the pattern.

B. Probability Density Variability

During a balancing task the velocity of the supporting frames control the placement of the COM and hence the stability of the body. The largest eigenvalue associated with the velocity of the hip, knee and ankle joints are shown on a symmetry graph in Figure 7 where the axes are the eigenvalues from balancing on the left and right leg in the same session. The expected ratio for uninjured subjects is unity (shown as a line for reference) with a small bias due

to a natural left or right leg preference. The injured athlete (shown in red) has a higher variance in the right leg balance for the first session, which is the same leg that had undergone surgery, and approaches unity on the subsequent trials. The second injured athlete (shown in green) displayed an even higher variance with the right leg balance test and is a clear outlier. Additional trials with this athlete is a topic of further investigation.

Fig. 7. (a) Symmetry of static single-leg balance using the largest eigenvalue of x and y-axis velocity features of the supporting leg where each data point is the result of one trial. The recovering athlete is marked in red and the markers are scaled in size from earliest (largest) to latest (smallest). A second injured athlete is marked in green. The remaining points are the control group (blue - male, orange - female). (b) Equivalently labelled symmetry graph for angular velocity.

C. Gaussian Mixture Model Cumulative Change

Since the goal of the static single leg balance task is to remain as stable as possible we assume the supporting leg has minimal velocity. Therefore the input data for the GMM here was the thigh, shank and foot velocity vectors. The cumulative state changes, with sufficiently sensitive states, are increasing linearly over time as depicted in Figure 8. For the injured athlete (Subject 1) it is clear that the gradient of the cumulative graph is significantly different for each balancing leg. The ratio between these gradients approaches unity over the subsequent sessions. In Figure 9, the difference between the gradients is normalized such that the relative difference between the left and right leg, per recording session, is visualized. Therefore a large positive value corresponds to a higher gradient in state changes for the right leg compared to the left. For the two uninjured subjects, the relative difference of state changes between leg balance sessions is small compared to the initial sessions of the recovering athlete, which suggests this measure is detecting more significant changes than the normal variation between sessions.

V. DISCUSSION

Monitoring the rehabilitation of injured athletes using the methods presented in this paper indicates a progression in the fitness state compared to uninjured subjects. To validate the measures, however, further investigation is required into the most appropriate exercises to prescribe in order to classify motion quality. For example, the static single leg balance test

Fig. 8. GMM Cumulative state transition graph for the single leg balance using linear velocity data. Subject 1 (top) was injured and recovered over 4 sessions, while Subject 2 and 3 had suffered no injury. Each graph is displayed with a dashed line showing the gradient of cumulative state changes.

is a simple exercise which may only challenge a recovering athlete in the initial phases of rehabilitation. The difficulty resides in the range of motion available to a recovering athlete. Attempting exercises that one would use to train at peak fitness may cause further injury thereby restricting the set of exercises available for comparison across the entire recovery period. A range of dynamic tests which challenge the athlete to different levels throughout the recovery may be required to ensure the practicality of these monitoring methods. To record challenges to subjects throughout a rehabilitation data collection must be more frequent than the procedure in this work. As additional data is collected displaying the effects of

Fig. 9. Difference in the rate of GMM state changes ($R - L$). Positive values indicate a higher rate of change for the right leg. For the rehabilitation subject the sessions are ordered from the first (top) to the fourth.

particular injuries on standard exercises, it becomes feasible to validate a classification system based on the presented metrics.

The sensor location is designed for full-body motion capture and the centre of mass calculation. However, for the analyses utilizing the balancing leg velocities, namely the eigenvalue analysis and GMM, only 7 sensors are required. The deployment of a subset of sensors simplifies the data collection process and would permit a higher participation providing greater potential for long-term monitoring and classification.

Using the COM tipping distance one can evaluate the risk of a fall while maintaining a static posture. For a precise evaluation of stability in dynamic motion the COP is typically measured with either foot mounted pressure sensors or a force plate. In the absence of pressure sensors the COP can be calculated through another relation, the zero moment point (ZMP), which equates to COP on even surfaces and converges to the COM in static conditions [17]. Extending the analyses to COP-ZMP may help to elucidate changes in more challenging rehabilitation exercises.

VI. CONCLUSION

This paper investigates computational methods for tracking the rehabilitation of injuries using data measured from MEMS inertial sensors. The three methods proposed were based on the distance from the centre of mass of the body to the ground support polygon edge, the largest eigenvalue associated with the joint velocities of the supporting leg and the rate of state changes in a GMM of the joint velocities. Through an examination of the symmetry between the legs using these indicators it was clear that significant changes are detected for an injured subject compared to repeated measurements of a control subject. The experimental results demonstrate that MEMS sensors in combination with the metrics presented have potential for applications in rehabilitation and medical diagnosis. Further development and validation of these invariant metrics is the focus of ongoing research.

ACKNOWLEDGMENT

The authors wish to acknowledge the assistance of the St. George Illawarra Dragons High Performance Unit.

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