Human Motion Identification for Rehabilitation Exercise Assessment of Knee Osteoarthritis

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Abstract

Osteoarthritis (OA) is one of the majority of chronic lower limb musculoskeletal conditions, affecting approximately 15% of the population. Rehabilitation exercise has been considered as a common and essential medical treatment for mild to moderate stages of knee OA. However, there are some issues and challenges should be tackled while OA patient performs rehabilitation exercise without supervision of therapist, such as improperly implement rehabilitation exercise and patient adherence. The objective of this study is to propose a machine learning-based human motion identification system to automatically classify rehabilitation types and the motion states. The overall accuracy for types recognition is 100% and for motion identification is 97.7%. The results show that the feasibility of the proposed human motion identification algorithm for home-based rehabilitation.

Key words: machine learning, human motion identification, wearable sensor.

Introduction

Osteoarthritis (OA) is one of the majority of chronic lower limb musculoskeletal conditions, affecting approximately 15% of the population [1]. The prevalence of OA is projected to double by the year 2020 due to an ageing population and an ever-increasing prevalence of obesity [2]. The previous study also shows that OA is the leading cause of lower extremity disability amongst older adults with an estimated lifetime risk for knee OA being approximately 40% in men and 47% in women [2]. Knee joint not only bears the most weight of the human body [3], but also is the site of predilection for degenerative OA, affecting cartilage primarily. Some risk factors for OA include overweight, increased age, joint damage, joint structure abnormalities, defects in articular cartilage genetic defects, joint stress due to work or exercise.

Rehabilitation exercise has been considered as a common and essential medical treatment for mild to moderate stages of knee OA [4]. OA patient performs rehabilitation exercise, and supervised by physical therapist in medical center for about 6 weeks. Then, OA patient is given with instruction to execute rehabilitation exercise at home [5]. However, there are some issues and challenges should be tackled while OA patient performs rehabilitation exercise without supervision of therapist. For example, OA patient may improperly implement rehabilitation exercise, improper alignment during rehabilitation exercise, which may slow down the recovery progress or intensify unnecessary load joint. The previous study also shows that patient adherence is another challenge, which influence the progression of rehabilitation exercise. Up to 65% of patients are non-adherent or only partially adherent to their rehabilitation exercise programs, and over 10% fails to complete their programs [5]. Therefore, it is essential to develop an OA rehabilitation exercise assessment system to assist patient correctly execute rehabilitation exercise, especially in recent years, the demand for more effective medical care and the quality of health care has led to an increase in the importance of the home-based rehabilitation.

With the progress of the microelectromechanical systems (MEMS) and the popularity of the wireless network (WSN), various rehabilitation assessment systems based pervasive computing and technology have been developed for home-based rehabilitation. Such rehabilitation assessment system has the potential to provide the objective, successive and unobstructive information during rehabilitation progress for physical therapist and patients [6 7].The objective of this study is to propose a machine learning-based human motion identification system to automatically classify rehabilitation types and the motion states.

Related work

Vision sensor is one of the general sensor types to develop a rehabilitation assessment system. For example, Schmitz et al. [8] used Kinect camera to measure unlabeled joint angles. Depth of field and image data were output by Kinect. Joint angles were calculated using continuous body rotation and motion capture system marker data filtered trajectories of the marker clusters were used to compute the orientation of the distal segment relative to the proximal segment using Cardan angles. Wenbing Zhao, et al. [9] used Kinect sensor approach to real-time motion assessment for rehabilitation exercises based on the integration of comprehensive kinematic modeling with fuzzy inference in different exercise

Wearable sensors such as tri-axial accelerometers (TAs) and gyroscope meters have been widely used to detect and capture human motion. Taylor et al [5] proposes using 5 TAs mounted on the waist, thigh and shin of both legs to assess exercise quality by building a classifier that labels incorrect exercises. Giggins et al. [10] used 3 TAs wear on thigh, shank, and foot for a cross-sectional analysis study. The author extracted nine features from acceleration to classification, and used logistic regression to determine whether the correct action or not. Furthermore, the Multi-Label Classification algorithm is utilized for the incorrect action to identify the error label of incorrect action. The overall correct classification accuracy rate of 81% and error label classification accuracy up to 63%.

The process to identify interesting human motion from continuous sensing data is one of the challenges for home rehabilitation assessment system. Lin et al. [11] extends the HMM (hidden markov model) by combining aggregated velocity zero-crossing technique and template-based HMM to provide better segmentation accuracy in case of higher dimensional data with large number of degrees of-freedom (DoF) However, existing probabilistic models only provide

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limited accuracy for rehabilitation exercise segmentation due to their lack of sensitivity in repetitive movements.

A general research is to depends on known motion to assist in the identification of motions. However, it is difficult to directly observing data from temporal and spatial variability. Dynamic time warping (DTW) is an example of a template-based method. DTW [12], [13] identifies the temporal variations between the observed data and the motion template by selectively warping the time scale of an observation sequence to the template.

Materials and Method

The architecture of human motion identification system is proposed in this paper, as shown in Figure 1. Raw data acquired from two inertial sensors are through pre-processed denoise, and extract acceleration signals frame of gravity. Afterwards, signals frame from inertial sensors are used to calculate tilt angle, and transformed into knee angle. Finally, the information of rehabilitation type and motion state information can be obtained with the rehabilitation type recognition and motion state identification.

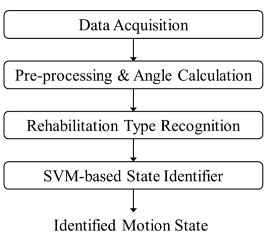
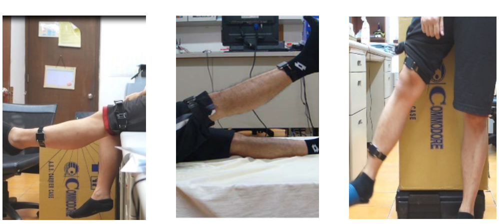


Figure 1. The overview of human motion identification system.

As shown in Figure 2, there are three types of lower-body rehabilitation exercises in this study, including Hip Abduction, Straight Leg Raise (SLR) and Seating Knee Extension. These rehabilitation exercises were studied as they are commonly prescribed to patients following a lower limb injury or surgery [14]. There are 4 subject (170cm in average height and 71kg in body average weight) asked to perform 3 sessions for the mentioned above types rehabilitation exercise, and the resting interval between sessions is 5 minute. According to the recommendations of physiotherapy textbook, a session contains 10 sets [15], where a set is composed of 4 motion states including rising (2-3 seconds) and holding duration (5-6 seconds) then slowly dropping (2-3 seconds) last is resting duration (5-6 seconds), the total 30 sets for each rehabilitation exercise.



(a) (b) (c)

Figure 2. Demonstrations of 3 types of lower body suggested by physiotherapists for knee OA rehabilitation. Signals are recorded via body-mounted wearable sensors (a) seating knee extension. (b) Straight leg raise (c) Hip abduction

A. Data acquisition

For this work, data is recorded using two Opal inertial measurement units (wireless 9DoF APDM Inc., Portland, OR), and mounted on the thigh (T) and shank (S). The sensors measurement range and sampling frequency is ±6 G and 64Hz respectively. For each sensor, only 6-axis signals (acceleration and angular velocity value) were considered to wirelessly transmit to the receiver (Access Point), which is connected to the computer through by USB. The Motion Studio is employed for data collection and sensor calibration, and the identification algorithm is developed on MATLAB R2016a.

B. Data Pre-processing & angle calculation

In order to reduce the undesirable noise like high frequency noise, and the time drift which might cause by the elastic vibration from fastening sensors, pre-processing is the important process of the human motion identification system to solve the problem. Therefore, the raw data is filtered by 5th order low-pass Butterworth filter with cutoff frequency 0. 6Hz.Then, the pre-processed data is transformed into two types of angle, Euler angle and joint angle.

Firstly, the Euler angles, pitch of thigh and roll of shank obtained according the equation (1) and (2), which represent the wearable sensors signal in different posture angle value respectively, and providing sufficient information to in different rehabilitation types recognition.

$$\rho = \tan^{-1}\frac{a_{Tx}}{\sqrt{{a_{Ty}}^2 + {a_{Tz}}^2}} \tag{1}$$

$$\varphi = \tan^{-1}\frac{a_{Sy}}{\sqrt{{a_{Sx}}^2 + {a_{Sz}}^2}} \tag{2}$$

Where a_{Tx}, a_{Ty} a_{Tz} and a_{Sx}, a_{Sy} a_{Sz} represent the thigh and shank sensor tri-axial components of the gravitational acceleration respectively.

Secondly the approach to gather the joint angle is based on Takeda et al [16], which is utilized to eliminate the acceleration components from accelerometer and keeps the gravitational components to calculate the inclination variation angles during rehabilitation exercise. Gyroscope signals are utilized to estimate the angular acceleration in each rehabilitation exercise considering the orientation of the segments is essential for the rehabilitation exercise assessment. As the sensor can measure the gravitational acceleration, the output of the thigh segment O_T can be expressed as:

$$O_T = a_T - g_T \tag{3}$$

Where a_T is the translational acceleration and g_T is the gravitational acceleration, and the calculations for the thigh segment can be divided into translational motion and rotational motion which can be expressed using the following equation:

$$a_T = a_K - \ddot{r}_{KT} \tag{4}$$

Where a_K is the acceleration at knee joint, $\ddot{r}_{KT}$ is the angular acceleration from thigh segment to knee joint. The angular acceleration can be divided into two components, the centripetal acceleration (${\omega_T}^2 \times r_{KT}$) and tangential acceleration ($\dot{\omega}_T \times r_{KT}$), which can be expressed as:

$$\ddot{r}_{KT} = \dot{\omega}_T \times r_{KT} + {\omega_T}^2 \times r_{KT} \tag{5}$$

The acceleration and angular velocity data from the thigh and the shank are used to estimate the knee flexion and extension.

As shown in the following Figure 3. θ_1 is the inclination angle of $a_K - g$ in relation to the thigh segment and θ_2 is the inclination angle of $a_K - g$ in relation to the shank segment.

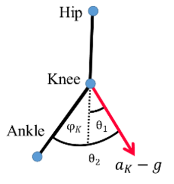


Figure 3 Measurement arrangements for hip and knee joint angles of the leg

The values of θ_1 and $\theta_2$can be calculated by the following equations in [16]:

$$\theta_1 = \tan^{-1}\frac{|O_T - \ddot{r}_{KT}|_z}{|O_T - \ddot{r}_{KT}|_x} \tag{6}$$

$$\theta_2 = \tan^{-1}\frac{|O_T - \ddot{r}_{KT}|_x}{|O_T - \ddot{r}_{KT}|_z} \tag{7}$$

Knee joint flexion-extension angle φ_K can be obtained by the difference between θ_2 and θ_1 .The values of φ_K can be calculated by the following equations

$$\varphi_K = \theta_2 - \theta_1 \tag{8}$$

C. *Threshold-based rehabilitation type recognition*

In the rehabilitation type recognition, the duration of the preparatory posture before the sessions beginning are utilized to recognize the main type of the rehabilitation exercise.

The three types of the rehabilitation exercises have different characteristic in preparatory posture. For example, preparatory posture of the sitting keen extension, straight knee extension, and hip abduction are sitting, lying, and standing. Therefore, the threshold-based rehabilitation type recognition is utilized to initial few window frames including preparatory posture duration are utilized with appropriate threshold, as shown in Figure 4.

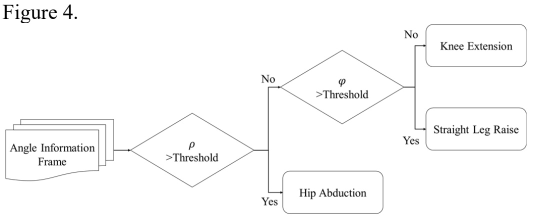


Figure 4. Illustration of threshold-based rehabilitation type recognition.ρ is the calculated Euler angle of wearable sensors on thigh X axis, similarly φ is Euler angle of shank y axis and the threshold is the degree value design for recognition the preparatory posture.

For example: If the ρ angle information frames value is larger than the threshold, the rehabilitation type recognition determine the preparatory posture is standing, and regard as after the readiness time participant will execute the rehabilitation type for hip abduction.

D. *SVM-based motion identification algorithm*

SVM is considered as a very competitive choice due to its ability to recognize certain features. Coimbatore et al. [17] demonstrates the power of SVM in Electroencephalography (EEG) signals classification. Zhou et al. [18] combines SVM with High-Order Cumulants to reach better performance of signal classification. Features based on High-Order Cumulants are extracted and normalized to train an RBF-SVM. The use of High-Order Cumulants is effective in removing the influence of Gauss noise, while RBF-SVM ignores however high dimension the sample is, granting reliably high classification accuracy.

Overall, SVM serves very well in solving problems with various dimensions, and is extremely easy to implement, making it a promising tool on this topic.

The human motion identification algorithm of this work is implemented based on SVM. In the training phase, training data will be separated into two categories based on ground truth label information and training data are divided by a hyperplane with the margins that are as wide as possible. In the testing phase, the trained identification model which identify testing data. Furthermore, binary identification can extend to multi-class identifier with more than two categories. There are two approaching types for multi-class SVM. One is combining several binary identifiers, and the other is considering all training data in one optimization formulation [16].

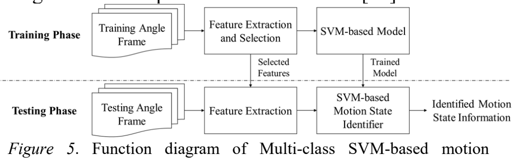


Figure 5. Function diagram of Multi-class SVM-based motion identification

In this work, we implement multi-class SVM method to create the multi-class identifier for four motion states using the one-versus-one design, where the kernel function is linear type. To train and test the identifier, the following features are extracted from each of the available angle frames, including signal mean, standard deviation, skewness, kurtosis, signal energy, level crossing rate, signal range, 25 percentiles, and 75 percentiles.

Sequential forward feature selection (SFS) proposed by Whitney [19] in 1971 is one of the commonly used heuristic methods for feature selection. In SFS, the feature is selected one by one for chosen the best performance of combination until enough number of features, or the recognition rate is good enough. The 10-fold cross validation is used to evaluate feature selection. Such cross-validation approach can assist us to realize the causal relationship between identifier es and features.

E. *Performance evaluation criteria*

True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN) is utilized to evaluate the proposed identification model. Accuracy, sensitivity, specificity and the f-measure rate, as shown in the equations (9) to (13). Accuracy measures the overall effectiveness of the identifier by computed the ground truth information and the predicted result with correct ratio. Sensitivity measures the overall effectiveness of the identifier at desired label and the specificity measures the identifier ability to identify the

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negative labels [20]

$$\text{ACCURACY} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{9}$$

$$\text{PRECISION} = \frac{\text{TP}}{\text{TN+FP}} \tag{10}$$

$$\text{SEPCIFICITY} = \frac{\text{TN}}{\text{TN+FP}} \tag{11}$$

$$\text{SENSITIVITY} = \frac{\text{TP}}{\text{TN+FP}} \tag{12}$$

$$\text{F-measure} = \frac{2\times\text{sensitivity}\times\text{precision}}{\text{sensitivity} + \text{precision}} \tag{13}$$

Result and Discussion

The performance of the proposed motion state identification for three rehabilitation exercises is presented in table I. Table I presents the overall average efficacy scores such as Accuracy, Sensitivity, Specificity, and F-measure for each motion states obtained using SVM-based identification for each rehabilitation exercise types.

Table I. The identification performance rate of each rehabilitation exercise

	Straight Leg Raise	Knee Extension	Hip Abduction
Accuracy	97.66%	97.25%	98.27%
Sensitivity	99.07%	96.33%	98.17%
Specificity	94.48%	98.11%	98.41%
F-measure	98.32%	97.38%	98.47%

The result of SVM-based motion state identification is shown in the figure 6, a set of knee extension was asked to execute by participant. The signals were transformed into joint angle information then extracted features and tested by the identifier.

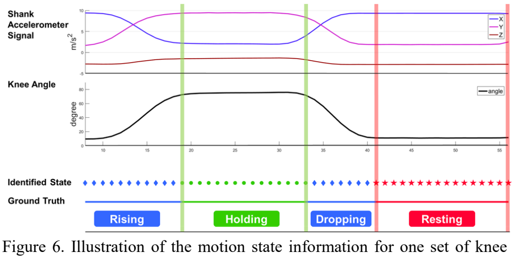

Figure 6. Illustration of the motion state information for one set of knee extension

As the figure 6 shown, there is no FP and FN in this testing set, the identified state is consistent with the ground truth. The overall accuracy for types recognition is 100% and for motion identification is 97.7%. The results show that the motion identification accuracy for knee extension is the lowest since there are more motion vibration as the transition from the shank segment in rising to holding and the holding to dropping.

Conclusion

In this paper, we proposed a machine learning-based human motion identification algorithm to automatically classify rehabilitation types and identify the four motion states. The results show that the feasibility of the proposed human motion identification algorithm for home-based rehabilitation.

The future work will include collecting more testing data set from patients and add another rehabilitation types to enhance the algorithm identify different rehabilitation exercise types.

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