Title	The limb movement analysis of rehabilitation exercises using wearable inertial sensors
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Publication date	2016-08-20
Publication information	Huang, Bingquan, Oonagh M. Giggins, Tahar Kechadi, and Brian Caulfield. “The Limb Movement Analysis of Rehabilitation Exercises Using Wearable Inertial Sensors.” IEEE, 2016.
Conference details	2016 IEEE 38th Annual Conference on Engineering in Medicine and Biology Society, Orlando, Florida, USA, 16-20 August 2016
Publisher	IEEE
Item record/more information	http://hdl.handle.net/10197/8225
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Publisher's version (DOI)	10.1109/EMBC.2016.7591773

The Limb Movement Analysis of Rehabilitation Exercises using Wearable Inertial Sensors

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***Abstract*— Due to no supervision of a therapist in home based exercise programs, inertial sensor based feedback systems which can accurately assess movement repetitions are urgently required. The synchronicity and the degrees of freedom both show that one movement might resemble another movement signal which is mixed in with another not precisely defined movement. Therefore, the data and feature selections are important for movement analysis. This paper explores the data and feature selection for the limb movement analysis of rehabilitation exercises. The results highlight that the classification accuracy is very sensitive to the mount location of the sensors. The results show that the use of 2 or 3 sensor units, the combination of acceleration and gyroscope data, and the feature sets combined by the statistical feature set with another type of feature, can significantly improve the classification accuracy rates. The results illustrate that acceleration data is more effective than gyroscope data for most of the movement analysis.**

I. Introduction

Exercise therapy plays an important role in physical rehabilitation, allowing a patient to develop, maintain and restore body movement and function after injury or surgery. Typically a physical therapy session includes an assessment of the patient, followed by the performance of physical exercises as prescribed by a physical therapist/rehabilitation specialist, based on severity of condition and the symptoms involved. With the worlds increasing population, and the increasing prevalence of chronic lower limb musculoskeletal conditions such as arthritis [2], it is becoming more and more difficult to meet the demands for physical therapy. Thus home-based exercise therapy has been considered to meet these demands.

Recently, inertial sensor based technologies have emerged as one of the dominant approaches to aid home exercise therapy. Inertial sensors combined with software that can be worn throughout a training session are used to analyse the motions and send feedback to patients [10]. Due to no supervision by any therapist in home based exercise programs, the techniques which can accurate assess movement repetitions and fast provide the feedback to patients are urgently required.

The classification of human movements is extremely challenging due to the following 4 main factors: 1) synchronicity of movements, 2) degrees of freedom (DoF) for each movement [12], 3) variability of different repetitions of the same exercise by the same subject and 4) variability of different subjects (e.g. age, gender, height, and weight) [6]. The synchronicity and the DoF can make the analysis process complex. The synchronicity and the degrees of freedom both show that one movement might resemble another movement signal which is mixed in with another not precisely defined movement. Therefore, a number of DoFs from the different sensors have to be considered to analyse the movements in exercises. Also the effective attributes (called features) have to be considered to address movements from those DoFs. So the data and feature selection in the analyse process are very important for the system performances in terms of assessment accuracy, computational overhead and memory usage.

Many studies have focused on the inertial sensor based movement classification for rehabilitation exercise [7], [9]. In the previous work, most of the researchers used the accelerators and gyroscopes information to extract time and frequency domain features, then used machine learning algorithms to analyse the movements [3], [13], [4]. Based on a number of body-worn tri-axial accelerometers, Taylor [13] extracted the mean, minimum and maximum as features, then he used a multi-classifier to assess exercise quality. In [4], [8], time/frequency domain features (e.g, skew, wavelet coefficients, mean, variances) were extracted, based on the acceleration and gyroscope data. Zhang [14] only used acceleration data to extract the peak values as features to assess the movements.

Most of the previous works does not provide the detail of the comparison between acceleration and gyroscopes data, and does not evaluate the features and their combination for the movement analysis of rehabilitation exercises. This paper evaluates the effect of DoF data, and evaluates different types of features and their combination for the movement analysis of rehabilitation exercises. Results provide useful information about the clinical application of wearable inertial sensors for rehabilitation exercises.

II. Methodology

A. Dataset Collection

The clinical dataset used in this paper is a record set of seven different lower limb rehabilitation exercises of 69 participants. The protocol of these exercises was approved by the Human Research Ethics Committee in University College Dublin.

The seven exercises are the heel slide (HS), the standing hip abduction (SHA), the standing hip extension (SHE), the standing hip flexion (SHF), the inner range quadriceps (IRQ), seated active knee extension (SAKE) and the straight leg raise (SLR) exercises. Participants performed ten repetitions of each of the seven studied lower limb exercises. Three of these exercises were performed in a standing position (SHA, SHE and SHF), one exercise was performed in a seated position on a standardised chair (SAKE), and three exercises were performed while lying supine on a plinth (HS, SLR and IRQ). According to the extended deviations of movements, the movement trials can be categorised into a number of classes (See the Table I). The detail of these exercises can be found in [4].

In the dataset, 69 participants performed the lower limb exercises, including 38 males and 31 females. The ranges of participant's age, height and weight are 43.5±23.5 years, 1.715±0.195m and 77±47.0 kg, respectively.

The devices used for data collection were three inertial sensor units (Wireless 9DoF IMU Sensor, Shimmer, Dublin, Ireland). They were mounted on the thigh (T), shin (S), and the foot (F) of a participant to gather signal data. The orientation and positioning of each sensor were kept consistent across all measurement sessions. With a dimension of 5.3cm× 3.2cm × 1.5cm and weight of 15 grams, these inertial sensors are unobtrusive, permitting unhindered subject movement.

Each of the employed sensors contained both a tri-axial accelerometer and a tri-axial gyroscope sampling at 100 Hz. The Shimmer 9DoF Calibration Application v1.0 was used to calibrate the accelerometer and gyroscope sensors of each sensor unit prior to the start of data collection. The Multi Shimmer Sync application for Windows was used to capture synchronised inertial sensor data over Bluetooth from the three sensors during each of the exercises. The raw inertial sensor data captured were saved onto a hard-drive.

TABLE I: The classes of movements

Exercises	Classes
HS	Normal
	Excessive Hip External Rotation
SLR	Normal
	Excessive Knee Flexion
	Excessive Ankle Plantarflexion
IRQ	Normal
	Excessive Plantarflexion
	Excessive Hip Flexion (Thigh Lifts)
SAKE	Normal
	Reduced Knee Extension ROM
SHA	Normal
	Trunk Lateral Flexion (To Contralateral side)
	Excessive Hip Flexion
SHF	Normal
	Excessive Trunk Flexion
SHE	Normal
	Trunk Forward Flexion
	Excessive Knee Flexion"

B. Methods

The movement analysis system in this paper for rehabilitation exercises consists of the preprocessing, segmentation, feature extraction and classification processes. They are described in the following.

1) Preprocessing: When obtaining kinematics data from the sensors, the preprocessing process reduces the undesired noise (referring to drift and high frequency components) and generates acceleration magnitude, pitch and roll information. The high frequency noise is the elastic vibration in the fasteners used to mount the markers to the limb. The drift noise is the long term variation of baselines. The high frequency noise can be reduced by passing a specified order low-pass Butterworth with the normalised cutoff frequency for kinematics data. Because the initial signal which indicates that no movement occurs, we subtract its dimensional values from velocity and displacement data. Beside the six distinct DoFs (namely acceleration X, Y and Z, and gyroscope X, Y and Z), three additional DoFs were calculated; namely overall acceleration magnitude, pitch and roll. 9 distinct DoFs were available all together for one sensor.

The 5th and 4th orders of Butterworth filters with -1 dB ripple were used to reduce the noise in the acceleration and oriented data respectively. The lower cutoff frequency of low-pass Butterworth filters for x-axial, y-axial, z-axial gyroscope data from the sensor mounted on any place is $\frac{1}{0.04}$ Hz. The lower cutoff frequencies of low-pass Butterworth filters for x-axial, y-axial, z-axial acceleration data are: $\frac{1}{0.04}$ Hz and $\frac{1}{0.02}$ Hz for the thigh and shin/foot respectively.

2) Segmentation: After reducing the noise, the analysis system employs the fast template matching segmentation algorithm to identify each movement repetition trial in the time series data of a sensor. The segmentation algorithm first extracts the zero velocity points as the candidate segment points, based on the different DoFs. Then the algorithm classifies and combines the segments in such a way to detect the trunks of movements. Simultaneously, the segmentation algorithm adapts the classifier (Very Fast Decision Tree [11]) by recently obtained segment samples to accommodate the new environment. Finally, the segmentation algorithm finds the movement edges by comparing the velocity magnitudes of movement trunks to the ones of the trunks neighbours.

3) Feature Extraction: Once a movement repetition is obtained, the system extracts a number of features for each DoF. These features are the statistical features, information-theoretic features, frequency features and time-frequency features. The 10 statistical features include the mean, standard deviation, skewness, kurtosis, maximum, minimum, range, 25th percentile, 75th percentile and cross-correlation. The frequency features are the 16 coefficients of the fast Fourier transform. The time-frequency features are the 32 wavelet coefficients using the Daubechies 6 mother wavelet with level 5. The information-theoretic features are the Lempel-Ziv complexity, cross-entropy and entropy rates. The procedure of information-theoretic feature extraction for each DoF is : 1) use the sliding window segmentation algorithm [5] with a threshold error to segment the signal series into a number of segments, 2) use the K-means algorithm to cluster the segments in such a way to discretise the data, and 3) use the cluster output (discrete data) to extract the information-theoretic features. Thus, 58 features were extracted for each of nine available DoFs, and 58×9 features were obtained for per sensor unit.

4) Classification: After obtaining the features of an observation movement trial, the classification is carried out by two main steps: 1) classify this observation (as normal or defect movement, and 2) if the observation is identified as a defect trial, predict what kind of defect movement it is. As mentioned above, this paper mainly focuses on data and feature selection for repetition movement classification of rehabilitation exercises. Therefore, we first use the acceleration data, gyroscope data and their combination to extract features and classify the movement trials. Secondly, we use a number of different feature combination subsets to classify the movements. Simultaneously, three types of sensor combinations were used to classify the movements, including one single sensor mounted on different locations, the combination of two sensors mounted on different locations and the combination of three sensors.

For each feature set, the movement classifications included 1) the classification between normal and defect movements, and 2) the classification of defect movements if the movements were classified as the defects. Logistic Regressions (LR), Decision Trees C4.5 (DT), Multilayer Perceptron Neural Networks (MLP), Support Vector Machines (SVM), Random Forest (RF) and Adaboost modelling algorithms were applied to classify the movements of rehabilitation exercises. The 5-fold cross-validation was used to evaluate each classification model.

TABLE II: The effect of mount locations of sensors for each exercise, the best locations are highlighted when using all of features

		1 sernsor					2 sernsors					3 sernsors				
Cl.	Exe.	Loc.	ACC	TP	TN	AUC	Loc.	Accu.	TP	TN	AUC	Loc.	ACC	TP	TN	AUC
Normal VS. Defect	HS	F	90.27	88.51	92.06	93.74	SF	96.12	94.98	97.27	97.47					
		S	94	92.44	95.59	96.39	TF	94.03	92.42	95.68	95.36	TSF	97.06	97.15	95.84	98.31
		T	90.62	89.14	92.13	92.98	TS	94.8	93.5	96.13	95.79					
	IRQ	S	68.62	37.76	83.63	69.22	SF	83.03	69.19	89.77	83.82					
		F	76.86	55.44	87.27	78.56	TF	86.21	76.42	90.98	87.05	TSF	87.91	89.35	81.62	90.97
		T	66.56	42.27	78.37	67.19	TS	78.74	60.93	87.4	78.46					
	SAKE	F	81.17	81.02	81.32	86.15	TF	87.26	83.92	90.64	90.07					
		S	84.72	86.53	82.9	91.13	SF	89.78	88.93	90.65	92.77	TSF	91.53	93.88	91.16	91.92
		T	70.01	67.62	72.43	75.4	TS	87.9	89.57	86.23	90.63					
	SHA	F	70.21	44.41	83.27	72.5	SF	79.48	64.56	87.03	81.24					
		S	73.96	52.89	84.63	77.46	TF	79.11	62.56	87.49	80.57	TSF	82.35	84.55	72.09	87.55
		T	72.21	50.77	83.07	74.68	TS	79.96	64.96	87.55	81.29					
	SHE	F	72.4	49.56	84.08	73.98	SF	78.2	60.27	87.37	78.72					
		S	73.61	52.11	84.61	76.42	TF	81.91	66.55	89.77	82.82	TSF	83.02	84.13	72.06	88.62
		T	71.57	44.25	85.55	72.03	TS	82.27	69.38	88.87	83.06					
	SHF	F	60.67	59.16	62.18	64.47	TF	73.57	73.81	73.34	76.32					
		S	61.46	58.47	64.42	64.91	SF	74	71.83	76.14	76.78	TSF	78.98	82.07	79.38	78.59
		T	59.99	58.61	61.36	62.73	TS	73.54	72.06	75.02	76.17					
	SLR	S	69.87	47	81.53	72.78	SF	88.07	82.04	91.15	89.91					
		F	85.75	75.83	90.81	89.03	TF	89.25	84.74	91.56	91.36	TSF	91.5	93.55	88.67	92.94
		T	61.49	21.49	81.87	54.6	TS	80.02	67.82	86.24	80.99					
Defect	IRQ	F	75.6	76.4	74.81	80.77	SF	84.29	86.29	82.28	87.77					
		S	78.34	81.36	75.31	85.23	TF	91.82	93.02	90.62	93.55	TSF	93.53	95.23	94.4	92.68
		T	90.58	90.93	90.24	94.24	TS	93.88	94.45	93.31	95.11					
	SHA	F	90.69	90.39	91.01	94.44	SF	94.97	94.38	95.58	96.84					
		S	90.69	89.71	91.71	94.46	TF	96.26	96.1	96.43	97.33	TSF	97.92	98.48	98.22	97.63
		T	94.09	94.43	93.76	96.21	TS	96.18	96.49	95.88	97.24					
	SHE	F	73.29	74.73	71.88	79.87	SF	84.62	83.69	85.56	88.54					
		S	83.55	81.78	85.31	89.22	TF	92.26	92.88	91.65	94.41	TSF	94.22	95.73	94.82	93.63
		T	85.13	86.84	83.45	90.23	TS	94.02	95.11	92.94	95.42					
	SLR	F	71.89	71.5	72.28	78	SF	84.23	80.6	87.85	87.18					
		S	79.2	77.68	80.71	84.69	TF	89.61	89.8	89.44	92.49	TSF	92.89	95.73	92.38	93.41
		T	71.77	74.28	69.29	78.08	TS	93.01	93.54	92.49	95.14					

III. Results and Discussion

This paper uses the overall accuracy, true positive rate (or sensitivity), true negative rate (or specificity) and the area under curve to evaluate the classification models. The overall accuracy rate (ACC) is the proportion of correctly classified samples in the testing data. The true positive rate (TP) is the proportion of positive samples that were correctly classified. The true negative rate (TN) is the proportion of negative samples that were classified correctly. The area under curve (AUC) is an abbreviation for the area under the ROC (receiver operating characteristic) curve, based on the minor class. The detail of these terms can be found in [1].

The classification results of the paper are presented by Tables III, II and IV. In these tables, the classification rates are ACC, TP, TN and AUC, each of which is the average of the relative 6 classification rates obtained by the 6 classifiers (LR, DT, MLP, SVM, RF and Adaboost). Tables III and II show:

- the significant locations where the sensors should be placed to improve the accuracy for each exercise.
- when using 1 sensor for an exercise, the classification rates are very changeable. When a sensor was mounted on a specified location, the effect of acceleration signal is higher than the gyroscope , their combination is the most effective, for most of the exercises. For the same exercise, generally, the classification rates obtained by combining multi-sensor units are much higher than the ones obtained by a single sensor unit.
- comparing the use of sensor unit combination, the classification obtained by using three-sensor units are the most stable. However, if the two sensors can be properly mounted at the significant locations, the approximate classification rates can be obtained as well. But the computational overhead of using more sensors also increases greatly.
- when 1 sensor unit was or 2-sensor units were used, the classification rates are sensitive to the locations where the sensors were placed and the signal selection for movement analysis. For example, when the two sensors were mounted on the thigh and foot and the combination signal of acceleration and gyroscope were used to classify the SLR movements, the classification rates are higher than other combinations (they can be 20% higher than the lowest ones).

Based on the combination of acceleration and gyroscope data from a number of sensor units, we obtained the classification rates for each type of feature sets of each exercise. Table IV summaries the results of defect and normal movement classification and the results of defect movement classification for each exercise. Table IV shows that:

- for the same exercise and the same signal data, the classification rates obtained by the information-theoretic feature set are the worst in these feature sets. That is, the information-theoretic features are less effective for the movement classification than others.
- the effects of using frequency feature set “Fourier transform coefficients” are approximately equal for the classification. One of reason might be that the properties and principles of Fourier transform and the Wavelet transform are quite similar.

- the statistical feature set is more effective than the information-theoretic feature set, time-frequency feature set and frequency feature set. But if the statistical feature set is combined with another feature set, the classification rates can be significantly improved.
- the use of 2 or 3 sensor units to classify the movements is more effective than the use of one sensor unit, when the same features were used.

TABLE III: The classification rates of each exercise, using acceleration, gyroscope and their combination

Cl.	Exe.	Data	Accuracy	TP	TN	AUC
Normal VS. Defect movements	HS	AG	95.86	94.5	97.25	96.87
		A	95.83	94.59	97.1	96.79
		G	90.68	88.89	92.51	93.49
	IRQ	AG	81.7	67.47	88.63	82.7
		A	81.74	66.26	89.27	82.32
		G	76.51	57.77	85.62	77.44
	SAKE	AG	87.07	86.33	87.83	90.94
		A	88.25	89.54	86.95	90.75
		G	81.15	79.45	82.87	85.63
	SHA	AG	78.73	64.96	85.7	81.8
		A	77.02	54.9	88.21	77.35
		G	76.2	59.71	84.55	78.23
	SHE	AG	79.37	63.39	87.54	80.95
		A	78.77	60.43	88.15	79.59
		G	76.81	58.83	86	77.84
	SHF	AG	73.37	73.45	73.3	76.54
		A	73.55	72.14	74.95	76.22
		G	62.28	60.01	64.52	65.49
	SLR	AG	84.5	73.52	90.1	85.67
		A	85.02	73.27	91.02	85.14
		G	77.77	63.75	84.93	80.12
Defect movements	IRQ	AG	88.79	89.16	88.44	92.26
		A	88.64	90.65	86.62	91.22
		G	86.94	88.35	85.52	90.02
	SHA	AG	96.26	96.74	95.78	97.79
		A	92.23	91.35	93.14	94.57
		G	96.09	96.46	95.73	97.67
	SHE	AG	88.95	90.76	87.16	92.34
		A	88.89	88	89.78	91.64
		G	86.71	87.25	86.19	90.33
	SLR	AG	85.87	86.3	85.46	89.89
		A	86.64	86.5	86.77	90.02
		G	82.89	81.46	84.33	86.81

TABLE IV: The classification rates, using different feature sets

		Classif: normal VS defect				defect Movement Classif.			
n. Sensors	features	ACC	TP	TN	AUC	ACC	TP	TN	AUC
1	fft+info	72.87	57.13	81.48	74.79	82.35	83.49	81.22	87.06
	info	68.26	45.9	79.55	68.37	71.57	75.67	67.36	76.7
	stat	75.73	61.89	83.32	77.99	84.28	84.19	84.37	88.57
	stat+fft	75.03	61.63	82.25	77.43	83.5	85.21	81.8	88.26
	stat+info	75.76	62.26	83.11	78.03	84.11	84.56	83.67	88.58
	stat+wf	75.45	61.09	82.93	77.78	83.68	84.26	83.11	88.49
	fft	72.73	57.42	81.03	74.53	82.08	82.12	82.05	86.5
	wf	71.86	54.85	80.54	73.84	79.83	80	79.65	84.71
2	fft+info	78.8	68.2	84.46	80.6	89.81	90.23	89.38	92.79
	info	71.17	51.35	80.93	71.63	75.07	77.34	72.72	79.37
	stat	86.74	78.74	90.97	87.97	92.65	92.47	92.84	94.5
	stat+fft	86.42	79.56	90.1	87.91	92.57	92.72	92.42	94.48
	stat+info	86.65	78.72	90.94	88.06	92.51	92.51	92.53	94.43
	stat+wf	86.21	78.4	90.33	87.48	92.64	92.37	92.91	94.45
	fft	78.53	68.28	83.88	80.4	89.86	90.24	89.49	92.79
	wf	76.6	64.36	82.77	78.6	88.14	87.09	89.19	90.81
3	fft+info	81.66	73.02	86.39	83.78	92.51	93.11	91.93	94.77
	info	72.88	55.55	81.35	73.38	77.39	80.23	74.5	81.13
	stat	88.08	82.45	91.06	89.42	95.51	95.94	95.08	96.82
	stat+fft	87.63	82.5	90.38	89.52	94.67	95.19	94.17	96.25
	stat+info	87.99	82.14	91.15	89.55	95.3	95.91	94.7	96.68
	stat+wf	87.59	82.13	90.39	89.1	95.23	95.55	94.91	96.87
	fft	81.25	73.08	85.62	83.35	92.74	93.37	92.11	95.04
	wf	79.22	69.29	84.15	80.89	92.15	92.92	91.37	94.16

IV. CONCLUSION AND FUTURE WORKS

In this paper, we evaluated 1) the effect of the acceleration data, gyroscope data and their combination, 2) evaluated the use of sensor unit combination, and 3) evaluated different types of features and their different combinations for the limb movement analysis of rehabilitation exercises. The experimental results have demonstrated the use of 2 or 3 sensor units, the combination of acceleration and gyroscope signal, and the feature sets combined by statistical features with another type of feature can significantly improve the classification accuracy. Therefore, we suggest that the significant data and features mentioned above should be selected for the limb movement analysis of rehabilitation exercises when using wearable inertial sensors.

The future work will include conducting more experiments with a larger set of testing data from more patients and reducing the feature dimensions to improve the classification accuracy. In addition, the movement segmentation will be studied to improve the performance of movement classification for rehabilitation exercises.

REFERENCES

[1] https://en.wikipedia.org/wiki/receiver_operating_characteristic, .

[2] Boulton Andrew, JM Loretta, Vileikyte Gunnel, Ragnarson-Tennvall, and Jan Apelqvist. The global burden of diabetic foot disease. *Lancet*, 366(9498):1719–1724, 2005.

[3] Harrison Philip Crowell and Irene S. Davis. Gait retraining to reduce lower extremity loading in runners. *Clinical Biomechanics*, 26(1):78–83, 2011.

[4] O. Giggins, K.T. Sweeney, and B. Caulfield. The use of inertial sensors for the classification of rehabilitation exercises. In *EMBC 2014*, pages 2965–2968, Aug 2014.

[5] Shatkay Hagit and Stanley B. Zdonik. Approximate queries and representations for large data sequences. In *Data Engineering, 1996. Proceedings of the Twelfth International Conference on*, pages 536–545. IEEE, 1996.

[6] Jeffrey M. Hausdorff, Dean A. Rios, and Helen K. Edelberg. Gait variability and fall risk in community-living older adults: a 1-year prospective study. *Archives of physical medicine and rehabilitation*, 82(8):1050–1056, 2001.

[7] Robert A. Hintermeister, Gregory W. Lange, Jeanne M. Schultheis, Michael J. Bey, and Richard J. Hawkins. Electromyographic activity and applied load during shoulder rehabilitation exercises using elastic resistance. *The American Journal of Sports Medicine*, 26(2):210–220, 1998.

[8] R. Houmanfar, M. Karg, and D. Kulic. Movement analysis of rehabilitation exercises: Distance metrics for measuring patient progress. *IEEE Systems Journal*, PP(99):1–12, 2014.

[9] Yack H. John, Collins Cynthia E, and Whieldon Terry J. Comparison of closed and open kinetic chain exercise in the anterior cruciate ligament-deficient knee. *The American journal of sports medicine*, 21(1):49–54, 1993.

[10] Leslie R. Martin, Summer L. Williams, Kelly B. Haskard, and M Robin DiMatteo. The challenge of patient adherence. *Therapeutics and clinical risk management*, 1(3):189, 2005.

[11] Domingos Pedro and Hulten Geoff. Mining high-speed data streams. In *Proceedings of the Sixth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 71–80, New York, NY, USA, 2000. ACM.

[12] Zhai Shumin and Milgram Paul. Quantifying coordination in multiple dof movement and its application to evaluating 6 dof input devices. In *Pro. of the SIGCHI conference on Human factors in computing systems*, pages 320–327, 1998.

[13] P.E. Taylor, G.J.M. Almeida, T. Kanade, and J.K. Hodgins. Classifying human motion quality for knee osteoarthritis using accelerometers. In *EMBC, International Conference of the IEEE*, pages 339–343, Aug 2010.

[14] Zhe Zhang, Qiang Fang, Liuping Wang, and P. Barrett. Template matching based motion classification for unsupervised post-stroke rehabilitation. In *International Symposium on Bioelectronics and Bioinformatics*, pages 199–202, Nov 2011.