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Analysis of Human Motions with Arm Constraint

Duk-Jin Kim, *Student Member, IEEE* and B. Prabhakaran, *Member, IEEE*

Abstract—**This paper investigates a quantization and clustering issue on human motion performance constrained by disabilities. In a longitudinal study of medical therapy on motion disorder, stages of patient disability condition change over time. We investigate four different stages of one arm constrained walking motions by restricting 0%, 10%, 16% and 22% of arm swing angles. For analysis we use One-way ANOVA and K-mean clustering to indentify the most significant features and to partition four different motion constrained groups. Our experimental result shows that all four arm constraints during walking motion are clustered with an average accuracy of 91.7% on two different feature conditions: a mixture of singular value decomposition (SVD) and power spectral density (PSD); and SVD only on selected gait cycles. The proposed method can be integrated with a ubiquitous system (using wearable sensors) for a remote distance patient monitoring system analysis.**

I. Introduction

As motion sensors become smaller in size and longer in battery life, human motion monitoring system is gaining more attentions ever before. Many interesting applications are developed. Gaming device companies such as Nintendo [8] (using motion sensors) or Microsoft [7] (using camera based motion detection) have adopted such technologies for better and easier control that enhances human-computer interactions. Medical application using such technologies is another highly active research area. Many medical researchers try to use human monitoring system to catch early motion disorder or to monitor daily activities of seniors who live alone as well as obesity patients who need daily exercise. In rehabilitation, motion monitoring system can be used to quantize the improvement kinetically. A patient with restricted joint movement has different motion trajectories from that of normal person. Gait analysis is often used to diagnose certain motion disorders such as Parkinson's disease (PD). Walking motion of such a patient has noticeably different walking patterns comparing to that of normal person. It is, however, not easy to come up with any quantization method to say whether an applied therapy works or not. In many cases the success of selected therapy depends on how the patient feels and doctors' experience. In order to scientifically prove or provide how the therapy works, medical practitioners have to have a template to compare with.

Gait analysis has been studied many decades. Many researchers tried to find the correlation between upper and lower extremities in order to find the walking patterns between motion constraint walking (real or synthetically generated motion) and normal walking [9]-[15]. Machine leaning techniques such as SVM[15] or Fuzzy clustering[14] have been used to identify abnormal gait pattern and normal gait patterns. However, all these studies are more focused on finding and separating the pattern of abnormalities against the normal walking patterns. One of the challenges is, however, to find the different stages of motion disorder developments. It is feasible to separate patient motions from normal motion, but it may not be easy to separate minor improvement after a few sessions of physical therapies since the motion change is very small.

In this paper, we investigate walking motions with arm constraint. For data representation, we use the Singular Value Decomposition (SVD) and the Power Spectral Density (PSD) to transform time sequence data into a concise data format without losing much of their patterns [16]. Four different stages of motion constraint on upper extremities are analyzed and quantized using singular value decomposition and power spectral density of a selected joint acceleration and angle. For comparing and analyzing these four different stages of motion constraint, One-way ANOVA and K-mean clustering techniques are used to identify significance of each joint movement as well as to partition data into four different stage groups which can be represented as a different stages of motion disorders. Our experimental result shows that our proposed technique can separate all four motion constrained groups with 91.7% average accuracy while a stride and cadence based classification has 51% accuracy.

Key point of this study is to quantize human motion performance and to group using clustering technique in order to show different level of motion constrained disabilities. This proposed method can be extended to a longitudinal study of medical therapy on motion disorder. Furthermore, such a ubiquitous system (using wearable sensors) can be mapped for remote distance patient monitoring system.

II. Data Collection

To generate different stages of an upper extremity constraint, pendulum movements of participant's arm swings are restricted by four different levels: level 1(22% restricted), 2 (16% restricted), 3 (10% restricted), and 4 (0% restricted.) Each level indicates a different stage of an arm swing condition. For instance, level 1 indicates the highest restricted arm movement which may represent an initial condition of a patient who did not have any physical therapy, and level 3 represents an improved condition of a patient after a few sessions of medical treatments. Level 4 has no restriction on arm swings which indicates a normal walking.

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Duk-Jin Kim and B. Prabhakaran is with the University of Texas at Dallas, Richardson, TX 75083 USA (corresponding author to provide e-mail: {duk-jin.kim, Prabha }@ utdallas.edu).

For capturing and analyzing 3D kinematic data in human gait, we use NDI Optotrak Certus motion tracker [1]. The captured 3D motion capture data gives the positional information of 13 body joints with frequency of 100 Hz. Fig 1 shows 13 marker locations and an angle of an arm swing respect to one's waist, shoulder and wrist.

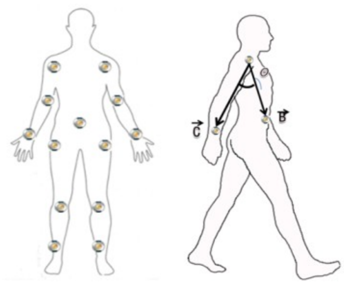


Fig 1. 13 marker locations (left) and a wrist angular vector Θ (right)

III. Feature Extraction

We segment one gait cycle from sequence of gait time series. For the cut point we use duration between the first peak point and the second peak point of z-axis (walking forward direction) of a left ankle joint vector. Detail information can be found in [2].

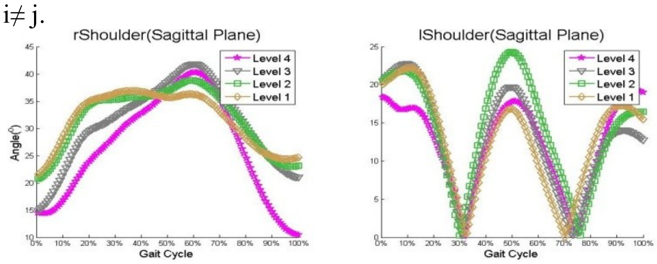
For quantization of each features (angle and acceleration of selected joints), Power Spectral Density (PSD), and Singular Value Decomposition (SVD) are used on a segmented gait cycle.

A. Acceleration and Angles of each joint

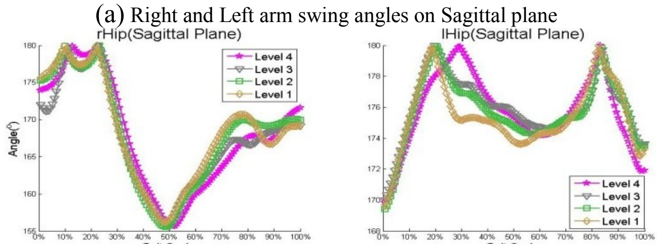
• **Arm and Leg displacement Angle:** For measuring an angle of a leg and a arm joint motion, we use a vector angle function. Participant's shoulders/hips, elbows/knees, and a waist are used to compute angular displacement of arms/legs respectively. We set a vector from an origin (shoulder or hip) to a waist as a base vector and use arccosine function to compute angles (Θ) of arm swings (See Eq 1, Fig 1 and 2.)

$$\Theta_{i,j}(t) = \arccos\left(\frac{|B_{i,j}(t) \text{ x } C_{i,j}(t)|}{B_{i,j}(t)\bullet C_{i,j}(t)}\right) \text{x} \frac{180}{\pi} \quad (1)$$

where $B_{i,j}(t)$, $C_{i,j}(t)$ are joint vectors, $i, j \in$ {x,y,z axis}, $i \neq j$.



(a) Right and Left arm swing angles on Sagittal plane



(b) Right and Left leg swing angles on Sagittal plane

Fig 2. Angular vector Θ of shourder and hip joint displasment.

• **Acceleration of wrists and ankles:** Along with position vectors in 3D motion capture data, acceleration can provide significant motion changes which may not be detected in position vectors. In this regard, we consider acceleration as our observation point and compute acceleration of four joints (a right/left wrist, a right/left ankle) from position vectors taken by the 3D motion capture system. In 3D kinematic data of any active motion, these selected joints have the most noticeable changes among body joints. In order to reduce noise factors during computation, we use 3rd order Butterworth filter with normalized cutoff frequency of 42Hz.

B. Quantization

Maxima of power spectral density and singular values of Singular Value Decomposition are used for the representations of acceleration and angle changes over selected joints during a gait cycle.

• **Power Spectral Density (PSD):** To show an activeness of given motion signals, we use power spectral density. A maximum value of power spectra shows the activeness of joint acceleration on frequency domain. The Cooley-Tukey algorithm based Fast Fourier Transformation (FFT) is used to transform time domain acceleration or angle vectors into frequency domain vectors. Let us say matrix M be a size N-by-1, matrix M_1 be size N_1-by-1, and M_2 be size N_2-by-1 matrix with arbitrary composition size N= N_1N_2. The Cooley-Tukey algorithm subdivides a matrix M into smaller matrix M_1 and M_2, then use Discrete Fourier Transforms (DFT) to transform power spectral vectors in a frequency domain. The DFT is defined by Eq 2.

$$f(\chi_\kappa) = \sum_{n=0}^{N-1} \chi_n \, e^{\frac{-2\pi i}{N} n\kappa} \quad (2)$$

where $e^{\frac{2\pi i}{N}}$ is a primitive N'th root of unit; an integer κ is ranging from 0 to N-1; i is the imaginary unit; and the X_κ can be viewed as coefficients of T in an orthonormal basis.

Then, a maximum value of PSD is selected from each x,y and z axis (Sagittal, Coronal, and Transverse plane) of acceleration and angle of joints (Eq 3.)

$$PSD_i = \mathrm{Max}\{f\left(\chi_i(t)\right)\} \quad (3)$$

where function *f*() indicates FFT, $\chi_i(t)$ indicates time sequence of acceleration or angle of selected joint, $i \in \{x, y, z \text{ axis}\}$, and PSD_i is a maximum of power spectrum on an axis i of a selected joint.

PSD Example

$$\begin{array}{ccc} \mathbf{x} & \mathbf{y} & \mathbf{z} \end{array} \qquad\qquad \begin{array}{ccc} \mathbf{x} & \mathbf{y} & \mathbf{z} \end{array}$$

$$\begin{bmatrix} 149 & 35 & 19.4 \\ 150 & 36 & 19.7 \\ \dots & \dots & \dots \end{bmatrix} \Rightarrow [1.68 \quad 0.0137 \quad 0.2]$$

Joint $_k$ Angle PSD$_k$ Angle

• **Singular Value Decomposition (SVD):** For dimension reduction acceleration and angle matrix, we use singular values of Singular Value Decomposition (SVD) for representing acceleration and angular value of each joint on a gait cycle. SVD is one of very useful techniques for classification and identification issues. SVD can, also, be used to dimension reduction without losing signal's unique characteristic [3]. Let us say M_k be a n-by-3 matrix of a human joint *k*; and n represents time frames on a segmented gait cycle, then diagonal matrix $\Sigma_k$with non-negative singular value $[\sigma_1^k, \sigma_2^k, \sigma_3^k]$ are computed. These non-negative singular values σ_i^k, where $i \in \{x, y, z \text{ axis}\}$, are SVD_k of joint *k* during a gait cycle. SVD_k computation can be driven from Eq 4.

$$M_k = W\Sigma_k V^T,\ M_k \nu = \sigma_i^k \mu,\ M_k^T \mu = \sigma_i^k \nu \tag{4}$$

where $M_k$is a n-by-3 spatial time series matrix of human joint *k*, a matrix Σ_k is n-by-3 diagonal with non-negative real numbers on diagonal; V^T is a conjugate transpose of an 3-by-3 unitary matrix V; W is an n-by-3 unitary matrix; and μ and ν are unit-length vectors in real number field R^n and in real number field R^3 respectively.

<u>SVD Example</u>

$$\begin{array}{ccc} x & y & z \end{array} \qquad\qquad \begin{array}{ccc} x & y & z \end{array}$$

$$\begin{bmatrix} 149 & 35 & 19.4 \\ 150 & 36 & 19.7 \\ \ldots & \ldots & \ldots \end{bmatrix} \Rightarrow [269 \quad 0.48 \quad 0.007]$$

Joint $_k$ Angle SVD$_k$ Angle

IV. Experimental Results

The quantized motion performances of four stage groups are evaluated using two common statistical techniques. Section IV (A) explains about One-way ANOVA for feature selection and evaluation. Section IV (B) explains how these selected features are help to cluster different constraint stage groups so that a physician or a care-provider can use this information for patient care. These results are compared with a normalized stride and cadence based gait classification [15].

A. One-way ANOVA based analysis

• **One-way ANOVA**: One-way Analysis Of Variance (ANOVA) is one of statistical analysis techniques to identify the significance of testing variables. One-way ANOVA tests for the differences among two or more of independent group values. To see the difference among group, typically F-statistic and p-value are used. A p-value indicates cumulative distribution function which represents the level of significance between comparing groups, and F-statistic (F(x,y)) is the ratio of the mean squares with x degrees of freedom in the numerator and y degrees of freedom in the denominator. For instance, if a set X={x1,x2,..,xn} and a set Y={y1,y2,..,yn} have p=0.002 and F(2,40)=30, a set X and a set Y are significantly different with $p<0.01$ and F(2,40)=30. More information about ANOVA can be found in [2][4]. For data analysis, we set SVD and PSD of angle and acceleration of each joint as a testing variable; and group them with four different groups to feed into ANOVA to compute F-value and p-value.

Our experiment results show that SVD values of both acceleration and angle of arms are $p<0.01$. A noticeable difference of arm swing angles happens on coronal plane (right arm swing angle-F(3,36):15.73, p-value: $1.06\text{x}10^{-6}$; and left arm swing angle-F(3,36):8.06, p-value:0.0003.)

We find three joints (a right wrist, a left wrist and a right ankle) have much higher SVD values changes. Interestingly while the most significant changes on a right wrist happen on its forward (z-axis, F(3,36)=44.85, p-value: $3.015\text{x}10^{-12}$) and sideward direction (x-axis, F(3,36)=79.75, p-value:$5.5\text{x}10^{-16}$), significant value changes on a left hand happens on its sideward (x-axis, F(3,36)=13.09, p-value: $6.167\text{x}10^{-16}$) and upward direction(y-axis, F(3,36)=14.59, p-value: $2.22\text{x}10^{-6}$).

Maximum value of power spectral density (PSD) over frequency range of 1Hz to 50Hz has significant differences on both shoulder and hip joints among four motion constrained groups as well. All PSDs of angle of shoulder and hip were changed very significantly among these four motion constrained groups. Notice that PSDs of right shoulder angle changes have very high significance (x-axis: F(3,36)=68.3, p-value:$6.2\text{x}10^{-15}$, y-axis: F(3,36)=36.87, p-value:$4.5\text{x}10^{-11}$, and z-axis: F(3,36)= 29.19, p-value:$9.5\text{x}10^{-10}$.)

PSDs of acceleration also have similar result on those of right wrist. While all three PSDs (sagittal, coronal, and transverse plane) of a right wrist angle have very high significance, acceleration has only two directions which have the highest significance: upward (y-axis, F(3,36)=70, p-value:$4.32\text{x}10^{-15}$) and forward direction (z-axis, F(3,36)= 113, p-value:0.)

TABLE I
Accuracy, Recall, and Precision
(a) SVD and PSD based classification

	SVD				PSD				SVD+PSD			
	Level 4	Level 3	Level 2	Level 1	Level 4	Level 3	Level 2	Level 1	Level 4	Level 3	Level 2	Level 1
Precision(%)	100	81.8	77.8	80	100	81.8	47.3	47.3	100	80	63.6	77.7
Recall(%)	100	90	70	80	50	90	90	90	100	80	70	70
Accuracy(%)	100	92.8	88	90	87.5	92.8	78	78	100	90.4	84	88

(b) Cadence and stride based classification

	Level 4	Level 3	Level 2	Level 1
Precision(%)	18.7	28.6	31.8	25
Recall(%)	30	60	70	50
Accuracy(%)	50	52.5	55	50

B. Clustering based analysis

• **K-mean clustering**: is one of grouping methods in statistics and machine leaning. It partitions **n** observations into **k** clusters where each observation is in the cluster with the nearest mean. Let us say X be a set of observations and X = $\{x_1,x_2,..,x_n\}$be n observations. The k-means clusters the original set X into smaller k sets of S=$\{S_1,S_2,..,S_n\}$[5][6]. Eq (5) shows a k-mean clustering equation.

$$\arg\min_S \sum_{i=1}^{k} \sum_{x_j \in S_i} \left\| x_j - \mu_i \right\|^2 \tag{5}$$

where μ_i is the mean of set S_i.

In our experiment, we set k=4 since our observations divided into four categories: level 1, 2, 3, and 4 group. For the clustering variables, we select right wrist acceleration and a right shoulder angle based on ANOVA analysis result.

For normalization of SVD and PSD values for selected joint over four motion constrained groups, we use an equation 6 to set every value of x,y,z axis of each selected joint between 0 and 1. Since PSD and SVD of each joint had large value differences that accuracy of k-mean clustering drops down without normalization.

$$y_i^k(t) = \frac{x_i^k(t) - \min(X_i^k)}{\max(X_i^k) - \min(X_i^k)} \tag{6}$$

where X_i^k is a vector of SVD or PSD of human joint k over all four motion constrained groups with $i \in \{x, y, z\ \text{axis}\}$; $\min(X_i^k)$ and $\max(X_i^k)$ are a minimum value in X_i^k and a maximum value in X_i^k, $x_i^k(t) \in X_i^k$; and $y_i^k(t)$ is computed value corresponding to $x_i^k(t)$ with $0 \le y_i^k(t) \le 1$. We use k-mean clustering method to cluster the cadence and normalized stride based classification as well. For the stride normalization we follow polynomial normalization in [15]

K-mean clustering analysis result shows that both a SVD only and a mixture of SVD and PSD can separate all four motion constrained groups with high accuracy (SVD: avg accuracy of 92% and SVD+PSD: avg accuracy of 90.6%.) In our experiment on K-mean clustering, SVD with angle and acceleration had the highest accuracy with an average of 92.8% while a cadence and stride based approach has an average of 51.8% accuracy (TABLE I.)

V. CONCLUSION

The main purpose of this study is to evaluate and to quantize different stages of human motion constraint. Even though our proposed technique works over any human motion constrained disabilities, for demonstration purpose we choose human gait with an arm movement constraint. With proper understanding of gait coordination between upper and lower extremities, we can segment motion frames to extract features on positional and angular displacement of hand and foot; and also evaluate the most significance of those human joint movements. Our main focus is to find any distinguishable features on human joint over time and frequency domains of angular and acceleration displacement and to group them with proper constraint conditions.

Our study shows ANOVA and K-mean clustering analysis on PSD and SVD of angle and acceleration can identify and separate high significance over four motion constrained groups. PSD and SVD on our data set showed that angular displacement on right hand has the highest significant values on ANOVA analysis. An ANOVA based K-mean clustering analyses shows a good separation over four motion constrained groups with an overall average accuracy of 91.7%.

VI. FUTURE WORK

For everyday motion monitoring system, finding an appropriate wearable sensor location is critical in order to increase an accuracy of classifying different level of motion constraint due to the limitation of number of sensors as well as accuracy of sensor reading. This study result can guide to find the proper locations of motion sensors as well as provide a back end of a remote patient motion monitoring analysis framework. Our next step becomes to integrate this 3D motion analysis method with separately collected motion data from wearable sensors for a ubiquities motion monitoring and analysis framework.

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