QUANTITATIVE EVALUATION OF WALKING DISABILITY USING SINGULAR VALUE DECOMPOSITION

YINLAI JIANG[1], ISAO HAYASHI[2], SHUOYU WANG[1]

[1]*School of Systems Engineering, Kochi University of Technology,*
185 Miyanokuti, Tosayamada, Kami, Kochi 782-8502, Japan.
E-mail: jiang.yinlai@kochi-tech.ac.jp; wang.shuoyu@kochi-tech.ac.jp
[2]*Faculty of Informatics, Kansai University,*
2-1-1, Ryozenji-cho, Takatsuki, Osaka 569-1095, Japan.
E-mail: ihaya@cbii.kutc.kansai-u.ac.jp

Whenever a disaster occurs, on-site emergency care is critical in rescue operations. A precise and convenient method is being developed to automatically analyze the sufferers' movements in order to identify the injured effectively and thus to provide quick rescue. In this paper, we propose a method for evaluating gait disturbance of evacuees in disasters. Singular value decomposition is used to acquire feature patterns from the time-series acceleration data. In an experiment, in order to verify the usefulness of the proposed method, three levels of walking difficulty in the lower limbs are simulated by constraining the knee joint and ankle joint of the right leg, and the accelerations of the middle of shanks and the back of the waist are measured and analyzed. The results showed that the first singular values inferred from the acceleration data of the shanks decreased with increase of the constraint to the joints. The first singular values of the acceleration data of the shanks were suggested to be reliable criteria to evaluate walking difficulty.

Keywords: Singular Value Decomposition, Walking Disability, Singular Value, Gait Disturbance, Disaster, Rescue.

1 Introduction

On-site emergency medical services play a critical role in rescue operations in the occurrence of a natural disaster or a large-scale accident (Catlett 2011). The quick identification of the injured, especially the person with walking disability since walking is fundamental in evacuation, can lead to a timely rescue and improve the efficiency of evacuation. However, the emergency medical technicians are always shorthanded or unable to reach the sufferers because of transportation shutdown. A convenient and precise evaluation for walking ability, therefore, is highly desired.

In this paper, we aim at the development of a quantitative walking ability evaluation method which is convenient to use to automatically analyze the sufferers' walking. Walking analysis has been studied extensively and there have been varied approaches to handle walking analysis, ranging from kinematic models (Murray 1985) to gait feature analysis such as stride length and gait cycle (Moe-Nilssen 2004). We discuss a new walking analysis method to evaluate walking

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disability using singular value decomposition (SVD) (Skillicorn 2007). Applications which employ the singular value decomposition include computing the pseudoinverse, least squares fitting of data, matrix approximation, and determining the rank, range and null space of a matrix (Wall 2003). In our proposed method, we compose a matrix from the time-series acceleration data during walking and calculate the matrix's singular values by SVD. The walking ability is evaluated based on the singular values. We discuss the usefulness of the proposed methods using an example of three levels of walking difficulty.

2 Acceleration Measurement with Wearable Wireless Accelerometers

Accelerometers have been widely used to monitor body movements, including gait, sit-to-stand transfers, postural sway and falls. They have also been used to measure physical activity levels and to identify and classify movements performed by subjects (Lau 2008, Williamson 2000, Mathie, 2004, Wu 2007, Salarian 2004). In this study, the acceleration is measured by 3 wearable wireless 3-axis accelerometers (Motion Recorder MVP-RF8, Microstone Nagano, Japan): M1 on the back of the waist (B. Waist), M2 on the midpoint of the right shank (R. M. Shank), and M3 on the midpoint of the right shank (R. M. Shank), as shown in Fig. 1. Sampling rate of the sensor was 100 Hz. When the subject stands upright, the sensors' *x*-axis is front/back, *y*-axis up/down, and *z*-axis right/left. However, since the orientation of the sensors changes during walking, the coordination system will also change.

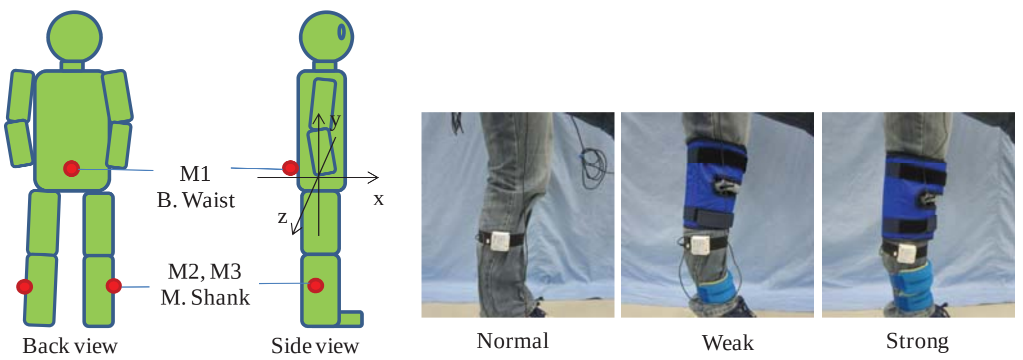


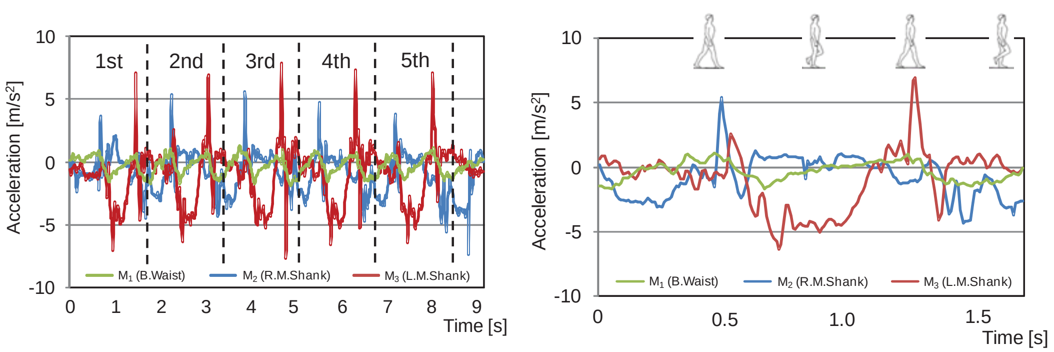
Figure 1. Attachment of accelerometers on the body.

In the experiment, we examined the acceleration of walking difficulty simulated by restricting the movement of the right leg with knee supporters and weight bands, as shown in Fig.1. The knee supporter bound around the knee joint decrease the range of movement (ROM) of the knee joint and the weight band bound around the ankle joint can simulate the weakness in muscle strength. The simulation is very important in testing our method since it does not endanger the safety of the disabled during the development phase of the method. Two levels of walking difficulty were simulated by two levels of restraint in the experiment. Weak restraint was simulated with one knee supporter and one weight band (1 kg), and strong restraint with two knee supporters and two weight bands (2 kg). Totally, 3 statuses (Normal without restraint, Weak, and Strong) were examined.

Six healthy volunteers (YJ, TK, KT, KS, TF, and RT, 5 males and 1 female) aged 21-31 yr (mean 26 yr) participated in the experiment. Subjects were instructed to walk straight about

4m along a straight line. The experiment was carried in the status order of Normal, Weak, and Strong. For each status, each subject walked 4 times.

The measurement time-series data in x coordinate of the three sensors when subject YJ walked in the status of Weak are shown in Fig. 2. The fluctuation of the acceleration was significant when the right foot or the left foot landing. There are 5 strides in Fig. 2a. Acceleration data of the first stride are extracted and shown in Fig. 2b. All the acceleration at the B. Waist, R. M. Shank, and L. M. Shank significantly fluctuated when the right foot pushed off from the floor or stepped on the floor. The fluctuation in the acceleration at L. M. Shank was more significant than that at R. M. Shank since the right leg was restricted by the knee supporter and the weight band. The fluctuation in the acceleration at B. waist was the smallest among the three measurement points. This showed that the trunk of the body, especially the waist, was relatively kept stable to maintain the body balance even when there is disability in lower limbs.



(a). Acceleration of one walking (b). Acceleration of one stride

Figure 2. X coordinate acceleration of YJ in the Weak status.

3 Acceleration Analysis Using Singular value Decomposition.

Singular value decomposition is used to acquire patterns from the time-series acceleration data. Suppose M is an m-by-n matrix. Then there exists a factorization of the form: $M = U\Sigma V^T$, where $U=(u_1, u_2, ..., u_m)$, $V=(v_1, v_2, ..., v_n)$, and the matrix Σ is m-by-n diagonal matrix with nonnegative real numbers on the diagonal. The matrix U contains the left singular vectors of M and the matrix V contains the right singular vectors of M.

Suppose that there are w measurement points ($P_1, P_2, ..., P_w$). On point P_i, the measured data series of acceleration is denoted as A, which consists of 3-dimentional data (A_X, A_Y, A_Z). We detect the time series $A_X^i = (x_1^i,\ x_2^i,\ \ldots,\ x_n^i)^T$ contains the x coordinate values of the P_i point. Then matrix M_X^i is defined as a collective of the change of x coordinate values of the gesture, $M_X^i = (A_X^{i,1},\ A_X^{i,2},\ \ldots,\ A_X^{i,3})$.

The matrix M_X^i can be decomposed into a product of U_X^i, Σ_X^i and V_X^i. Let us denote the singular values and the left singular vectors as $((\delta_X^{i,1}, u_X^{i,1}), (\delta_X^{i,2}, u_X^{i,2}), \cdots, (\delta_X^{i,l}, u_X^{i,l}))$, for

$u_X^{i,j} = (u_{X,1}^{i,j}, u_{X,2}^{i,j}, \cdots, u_{X,q}^{i,j})$ in descending order of the singular values. The parameter l represents the number of representative patterns under consideration, and the parameter q represents the number of elements of the singular vector. The left singular vectors $u_X^{i,1}$, $u_X^{i,2}$, ... , $u_X^{i,l}$ of M_X^i, represent the change patterns of the x coordinate acceleration on point P_i. The bigger the singular value is, the more dominant the corresponding pattern is (Skillicorn 2007, Wall 2003, Ide 2005).

We use the same calculation on y and z coordinate accelerations to get ($(\delta_Y^{i,1}, u_Y^{i,1})$, $(\delta_Y^{i,2}, u_Y^{i,2})$, $\cdots$, $(\delta_Y^{i,l}, u_Y^{i,l})$) and ($(\delta_Z^{i,1}, u_Z^{i,1})$, $(\delta_Z^{i,2}, u_Z^{i,2})$, $\cdots$, $(\delta_Z^{i,l}, u_Z^{i,l})$). The singular values are used as criteria for evaluating the walking difficulty.

We focused on the acceleration change around the time when the right foot pushed off and stepped on the floor. The acceleration data around right foot landing were analyzed. The matrix M was designed according to the local maximum turning points, as shown in Fig. 2. It took 5 strides to walk 4 m in the experiment. Acceleration data during the middle 3 strides, which do not involve initiation and termination of walking, were extracted for analysis. The data from 0.5s before the maximum turning point to 0.5s after the maximum turning point were extracted as column vectors. For each turning point, 9 column vectors (3 sensors, each has 3 coordinates) were extracted. The column vectors from the same acceleration data series composed a matrix M. Therefore, M was a matrix of 100 rows and 3 columns. In this paper, only the first singular value and the first left singular vector were considered. Thus parameter l was 1.

4 Results and Discussions

Table 1. Singular Values of Walking Experiment.

Subjects	Restraint Ambulation	M1			M2			M3		
		X	Y	Z	X	Y	Z	X	Y	Z
TF	Normal	17.7	23.4	21.8	57.9	52.7	50.9	46.8	55.6	33.4
	Weak	17.0	23.3	26.9	33.3	34.7	39.4	42.5	48.0	28.4
	Strong	17.6	22.8	27.3	31.7	30.3	37.7	40.4	43.1	27.8
YJ	Normal	11.4	9.4	12.1	45.9	40.5	22.2	47.3	48.2	18.9
	Weak	10.9	8.2	15.4	23.4	11.2	13.9	43.9	33.5	14.7
	Strong	18.3	10.4	18.5	19.5	10.2	13.0	42.0	25.6	13.7
TK	Normal	18.1	19.3	12.6	51.1	34.3	34.0	51.9	47.8	30.1
	Weak	20.6	20.4	17.0	27.5	25.1	26.4	45.7	45.8	27.3
	Strong	20.2	20.0	15.7	25.3	20.1	21.9	42.8	38.5	27.7
KS	Normal	20.2	19.0	12.8	60.4	58.8	36.3	57.3	66.4	25.8
	Weak	19.7	15.8	19.0	36.8	32.0	21.5	52.4	55.0	20.1
	Strong	18.8	15.9	19.2	33.5	29.3	18.9	39.6	34.6	19.3
RT	Normal	28.0	24.5	19.6	70.8	53.7	37.5	58.7	58.0	32.5
	Weak	24.5	22.3	17.8	60.7	34.9	27.3	56.9	58.1	30.4
	Strong	22.5	23.7	19.1	51.5	33.3	20.8	50.3	52.7	26.1
KT	Normal	23.4	27.5	17.9	57.1	65.3	40.3	60.6	74.3	32.0
	Weak	21.6	31.5	24.3	40.3	37.4	25.4	46.0	59.6	22.1
	Strong	18.5	24.3	22.4	38.5	26.8	16.0	38.5	46.4	16.4
AVG.	Normal	19.8	20.5	16.1	57.2	50.9	36.9	53.8	58.4	28.8
	Weak	19.1	20.3	20.1	37.0	29.2	25.7	47.9	50.0	23.8
	Strong	19.3	19.5	20.4	33.4	25.0	21.4	42.2	40.1	21.8

The first singular values extracted from the acceleration data with SVD are listed in Table 1. In spite of the individual differences in walking, similar singular value changes of all the 6 subjects were shown. The singular values of M2 and M3 decreased with the increase of walking difficulty, especially those of M2 decreased in all the X, Y and Z axes. However, the decrease did not show at M1. Waist is the center of the body and is always kept balanced during movement. Fig. 2 show that the waist was relatively kept stable to maintain the body balance.

An F-test is performed on the singular values at M2 is of significant difference among the three levels. The F-test results in Table 2 show that for all the three axes the singular values is significantly different. The first singular values of M2, therefore, are suggested to be effective criteria to evaluate walking difficulty. That is, the first singular values from the acceleration of the restricted leg decreases with the increase of walking difficulty. The bigger the first singular values of at M2, the more serious the walking difficulty is.

Table 2 Results of F-test on Singular Values of M2

Variation Factor		Sum of Squares	df	Mean Square	F	Sig.
X	Betw. Gr.	7902.4	2	3951.2	33.5	6.61E-11
	With. Gr.	8123.8	69	117.7		
	Total	16026.3	71			
Y	Betw. Gr.	9263.0	2	4631.5	47.7	9.56E-14
	With. Gr.	6690.9	69	96.9		
	Total	15954.0	71			
Z	Betw. Gr.	3073.5	2	1536.7	21.1	6.93E-08
	With. Gr.	5017.3	69	72.7		
	Total	8090.8	71			

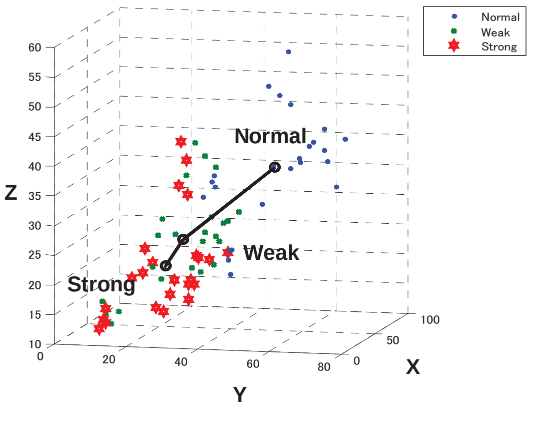


Figure 3 Singular Values of M2

The first singular values extracted from the acceleration data at M2 are plotted in 3D spaces in Fig. 3. Singular values of the 4 times of walking are plotted in different shape and color according to the 3 statuses. The average singular values of the 3 statuses are connected with black lines. Fig. 3 shows that the first singular values are clustered according to the statuses. The line connecting the average values can be considered as severity line of walking difficulty.

Conclusions

In this paper, we propose a method for evaluating gait disturbance of evacuees in disasters. Singular value decomposition is used to acquire feature patterns from the time-series acceleration data. In an experiment, in order to verify the usefulness of the proposed method, three levels of walking difficulty in the lower limbs are simulated by constraining the knee joint and ankle joint of the right leg, and the accelerations of the middle of shanks and the back of the waist are measured and analyzed. The results showed that the first singular values inferred from the acceleration data of the shanks decreased with increase of the constraint to the joints. The first singular values of the acceleration data of the shanks were suggested to be reliable criteria to evaluate walking difficulty.

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