Evaluation and Visualizaton of Evacuees' Walking Difficulty in Disasters

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***Abstract*—Identification of the evacuees with walking difficulty will definitely lead to quick rescue and thus improve the efficiency of evacuation in times of disasters or calamities. We are developing a new method using singular value decomposition for extracting features from the time-series data which is measured with various sensors such as an accelerometer, a motion capture system and a force sensor. In this paper, we apply this method to assess walking difficulty based on three dimensional acceleration data during walking. In order to verify the usefulness of the method, three levels of walking disability in the lower limbs are simulated by constraining the knee joint and ankle joint of the right leg. The accelerations of the middle of shanks and the back of the waist are measured and analyzed after normalization. Features related to walking difficulty are acquired from the time-series acceleration data using singular value decomposition. The results showed that the first singular values inferred from the acceleration data of the right and left shanks significantly related to the increase of the constraint to the joints. The first singular values of the shanks were suggested to be reliable criteria to evaluate walking difficulty. We propose a triangular tool to provide intuitive information extracted from the first singular values to assist the evaluation of the walking difficulty.**

I. Introduction

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. We are developing 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 to gait feature analysis such as stride length and gait cycle [1].

In previous studies [2], [3], we have proposed a new motion analysis method based on Singular Value Decomposition (SVD) [4]. Recently, the SVD has been used in time-series data analysis for data mining [5] and motion analysis to extract similarities and differences in human behavior [6]. A new walking difficulty evaluation method is proposed using the motion analysis method. The left and right singular vectors, and singular values are decomposed by SVD from a Hankel matrix defined from the time-series data measured during walking. Since the left singular vectors represent the characteristics of the Hankel matrix and the singular values mean the strength of the corresponding left singular vector, it is used more generally as a method for extracting characteristics from observed data. The walking ability is evaluated based on the singular values.

We discuss the usefulness of walking difficulty evaluation method with an experiment of three levels of walking difficulty. In the walking difficulty evaluation experiment, we examined the relationship between the levels of difficulty and the singular values. The first singular values were suggested to be reliable criteria to evaluate walking difficulty. Furthermore, we propose a triangular tool to provide intuitive information extracted from the first singular values to assist the evaluation of walking difficulty.

II. Walking Dynamics Measurement

We examined the acceleration of walking difficulty simulated by restricting the right leg with knee supporters and weight bands (Fig.1). The knee supporter bound around the knee joint decreases 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. A weak restraint was simulated with one knee supporter and one weight band (1 kg), and a strong restraint with two knee supporters and two weight bands (2 kg). In total, three statuses (Normal without restraint, Weak, and Strong) were examined.

Acceleration is widely used to study walking dynamics [7], [8]. In this paper, acceleration is adopted since it can be conveniently measured by a wearable accelemeter on the body, while trajectory and speed have to be measured by a sensing system such as a motion capture system outside the body. The acceleration during walking was measured by three wearable wireless three-axis accelerometers (Motion Recorder MVP-RF8, Microstone Nagano, Japan): P_1 on the back of the waist (B. Waist), P_2 on the midpoint of the right shank (R. M. Shank), and P_3 on the midpoint of the left shank (L. M. Shank), as shown in Fig.1. The sampling rate of the sensor was 100Hz. When the subject stands upright, the sensors' x-axis is front/back, the y-axis is up/down, and the z-axis

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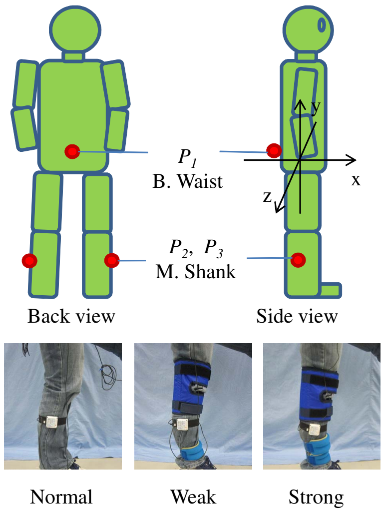


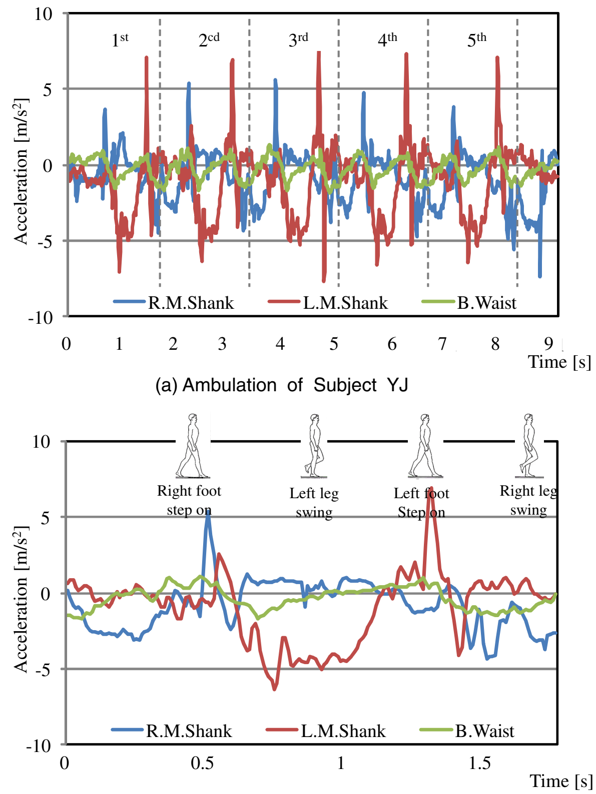
Fig. 1: Experiment Settings for Ambulation

is right/left. However, the coordination system changes since the orientation of the sensors changes during walking. 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. The subjects were instructed to walk along a straight line for approximately 4m. The experiment was carried out in the status order of Normal, Weak, and Strong. For each status, each subject walked four times.

The measurement time-series data in the 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 was landing. Fig.2(a) shows five strides. The acceleration data of the first stride were extracted and are shown in Fig.2(b). 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 kept relatively stable to maintain the body balance even when the lower limbs were disabled.

III. Acceleration Analysis Using SVD

Suppose M is an m-by-n matrix. Then a factorization of the form is M=$U\Sigma V$, where U=(u_1, u_2, $\cdots$, u_m) contains the left singular vectors of M, V=(v_1, v_2, $\cdots$, v_n) contains the right singular vectors of M, and the matrix Σ is an m-by-n diagonal matrix, with nonnegative real singular values on the diagonal. The SVD is an important factorization of a rectangular real or complex matrix, with many applications in signal processing and statistics. Applications using SVD include computing the pseudo inverse, least squares data fitting, matrix approximation, and determining the rank, range, and null space of a matrix [4].



(a) Ambulation of Subject YJ

(b) Two Steps of Subject YJ

Fig. 2: Example of Ambulation

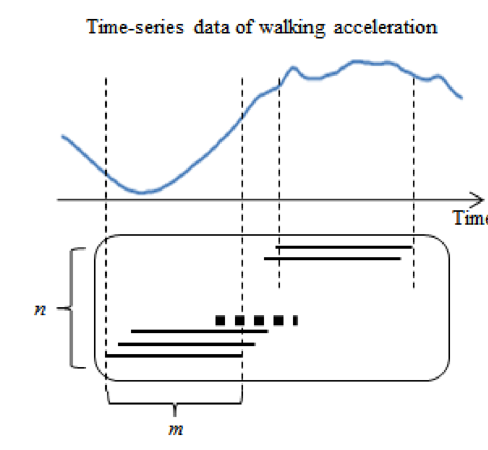


Fig. 3: Design of Matrix $M_X^{i,G}$

Suppose that there are w measurement points $(P_1, P_2, \cdots, P_w)$ on the human body to measure the body motion. On point P_i, the measured data series of movement G is denoted as $\tau^{i,G}$. The data series of $\tau^{i,G}$ consists of three-dimensional data $(X^{i,G}, Y^{i,G}, Z^{i,G})$. From this time-series data $\tau^{i,G} = (X^{i,G}, Y^{i,G}, Z^{i,G})$, n vectors by m data sampling are extracted by overlapping, and the matrices $M_X^{i,G}, M_Y^{i,G}$, and $M_Z^{i,G}$ are constructed as a collective of the measurement data on the X, Y, and Z coordinates of the gestures, respectively. Fig.3 shows a design for constructing the matrix $M_X^{i,G}$. The matrices $M_X^{i,G}, M_Y^{i,G}$, and $M_Z^{i,G}$ are described as follows:

$$M_X^{i,G} = (X_1^{i,G}, X_2^{i,G}, \cdots, X_n^{i,G})^T \quad (1)$$
$$M_Y^{i,G} = (Y_1^{i,G}, Y_2^{i,G}, \cdots, Y_n^{i,G})^T \quad (2)$$
$$M_Z^{i,G} = (Z_1^{i,G}, Z_2^{i,G}, \cdots, Z_n^{i,G})^T \quad (3)$$

where, $X_p^{i,G} = (x_{p,1}^{i,G}, x_{p,2}^{i,G}, \cdots, x_{p,m}^{i,G}),\ p = 1, 2, \cdots, n$, and x is a datum on the X coordinate. We define $Y_p^{i,G}$ and $Z_p^{i,G}$ in the same way.

Suppose $M_k^{i,G},\ k = \{X, Y, Z\}$ is an m-by-n matrix as general format of $M_X^{i,G}, M_Y^{i,G}, M_Z^{i,G}$. The SVD of the matrix $M_k^{i,G}$ is:

$$M_k^{i,G} = U_k^{i,G} \Sigma_k^{i,G} \{V_k^{i,G}\}^T \quad (4)$$

where $U_k^{i,G} = (u_{1,k}^{i,G}, u_{2,k}^{i,G}, \cdots, u_{m,k}^{i,G})$ is an m-by-m unitary matrix, $\{V_k^{i,G}\}^T$ denotes the conjugate transpose of $V_k^{i,G} = (v_{1,k}^{i,G}, v_{2,k}^{i,G}, \cdots, v_{n,k}^{i,G})$ which is an n-by-n unitary matrix, and the matrix $\Sigma_k^{i,G}$ is a m-by-n diagonal matrix. The diagonal entries of $\Sigma_k^{i,G}$ are the singular values of $M_k^{i,G}$. The matrix $U_k^{i,G}$ contains the left singular vectors of $M_k^{i,G}$ and the matrix $V_k^{i,G}$ contains the right singular vectors of $M_k^{i,G}$.

Now, take $M_X^{i,G}$ as an example of matrix $M_k^{i,G}$ to discuss motion analysis. SVD can decompose the matrix $M_X^{i,G}$ into a product of $U_X^{i,G}$, $\Sigma_X^{i,G}$, and $V_X^{i,G}$. Intuitively, the left singular vectors in $U_X^{i,G}$ form a set of patterns of $M_X^{i,G}$ and the diagonal values in matrix $\Sigma_X^{i,G}$ are the singular values, which can be considered as scalars by which each corresponding left singular vectors affect the matrix $M_X^{i,G}$. Suppose that the number of left singular vectors is l, and the element number of the j th left singular vector is q. Let us denote the couples of the singular values and the left singular vector as $((\sigma_{1,X}^{i,G}, u_{1,X}^{i,G}), (\sigma_{2,X}^{i,G}, u_{2,X}^{i,G}), \cdots, (\sigma_{l,X}^{i,G}, u_{l,X}^{i,G}))$, for $u_{j,X}^{i,G} = (\hat{u}_{1j,X}^{i,G}, \hat{u}_{2j,X}^{i,G}, \cdots, \hat{u}_{hj,X}^{i,G}, \cdots, \hat{u}_{qj,X}^{i,G})$ in the descending order of the singular values, where $\hat{u}_{hj,X}^{i,G}$ is the h th element of the j th left singular vector$u_{j,X}^{i,G}$. The left singular vector expresses the characteristic of the whole time-series data better if its corresponding singular value singular is larger. That is, the greater the singular value is, the more dominant the corresponding pattern is. We have utilized the left singular vectors to classify hand gestures in a previous study [2]. In this study, we evaluate the walking difficulty using the singular values.

IV. Walking Difficulty Evaluation based on the Singular Values

We focused on the acceleration change around the time when the right foot stepped on the floor. The acceleration data around the right foot landing were analyzed. Matrix M for SVD was designed according to the local maximum turning points, as shown in Fig.2. It took five strides to walk 4 m in the experiment. The acceleration data of the middle three strides, which do not involve the initiation and termination of the walking movement, 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, nine column vectors (three sensors, each of which has three coordinates) were extracted. The column vectors from the same acceleration data series composed 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, which means that only the first singular value was considered.

TABLE II: Results of F Test on P_2

Variation	Factor	Sum of Sq.	df	Mean Sq.	F Val.	P Val.
X	Be.Gr.	7902.4	2	3951.2	33.56	6.61E-11
	With.Gr.	8123.9	69	117.7		
	Total	16026.3	71			
Y	Be.Gr.	9263.1	2	4631.5	47.76	9.56E-14
	With.Gr.	6690.9	69	97.0		
	Total	15954.0	71			
Z	Be.Gr.	7902.4	2	1536.8	21.13	6.93E-08
	With.Gr.	8123.9	69	72.7		
	Total	16026.3	71			

The first singular values extracted from the acceleration data are listed in Table I. In spite of the individual differences in walking, similar changes of the singular values of all six subjects are shown. The singular values of P_2 and P_3 decreased with the increase of walking difficulty, and especially those of P_2 decreased in all three axes, X, Y, and Z. However, the decrease did not show at P_1. The waist is the center of the body and is always kept balanced during movement. Fig.2 shows that the waist was relatively stable to maintain the body balance. An F-test was performed on the singular values at P_2 to assess the significance of the difference among the three levels. The F-test results in Table II show that for all three axes, the singular values are significantly different between the three levels. The first singular values of P_2, 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.

In order to provide an understandable presentation of the data to evaluate the walking difficulty difficulty from the walking acceleration, we developed a triangular presentation of the the singular values, as is shown in Fig.4. Three lines, the angles between which are $2\pi/3$, are drawn from the original O. The lengths of the lines are proportional to the first singular values at P_2 of the X (SV_X), Y (SV_Y) and Z (SV_Z) axes, respectively. Thus a triangle is defined by the ends of the three lines. The information related to walking difficulty, such as the longest line L, the area of the triangle S, the position of the center C is visualized by the triangle. Furthermore, if the singular values are calculated and the triangle is plotted in real time when a subject is walking, the changes of L, S, and C also provide important information to evaluate walking difficulty. Further study will develop an algorithm evaluate

TABLE I: Singular Values of Ambulation Experiment

Subjects	Restraint Ambulation	P_1 X	P_1 Y	P_1 Z	P_2 X	P_2 Y	P_2 Z	P_3 X	P_3 Y	P_3 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
Ave.	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	33.3	25.0	21.4	42.3	40.2	21.8

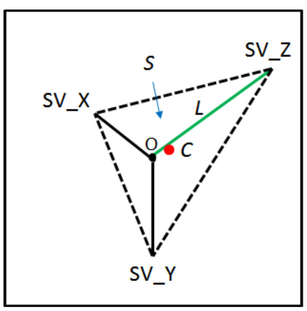


Fig. 4: Triangular Presentation of Singular Values

walking difficulty based on the triangular information.

V. Conclusion

The method for evaluating gait disturbance of evacuees in disasters is proposed by using SVD. Three levels of walking difficulty in the lower limbs are simulated in the verification experiment. The usefulness of evaluating the walking difficulty with the singular values was shown by the significantly different first singular values among the three levels at the measurement point on the constrained leg.

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