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Motion Recognition from Contact Force Measurement

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Abstract— **Optical motion capture systems, which are used in broad fields of research, are costly; they need large installation space and calibrations. We find difficulty in applying it in typical homes and care centers. Therefore we propose to use low cost contact force measurement systems to develop rehabilitation and healthcare monitoring tools. Here, we propose a novel algorithm for motion recognition using the feature vector from force data solely obtained during a daily exercise program. We recognized 7 types of movement (Radio Exercises) of two candidates (mean age 22, male). The results show that the recognition rate of each motion has high score (mean: 86.9%). The results also confirm that there is a clustering of each movement in personal exercises data, and a similarity of the clustering even for different candidates thus that motion recognition is possible using contact force data.**

I. Introduction

Motion capture systems have now spread in various research environments; in particular they are often used in for medical research and for entertainment [1][2][3]. However, it is difficult to use these motion capture systems into homes because they are of large costs and require space and technical knowledge to be used adequately. Moreover, several markers must be pasted on the body for accurate experiments, which requires time and know-how. Therefore a system, which is reasonable in cost, time and space, is needed [4].

In most rehabilitation and healthcare applications, not only the motion data is necessary, the contact forces are also mandatory information to measure. In such cases the use of force-plate is common. Recently, fairly low-cost contact force measurement devices have appeared on the market, in particular the Nintendo Wii balance board. It can connect easily to a PC via Bluetooth and it provides the contact force information with sufficient accuracy. Thus, it is expected that such devices will be significantly used for personal healthcare and rehabilitation. The contact force information is more accessible than the whole body motion and it contains crucial information regarding the dynamics of the movement executed.

In this paper, we focus on using the contact force information to recognize within a set of prescribed motions, the motion that is performed by several subjects.

In our preliminary work [5], we proved that it is possible to recognize some motions using only the contact force measurement regardless of the person characteristics. In this study, we propose a novel motion recognition algorithm based on the feature vectors that are calculated from the contact force information. From the clusters formed by the PCA of the feature vectors we can recognize the motion after adequate training of the recognition algorithm.

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II. Feature vector of the contact forces

The contact force vector is shown in equation (1). The contact force sensor (Force plate) can get three components of forces: F_x, F_y, F_z, the three components of moments: M_x, M_y, M_z, and the coordinates of center of pressure (CoP): ax, ay. In our study, instead of the three moments, we use T_z, the moment at the CoP. It is a function of F_x. F_y, M_z and the coordinates of the CoP as shown in (2). Using T_z prevents the data from being influenced by individual position differences when stepping on the force plates.

A feature vector is a vector that contains characteristics that could quantify various data. It is obtained by computing the auto-correlation matrix of the considered data. Here the contact forces given by (1). We compute the auto-correlation matrix $\boldsymbol{O}_i(l)$ [6] as equation (3). l is a time constant difference, here we set $l = 2$, because we can reflect the information of motion speed. Then we arrange the elements of $\boldsymbol{O}_i(l)$ into a single column vector. The result, as (4), is the feature vector for the given force data for motion i

$$\boldsymbol{q}_i[k] = [F_x \quad F_y \quad F_z \quad T_z] \in R^{4dof} . \tag{1}$$

$$T_z = M_z - F_y \times ax + F_x \times ay . \tag{2}$$

$$\boldsymbol{O}_i[l] = \frac{1}{T_i - 2} \sum_{k=l+1}^{T_i} \boldsymbol{q}_i[k] \boldsymbol{q}_i^{\mathrm{T}}[k-l] . \tag{3}$$

$$= [\boldsymbol{Q}_1(l) \quad \cdots \quad \boldsymbol{Q}_4(l)] \in R^{4dof \times 4dof} .$$

$$\boldsymbol{o}_i(l) = \begin{pmatrix} \boldsymbol{Q}_1(l) \\ \boldsymbol{Q}_2(l) \\ \boldsymbol{Q}_3(l) \\ \boldsymbol{Q}_4(l) \end{pmatrix} \in R^{16dof} . \tag{4}$$

Where: F_x: Force of x-axis [N], F_y: Force of y-axis [N], F_z: Force of z-axis [N], T_z: Moment around the z-axis at the CoP [Nm], ax: x-coordinate of CoP, ay: y-coordinate of CoP, k: Data time, i: Motion number, l: Time constant, T_i: Data length

III. Recognition method

Principal Component Analysis (PCA) of the obtained feature vector provides information of the clustering possibility of the training data-set. Consequently, it gives information on the possibility to discriminate a data-set from another data-set. Applied to motion recognition, it means that it gives information on the differences and resemblances of different motion data-set; it allows discriminating between several motions, for which algorithm has been trained. Depending on the resemblances, points create clusters of various shapes, in the space of principal components, which are dense or scat-

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tered. It is also possible to find whether a motion belongs to the training data or not, and perform incremental learning.

Often the three dimensional space of the first three principal components is used. The two dimensional space can also be used if the cluster structure is clear enough using only the first two components. The shape of a cluster highlights data-set with similarities, while scattered points represent data-set with little similarity to each other.

The recognition is based on the clustering of the PCA of the feature vectors [7]. In the feature vector space, we calculate a feature value using the center point of each cluster and the approximate straight line by the least-squares method of each cluster as shown in Fig. 1. In this section, we use the two dimensions space for explanation, with 4 motions and 5 training data per motion (four clusters C1 - C4, each of 5 points). It applies to any dimension, depending on the cluster formation of the training dataset. The training data are labelled manually. We observe a cluster structure, yet our recognition algorithm does not need to identify the cluster themselves (no use of k-mean, or dbscan…).

When a new test-data such as shown in Fig. 2 is provided, we calculate the Euclidian distance of the new data to the center point of each cluster and the Euclidian distance to the approximated straight line of each cluster C1 – C4.

The Euclidian distance from test-data to center point A_j of each cluster Cj is given by the following equations (6).

$$A_j(x_j, y_j) = \frac{1}{n}\sum_{i=1}^{n}(x_i, y_i)\,. \tag{5}$$

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}\,. \tag{6}$$

Moreover, the Euclidian distance h_{ij} from the new test-data to the approximate straight line of each cluster Cj is given by equation (8).

$$y_j = P_{j1}x_i + P_{j2}\,. \tag{7}$$

$$h_{ij} = \frac{\left|P_{j1}x_i - y_j + P_{j2}\right|}{\sqrt{P_{j1}^2 + 1}}\,. \tag{8}$$

The feature value S_{ij} is defined as the sum of d_{ij} and h_{ij}. Where, depending on the shape of the cluster we can use L and K, the weight coefficients. Those coefficients act in shaping the cluster and thus facilitate the recognition. If the shape of the cluster in unknown our the distribution around the center of the cluster is a Gaussian we can set L=K=1;

$$S_{ij} = Lh_{ij} + Kd_{ij}\,. \tag{9}$$

The minimal value of the S_{ij} gives the closest cluster to the new tes-data, thus allowing for recognition.

In this study, we used the three dimensional space of the PCA of the feature vectors. Therefore, the following equations are used to compute the feature value S_{ij}.

$$A_j(x_j, y_j, z_j) = \frac{1}{n}\sum_{i=1}^{n}(x_i, y_i, z_i)\,. \tag{10}$$

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2}\,. \tag{11}$$

$$P_{j1}x + (Q_{j1} - 1)y - z + (P_{j2} + Q_{j2}) = 0\,. \tag{12}$$

$$h_{ij}\sqrt{\frac{\left|P_{j1}x_i - y_j + P_{j2}\right|^2}{\sqrt{P_{j1}^2 + 1}} + \frac{\left|Q_{j1}y_i - z_j + Q_{j2}\right|^2}{\sqrt{Q_{j1}^2 + 1}}}\,. \tag{13}$$

IV. Experiments

Fig. 3 is an image during our experiment. The contact force data is measured with a force plate (Bertec EP4060-10). The set of prescribed motion is chosen among a Japanese daily television exercise program. The candidate where shown a video of the motions they have to perform, prior to the experiment. During the experiments, the same video was shown so that candidates can synchronize with the video.

We measured the contact force information for each of the chosen seven sequences of movements (M1 - M7) as shown in Table I. These sequences are part of the movements used in our previous study. The sequences of two candidates, repeated three times, were recorded. Some sequences include a repetition of the same movement, so finally the total number of trials differs from one movement to another.

V. Result and Consideration

The motions of Table I for the two candidates (mean age 22, male) are segmented manually. Moreover, each motion

TABLE I. The 7 types of movements recorded and the number of repetitions and variants

M1	Arm circles	inner outer inner outer
M2	Side-bending	right right left left
M3	Front bending	1 time
M4	Waist rotations	right left
M5	Legs and arms	1 time
M6	Touch your foot	right left
M7	Small jumps	8 times

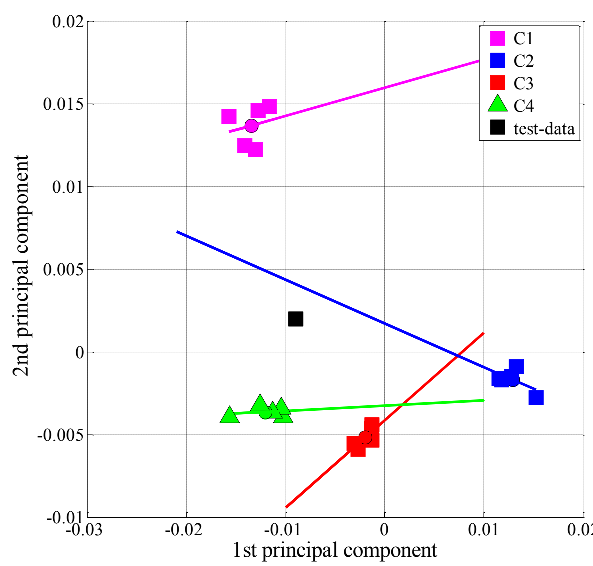

Figure 1. Feature vector space with barycenters and liner approximations.

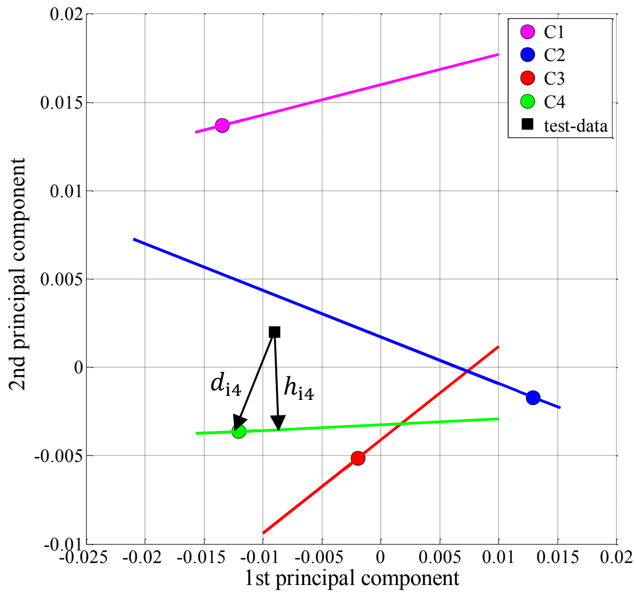

Figure 2. Concept of the proposed algorithm.

Figure 3. A snapshot of one candidate performing M4 during our experiments

is repeated several times, thus we obtain a database of motion that contains (add here the number) motions. The feature vectors are calculated according to section III. The result is given in Fig. 4. To avoid the effect of the PCA, that is principal components are determined by descending order of dispersion, we normalize the value of each principal component to obtain a parameter varying between [-1,1].

We then apply our recognition algorithm, using a leave one out method; and we compute the recognition performances of our proposed algorithm.

Figure 4 and Table II show the results about M1 - M7. From this figure, we can understand that M7 have strong differences compared to the clusters of M1 - M6. This can be explained easily, M7 is the only motion consisting in small jumps, thus the force profile is dramatically different than any other, and consequently the cluster obtained is clearly apart from the others. For this reason, the similarity of M7 and the other movements M1 - M6 is low. The recognition rate for M7 is high. Though it is not clear from Fig.4, from Table II, we can also found that the recognition of M5 is 100%. M5 is also different as it includes arms and legs motion simultaneously. However as expected, movements M1- M4 and M6 are more difficult to recognize. Because in the PCA representation the cluster of M1 - M4 and M6 are affected by the cluster of M5 and M7, the difference between the clusters decreases due to the presence these two movements. We thus now exclude M5 and M7 from the training data and apply again our recognition algorithm. (exclusion method)

Figure 5 shows the result that calculated PCA about M1 - M4 and M6. From this figure, we can found that the clustering has improved, the differences between those motion is clearer. Table III shows the recognition rate using these PCA results. From this table, we can found that recognition rate of M1 - M4 and M6 increases. The recognition rate of M1 is now 100%, which means that M1 can be recognized without error. However, the recognition rate of M3 and M6 is still low, once again, because it is affected by the cluster of M1. Again, we exclude M1 from the training data and perform again the recognition.

Figure 6 shows the result of the PCA about M2 - M4 and M6. From this figure, we can see, again, that the clustering has improved. Table IV shows the result of the recognition rate using these PCA results. From this table, we can see that the recognition rate of M2, M3 and M4 is high. However, the recognition rate of M6 shows low score, because M6 presents many similarities with M3, as can be seen from the confusion matrix given in Table VI.

Finally, Table V shows the recognition rates obtained for the whole procedure mentioned above. From this table, we can confirm an average 86.9% of successful recognition.

TABLE II. RECOGNITION RATE [%] (M1 - M7).

M1	M2	M3	M4	M5	M6	M7
58.3	75.0	16.7	33.3	100	33.3	100

TABLE III. RECOGNITION RATE [%] (M1 - M4 AND M6

M1	M2	M3	M4	M5	M6	M7
100	83.3	50	83.3	-	50	-

TABLE IV. RECOGNITION RATE [%] (M2 - M4 AND M6)

M1	M2	M3	M4	M5	M6	M7
-	83.3	83.3	91.7	-	50	-

TABLE V. RECOGNITION RATE [%] (M1 - M7) MEAN: 86.9%

M1	M2	M3	M4	M5	M6	M7
100	83.3	83.3	91.7	100	50	100

VI. CONCLUSION

In this paper we have used the contact force information to classify and recognize 7 types of exercise motions. We can confirm the three following points:

1. There is a strong clustering of the features obtained for each motion, though we solely use the contact

force information.

2. The similarity is not inter-personal, it is also intra-personal. As suggested by the results of the two subjects.
3. Using the feature value approach as well as the exclusion approach, we can recognize the motion with an average rate of 87%,

In order to obtain significant results it is necessary to choose motions that are highly repeatable, if not it is difficult to train the algorithm and a large variability in motion results in large clusters with low density. The method can also be used to quantify the differences in executed motions, for example compare a realized motion to a prescribed motion.

Future works include: making a high quality database by increasing the number of subjects, and the number of movements. Moreover, here the exclusion was set manually to verify the feasibility, for further applications in rehabilitation and sports training like “Radio Exercises” at typical homes, an automatized recognition is mandatory. Finally to evaluate health and rehabilitation easily with inexpensive contact force measurement further experiments using the Nintendo Wii balance board as force-plate are required. It has a pressure sensor at the four corners; it is possible to measure the contact force information. Thus, we think it can provide the necessary measurements for our study.

TABLE VI. CONFUSION MATRIX (M1- M7)

	M1	M2	M3	M4	M5	M6	M7
M1	1	0	0	0	0	0	0
M2	0	0.83	0	0.17	0	0	0
M3	0	0	0.83	0	0	0.17	0
M4	0	0.08	0	0.92	0	0	0
M5	0	0	0	0	1	0	0
M6	0	0	05	0	0	0.5	0
M7	0	0	0	0	0	0	1

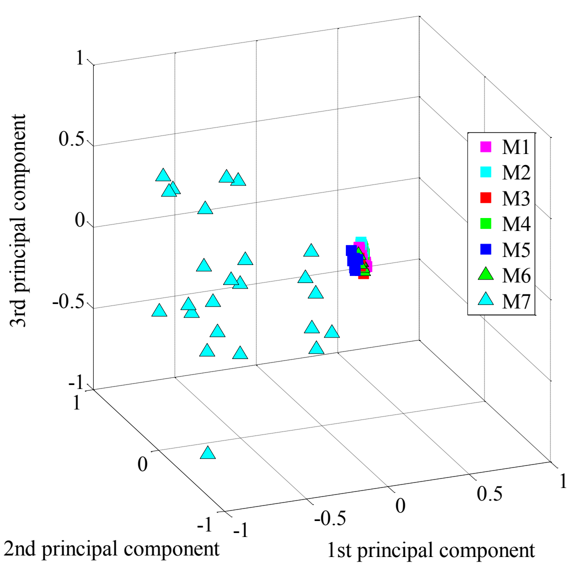

Figure 4. The result of PCA (M1 – M7).

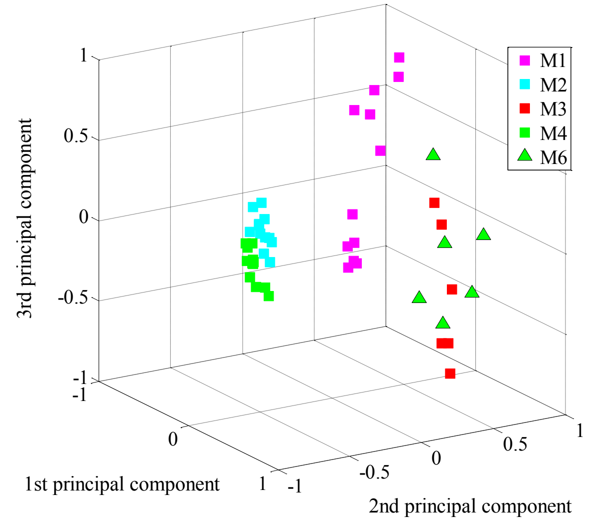

Figure 5. The result of PCA (M1 – M4 and M6).

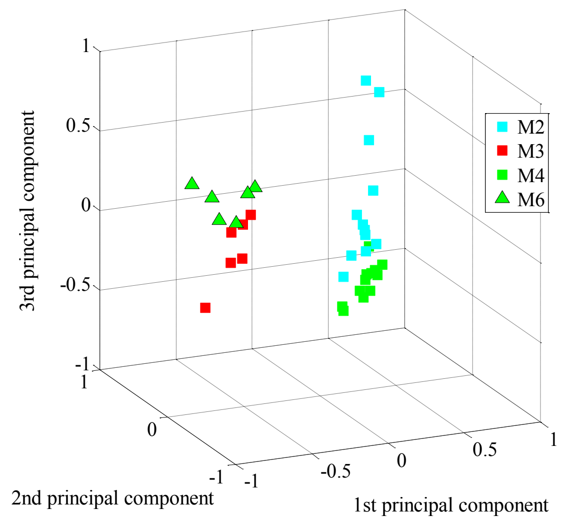

Figure 6. The result of PCA (M2 – M6).

REFERENCES

[1] M. Z. Patoli, et al. “Real time online motion capture for entertainment applications”. In The 3rd IEEE Int. Conf. on Digital Game and Intelligent Toy Enhanced Learning DIGITEL 2010, pp. 139-145, 2010.

[2] A. Fern’ndez-Baena, et al.”Biomechanical Validation of Upper-Body and Lower-Body Joint Movements of Kinect Motion Capture Data for Rehabilitation Treatments”. Proc. 4th Int. Conf. on INCoS 2012, pp. 656-661, 2012.

[3] F. Loula, et al. “Recognizing people from their movement”, –J. of Experimental Psychology: Human Perception and Performance, 31(1): 210-220, 2005.

[4] C. Canton-Ferrer, et al, “Towards a low cost multi-camera marker based human motion capture system”, Proc. 16th IEEE Int. Conf. on ICIP 2009, pp.2581-2584, 2009.

[5] G. Venture, et al. “Motion Recognition From Contact Forces Information and Identification of the Human Body Dynamics”, IEEE/RAS-EMBS Proc. Int. Conf. on Biomedical Robotics and Biomechatronics, pp.295-300, Tokyo, Japan, 2010.

[6] H. Kadone, et al. “Symbolic memory of motion patterns by an associative memory dynamics with selforgnizing nonmonotonicity”, Currnt Biology, vol.18, no.8, pp.329-300, 2008.

[7] T. Zhang, et al. “Individual Recognition from Gait using Feature Value Method”, Cybernectics and Information Technology, Vol. 12, No 3, pp. 86-95, 2012.