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Statistical Analysis of Gait Patterns of Persons with Cerebral Palsy

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M. Anthony Wong, Sheldon Simon, Richard Olshen,
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WP # 1221-81 May 1981

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AUTHORS' FOOTNOTE

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ABSTRACT

Patients at Boston's Children's Hospital who were diagnosed as having Cerebral Palsy were filmed walking. These films were digitized and translated into measurements associated with leg motion. Using a kth nearest neighbour clustering procedure, five subpopulations are identified from the modes of a uniformly consistent estimate of the underlying measurement-space density.

Graphical profiles and F-ratios were used to identify individual measurements which are most useful in distinguishing the membership of the various observed clusters. Walking velocity and patterns of hip and ankle movements are seen to be markedly different for each cluster. Traits associated with patients in two of the clusters are identified with severe gait pathologies, while the remaining three clusters exhibit characteristics more closely approximating normal gait.

Using the recursive partitioning classification rule, it is demonstrated that the effects of corrective measures such as surgery or assistive devices on the gait patterns of individual patients can be examined.

KEYWORDS: Cerebral Palsy; gait analysis; kth nearest neighbour clustering procedures; graphical profiles; recursive partitioning classification rule.

1. INTRODUCTION

The evaluation of human movement has long been recognized as a necessary and important aspect of the clinical workup of a subject suffering from any one of a variety of disorders. And with the numerous developments in the computer and electronic technological applications to this area of medicine in the last decade, there currently exist a plethora of instruments and methodologies which can acquire, process, and display human movement data accurately and reproduceably within a clinically useful, short period of time. Although such devices and methodologies have their widest clinical application currently in evaluating subjects with locomotive disorder (walking on level ground), there is increasing interest and every reason to believe that its utilization will be expanded to include a wide variety of human tasks; for example, bending, lifting, going up and down stairs or ramps, writing, feeding oneself, and in general, performing all the activities of daily as well as recreational living. It is also clear that such information will be invaluable to a wide variety of clinicians working in the fields of rehabilitation, orthopedics, neurology, and sports medicine, to name but a few. In all these areas, testing of human performance could be utilized to (a) understand the pathodynamic manifestations of a given organic disorder, and (b) monitor the progress of an untreated as well as a treated subject. The consequences that this could have towards the improvement of patient care are many.

Unfortunately, in spite of the continued improvement in tbe instrumentation and methodologies of evaluating human peformance, objective measurements of human performance still lack the widespread everyday clinical utility that X-ray currently has, owing to the inability of the clinician to properly interpret the data. The major reason for this is that the evaluation of human movement requires the monitoring of many movements and many forces creating these movements, each one needing to be monitored many times in a given time period. And the problem of properly interpreting this vast amount of data is formidable. (See however, Sutherland et al (1980), for a statistical study of the development of mature gait.) In this paper, the gait measurements obtained for 62 Cerebral Palsy patients at Boston's Children's Hospital are used to illustrate how various statistical methodologies including clustering procedures and classification rules can be usefully applied to the analysis and interpretation of human movement data.

A detailed description of the various gait measurements obtained for each patient in this study is given in Section 2. In Section 3, a cluster analysis of the gait measurements data is presented. The Cerebral Palsy patients are grouped on the basis of the various gait measurements using the kth nearest neighbour clustering procedure given in Wong (1981). And it is found that the five resulting clusters can be identified with different severeness levels of abnormal gait. Various graphical profiles are given in Section 4 to illustrate the relative characteristics of these clusters. F-ratios are also computed and are used to identify individual variables that are important in distinguishing the observed clusters. The variables identified include walking velocity, cadence of steps, and step length. These variables agree with the measurements cited in Sutherland et al (1980) as important determinants of gait development in normal children, and they are useful in illustrating the types of motions which are most affected by Cerebral Palsy. In section 5, the recursive partitioning classification rule given in Friedman (1977) is used to construct a classification scheme based on the groupings obtained by the clustering method. This classification scheme is useful in examining the effects of corrective measures such as surgery or assistive devices on the gait of individual patients. The results given in Section 5 indicate that, in general, operation is effective while the significance of assistive devices are hard to detect.

2. DESCRIPTION OF DATA

The sample used for this study is consisted of 62 patients at Boston's Children's Hospital, ranging in age from three to twenty-four, all of whom were dignosed as having some of the traits associated with Cerebral Palsy. Using high-speed movie cameras, these patients were filmed walking. These films were then digitized and translated into measurements associated with leg motion. Measurements used for the analysis were taken over the course of one gait cycle. A gait cycle begins when the heel or toe of one foot strikes the floor, and ends when that same heel or toe strikes the floor next. Measurements associated with the speed of gait, the length of steps, the time spent on one leg or both legs, and the angular motion of the hip, knee, and ankle were available for all patients. Those used included:

*cycle time--how many seconds to complete a gait cycle.

*cadence--the number of steps per minute, based on the cycle time observed.

*swing time--time spent with only one foot on the floor; measured as a percentage of cycle time for both right and left sides.

*double limb stance time--time spent with both feet on the floor; measured as a percentage of cycle time for both right foot forward and left foot forward.

*step length--measured for both steps.

*stride width--distance in inches between heels in the frontal plane.

*cycle velocity--feet per minute, based on cycle time and step length.

The following measurements of angular motion were made for the left and right sides of each patient:

*hip motion, x-direction--movement in the sagittal plane, taken from the side view. The measurement was arrived at by finding the angle between the line segment for the sacral stick (a stick extending straight out from the patient's back) and the line segment from the hip center to the knee center. If the angle measured 90 degrees, hip motion in this direction was defined to be zero degrees. See (a) in Figure A.

*hip motion, y-direction--movement in the frontal plane. It is measured from the angle formed by the line segment between the marker spots on the pelvic belt and the line segment between the hip and knee centers. If this angle is 90 degrees, then motion in this direction is defined to be zero degrees. See (b) in Figure A.

*hip motion, z-direction--motion in the transverse plane which requires readings to be taken from the front and side views at corresponding times of the cycle. From each view, a line segment was found which intersected the front of the knee, and was perpendicular to the line between the hip and ankle centers. The angle of rotation is measured to be zero if the hip, patella and ankle fall in a straight line as seen from the front. Movement of the patella away from the hip is defined as rotation. See (c) in Figure A.

*knee motion, x-direction--measured from the angle formed by the line segments from the hip to knee centers and the knee to ankle centers. Zero degrees motion occurs when the two line segments fall in a straight line. See (d) in Figure A.

*ankle motion, x-direction--measured from the angle formed by the line segment from the knee center to ankle center and the line of the floor. See (e) in Figure A.

*ankle motion, z-direction--measures foot rotation. The measurement points are taken to be the center of the ankle and a marker placed between the second and third toes. When these two points line up from the front, the angle of rotation is zero degrees. See (f) in Figure A.

(Remarks: It should be pointed out that measurements of foot rotation are much more subject to measurement error than the other angular measurements because of the small distance between measurement points. And foot rotation measurements for the patients' left side were not included in this analysis due to large amounts of missing data).

Each of the angles described above was measured in each frame of film throughout a gait cycle. (The cameras were run at a speed of fifty frames per second.) The resulting measurements form a time series x_t, which can be approximately represented by a thirteen terms Fourier series $x(t) = A_0 + A_1 \cos(t) + B_1 \sin(t) + \ldots + A_6 \cos(6t) + B_6 \sin(6t)$ for each frame t, using the least squares method. For each patient, the set of coefficients so obtained for a given angle is used to describe the corresponding angular motion.

Because the thirteen terms representation of each angle resulted in an excessive number of variables available for analysis, a procedure was required which would significantly reduce the number of coefficients used for each angle. The informal rule that was used for selecting coefficients consisted of two steps. In Step One, for any given patient and for any angular motion, those coefficients which were over twice as large in magnitude as the root mean square (RMS) were defined as "significant" coefficients; that is, coefficient C is significant only if $|C|/RMS \geq 2$, where

$$RMS = \left[\sum_{i=1}^{N} (x_t - \hat{x}_t)^2/(N - 13) \right]^{\frac{1}{2}}$$

$\hat{x}_t$ is the fitted value of the series at frame t, and N is the number of frames used to film the gait cycle. This definition was then applied to a random subset of twelve patients in Step Two, and a coefficient was included in the analysis if two or more patients had "significant" values for that coefficient. As a result of this procedure, 37 terms are used to represent the eleven different angular motions instead of the orginal 143 possible. Although it lacks the formal significance of t-tests, this method of data reduction is not an unreasonable one as the high noise levels of the angular measurements render them not to be too useful for fine discrimination between patients anyway.

3. CLUSTER ANALYSIS OF GAIT MEASUREMENTS

One purpose of this study is to group the sampled Cerebral Palsy patients on the basis of the various gait measurements, with the hope that the resulting clusters would identify with different severeness levels of abnormal gait. Since the gait measurements of a patient can be perceived as a point in the 46-dimensional Euclidean space, and clusters of patients can be thought of as high-density point-clouds in this measurements-space separated from other such point-clouds by regions of low point-density, the high-density clustering model given in Hartigan (1975, p. 205) and Wong (1981) is appropriate for this clustering problem. Under this clustering model, the kth nearest neighbour clustering procedure given in Wong (1981) is known to be asymptotically set-consistent for high-density clusters; it has also been shown to be useful for identifying high-density clusters in small samples. Hence this clustering technique is used here to obtain a hierarchical clustering of the Cerebral Palsy patients.

The clustering tree obtained when the kth nearest neighbour clustering procedure (with $k = 2$) is applied to the gait measurements of the 62 patients is shown in Figure B. This sample hierarchical clustering corresponds to the tree of high-density clusters defined on the kth nearest neighbour estimate of the underlying measurements-space density. Five modal clusters can be identified in the sample clustering tree, but two of these clusters (modes 3 and 5, as shown in Figure B) may correspond to local bumps present in the estimated density function when $k = 2$ is used; indeed, for larger values of $k (k = 3, 4, \text{ and } 5)$, only two modal clusters (modes 1 and 4) can be identified in the resulting hierarchical clusterings. However, since it is of clinical interest to explore and find any homogeneous subgroup of patients whose gait characteristics are different from the majority of Cerebral Palsy patients, the clustering solution obtained for $k = 2$ will be further examined in the following section, in spite of the possibly artificial nature of some of the identified subpopulations. The labels of the patients in each modal cluster shown in Figure B are listed below:

Cluster 1:	S473.R7	S561.R1	S405.R10	S592.R3	S595.R9	S410.R3
	S506.R16	S499.R2	S593.R6	S450.R4	S557.R8	
Cluster 2:	S455.R3	S497.R6	S452.R4	S400.R2		
Cluster 3:	S439.R3	S413.R4	S454.R1	S398.R6	S568.R1	
Cluster 4:	S427.R3	S428.R4	S429.R11	S432.R4	S434.R3	
Cluster 5:	S470.R3	S507.R4	S542.R8	S415.R4		

4. CLUSTER PROFILES AND CHARACTERISTICS

Summary statistics of the five identified clusters were computed for each of the 46 gait measurements, and they are given in Table 1. Moreover, for each measurement, a one-way analysis of variance was performed across clusters and the resulting F-ratio is also shown in Table 1. Since the groupings are specificed by the clustering procedure, the computed F-ratio will not conform to the usual F-distribution but will be larger just by chance, so they cannot be used to perform the usual significance testing. However, these pseudo-F ratios serve the purpose of identifying individual variables that are very different across the five clusters; for example, cycle velocity ($F = 115.9$) is seen to be drastically different among the clusters.

Insert Table 1 here

To illustrate and compare the characteristics of the various clusters, graphical profiles of the mean vector of the strength measurements (Figure C) the hip movements (Figure D), the knee movements (Figure E), and the ankle movements (Figure F) for each cluster are plotted. In all of these figures, the measurements are identified on the horizontal axis. In Figure C, the vertical axis shows the relative magnitude of the mean for each cluster to the largest cluster mean for that variable (or measurement). Cluster 3 is distinguished from the rest by having longer cycle time, shorter swing time and longer double-limb stance time, shorter step lengths, and lower cycle velocity. Patients in Cluster 1 appear to be physically stronger than those in Cluster 3, but they are consistently worse than those in the remaining clusters. Clusters 2, 4, and 5 exhibit similar characteristics, having relatively short cycle time, fast cadence, long swing time, and high cycle velocity; however, Cluster 2 can be seen to be the strongest group physically. Hence, Clusters 3, 1, 4, 5 and 2 are in the order of increasing gait strength.

The absolute relative magnitudes of the means of the hip movement coefficients are shown in Figure D. The corresponding plots for knee and ankle movements are given in Figure E and Figure F respectively. It should be pointed out that the absolute value of each Fourier coefficient reflects its importance in determining the overall shape of the original waveform; hence the larger the absolute value of the coefficient, the more effect it has in determining the shape of the waveform. For the hip and ankle movements (Figures D and F), it can be seen that the absolute relative magnitudes of the Fourier coefficients for Cluster 3 tend to be very small, indicating less angular motion in the hip and akle than the other clusters. On the other hand, Clusters 2, 4, and 5 consistently have large absolute relative magnitudes in these movements, indicating a higher degree of muscular control over these leg motions, and hence a less pathological gait (see also the relative physical strength shown by these clusters in Figure C); it can also be noted that Cluster 4 distinguishes itself from the other two clusters by showing relatively limited right ankle movements (see Figure F). However, no systematic pattern across clusters can be detected for the knee coefficients shown in Figure E. And the above observations point to the significance of hip and knee movements in indicating the physical strength of a patient's leg motion, while showing that the correlation between the knee movements and the gait strength of a patient is very low.

The variation of medical history of the patients across clusters are also examined, and are given in Table 2. Most of the patients in the two physically weakest groups (Clusters 1 and 3) were diagnosed as having quadriplegia (i.e. all four limbs are affected), while none of the patients in the physically strongest group (Cluster 2) had the same diagnosis. On the other hand, a patient diagnosed as having diaplegia (i.e. only two limbs are affected) can be in any one of the five identified clusters; hence, the present diagnosis system is not suitable for indicating the physical status of a Cerebral Palsy patient. Moreover, it can be seen in Table 2 that the patients in Clusters 1 and 3 were more likely to have been operated on (69%) than the other three clusters (38%). It is apparent that physicians are presently more inclined to recommending surgery to physically weaker patients than to the stronger patients.

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Insert Table 2 here

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5. DISCUSSION AND FURTHER ANALYSIS

One purpose of this study is to identify the different severity stages, if any, of Cerebral Palsy by examining the gait measurements of a sample of Cerebral Palsy patients. In Sections 3 and 4, it is shown that several severity stages of Cerebral Palsy could be identified using the kth nearest neighbour clustering procedure; gait cycle velocity and other strength characteristics play a predominant role in distinguishing the identified stages, although the magnitudes of hip and ankle movements are also useful in discriminating the various stages. However, the validity of the identified clusters is still questionable, and additional samples are needed for further analysis and cross-validation purposes. Alternatively, the discriminating power of the clustering procedure used can be determined by examining its effectiveness in distinguishing samples from known distinct populations with different gait patterns, but the relevant gait data have yet to be measured or collected.

Subsequent to cluster analysis which is useful for groupings-identification, it is important to develop a classification scheme so that patients can be assigned to one of the identified clusters. Such a classification scheme might provide a useful typology for classifying Cerebral Palsy patients; for example, it might be found that the effectiveness of corrective measures, such as surgery or assistive devices like crutches, varies across the clusters (or equivalently, across different severity stages).

For illustration purposes, the recursive partitioning decision rule given in Friedman (1977) is used to construct a classification scheme based on the groupings obtained by the clustering method. The resulting classification tree is given in Table 3. By virtue of his or her gait measurements, a patient can then be classified into any one of the five identified clusters by descending along the appropriate branches of the classification tree. Among the gait measurements considered in this study, the most important one in discriminating between the identified clusters is seen to be gait cycle velocity, which is used for discrimination along most branches of the classification tree. However, the angular motion of the right knee is important in distinguishing Cluster 4 from Clusters 2 and 5.

Although the error rate found in this classification scheme is only 1 out of 29, it is a deflated figure and is not useful for evaluating the effectiveness of the classification procedure because the original groupings are based on the results of a clustering method. But this classification tree is useful in assigning a new gait observation to one of the identified clusters. In three different instances, measurements taken on a patient before and after surgery resulted in different assignments to the identified groups according to the above classification scheme; in one case, the patient improved from Cluster 4 to Cluster 2 after knee surgery, and in the remaining two cases, the patients moved up from Cluster 3 to Cluster 1. But similar improvements were not detected for patients who were given assistive devices such as braces.

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Insert Table 3 here

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Table 1. SUMMARY STATISTICS for CLUSTERS

	Measurements		Cluster 1 Mean	Cluster 1 S.D.	Cluster 2 Mean	Cluster 2 S.D.	Cluster 3 Mean	Cluster 3 S.D.	Cluster 4 Mean	Cluster 4 S.D.	Cluster 5 Mean	Cluster 5 S.D.	F-Ratio
1	Cycle Time		1.04	0.19	0.81	0.07	2.05	0.31	0.86	0.08	0.90	0.11	51.3
2	Cadence		119.13	22.73	150.00	13.61	59.63	9.66	139.71	11.45	134.79	15.06	25.4
3	L. Swing %		35.14	3.42	40.67	2.66	20.87	11.05	37.15	3.64	37.03	3.54	11.6
4	R. Double %		15.92	4.19	10.19	1.75	27.31	8.00	12.22	3.73	12.02	3.03	13.6
5	L. Double %		13.75	3.81	11.47	1.05	36.30	13.20	10.35	1.08	13.70	3.77	18.8
6	R. Step Length		1.18	0.23	1.60	0.11	0.67	0.29	1.54	0.14	1.48	0.19	19.1
7	L. Step Length		1.29	0.37	1.65	0.10	0.60	0.47	1.66	0.14	1.57	0.22	12.2
8	Stride Width		0.41	0.11	0.47	0.10	0.55	0.27	0.44	0.19	0.43	0.10	0.8
9	Cycle Velocity		143.05	13.94	243.39	18.25	39.12	21.81	223.98	30.92	203.15	12.22	115.9
10	R. Hip X	A_0	5.83	5.01	0.34	6.04	-0.09	9.13	-20.00	9.76	6.56	3.18	17.2
11		A_1	-3.54	2.83	-2.55	2.96	-0.09	2.28	11.00	5.67	-6.54	3.90	21.4
12		B_1	-3.32	3.86	-6.21	4.45	-1.73	3.44	-4.98	5.91	-3.54	4.96	0.7
13	R. Hip Y	A_0	-6.95	14.04	-28.03	15.40	-15.07	10.21	17.78	14.06	-10.83	18.70	5.8
14		A_1	1.33	5.06	-3.17	1.34	0.49	4.53	3.80	9.50	0.48	2.39	1.1
15	R. Hip Z	A_0	43.93	10.45	30.67	8.79	40.86	15.24	-34.38	7.39	34.38	4.73	63.2
16		A_1	13.32	6.25	6.99	4.49	1.13	8.69	-10.02	9.06	12.09	5.40	12.9
17		A_2	0.11	3.63	1.03	1.86	0.49	3.54	1.83	3.80	-1.97	5.51	0.9
18		B_1	9.57	4.93	19.04	4.74	5.89	5.37	-13.65	6.43	16.91	10.22	18.2
19		B_2	-7.04	5.09	-10.29	8.71	-3.01	3.05	-7.26	4.95	3.99	10.88	4.4
20	L. Hip X	A_0	6.33	4.93	3.24	2.86	2.11	4.48	-10.81	11.55	2.67	3.45	8.0
21		A_1	5.87	3.23	6.89	4.66	0.80	2.38	-5.15	4.98	5.38	3.15	11.3
22		B_1	1.94	3.21	3.30	5.91	2.23	1.21	0.44	10.28	2.34	6.88	0.1
23	L. Hip Y	A_0	-12.11	14.45	9.62	5.38	-6.81	10.39	11.04	24.82	-18.41	15.90	4.5
24		A_1	-2.67	5.76	2.57	3.98	-1.38	4.21	-3.47	5.77	3.16	2.96	3.1
25	L. Hip Z	A_0	37.17	3.89	37.46	6.80	44.06	13.97	-28.04	10.33	31.43	5.79	72.5
26		A_1	-9.50	6.17	-5.03	5.45	-1.09	6.57	6.45	3.07	-10.83	6.28	9.3
27		A_2	2.63	2.62	3.41	1.82	0.88	3.29	1.17	4.77	2.36	3.56	0.5
28		B_1	-12.20	5.50	-21.35	4.30	-3.52	5.83	15.23	5.34	-17.38	7.27	31.5
29		B_2	-4.66	3.83	-7.05	4.77	0.89	3.64	-4.76	5.57	4.89	12.69	3.0
30	R. Knee X	A_0	-8.94	7.96	-15.04	8.29	-6.13	11.50	20.18	8.00	-11.96	9.97	12.3
31		A_1	0.71	3.45	-0.91	2.20	-1.09	1.75	-1.45	2.90	-0.05	3.32	0.7
32		A_2	0.87	1.70	0.30	3.75	0.88	1.38	1.06	1.99	-0.54	2.72	0.7
33		B_1	1.66	2.89	-4.54	8.41	-0.16	2.30	2.63	5.87	-1.23	6.15	1.6
34		B_2	-0.21	2.42	1.40	3.48	0.80	1.06	-1.07	2.36	-0.11	2.94	0.7
35	L. Knee X	A_0	-16.43	9.81	-1.47	2.43	-7.76	7.12	15.56	16.63	-18.55	8.45	12.4
36		B_1	0.13	4.46	-4.10	3.70	-0.30	2.78	-1.81	11.72	4.50	4.84	2.1
37		B_2	0.29	2.01	-0.10	2.13	-0.81	1.57	-0.04	2.59	0.72	4.08	0.3
38	R. Ankle X	A_0	8.44	13.18	12.63	11.21	-2.36	20.22	-0.47	8.31	26.21	18.69	4.2
39		A_1	0.46	3.38	3.43	3.87	-0.70	5.21	-0.91	5.88	4.56	4.16	2.4
40		B_1	-0.36	5.30	-0.82	5.15	0.39	1.75	0.80	4.50	-1.39	5.27	0.2
41	R. Ankle Z	A_0	32.41	9.10	33.82	5.28	40.70	7.39	-29.29	7.31	28.62	10.76	54.7
42		A_1	8.66	4.96	17.10	5.20	2.33	5.63	-11.41	7.62	8.85	5.47	17.7
43		B_1	-16.60	5.90	-20.63	2.62	-6.51	8.07	16.14	3.93	-21.67	5.82	41.0
44	L. Ankle X	A_0	19.70	10.30	10.64	10.59	7.17	23.40	-1.63	2.91	38.67	8.37	10.5
45		A_1	-0.54	3.91	-5.96	3.80	-1.59	4.27	-3.07	3.88	-6.01	3.57	3.4
46		B_1	-0.22	2.73	-0.25	3.70	-1.16	2.95	-1.91	5.61	0.58	2.16	0.6

Table 2. Variation of medical history of patients across clusters

	Diagnosis					Surgery Performed		
	Quadriplegia	Diaplegia	L. Hemiplegia	R. Hemiplegia	Other	YES	NO	NA
CLUSTER 1	5	3	1	0	2	7	2	2
CLUSTER 2	0	3	1	0	0	1	2	1
CLUSTER 3	4	1	0	0	0	4	1	0
CLUSTER 4	2	2	0	0	1	2	2	1
CLUSTER 5	2	1	1	0	0	2	2	0
TOTAL COUNT	13	10	3	0	3	16	9	4

Table 3. Recursive Partitioning Classification Tree

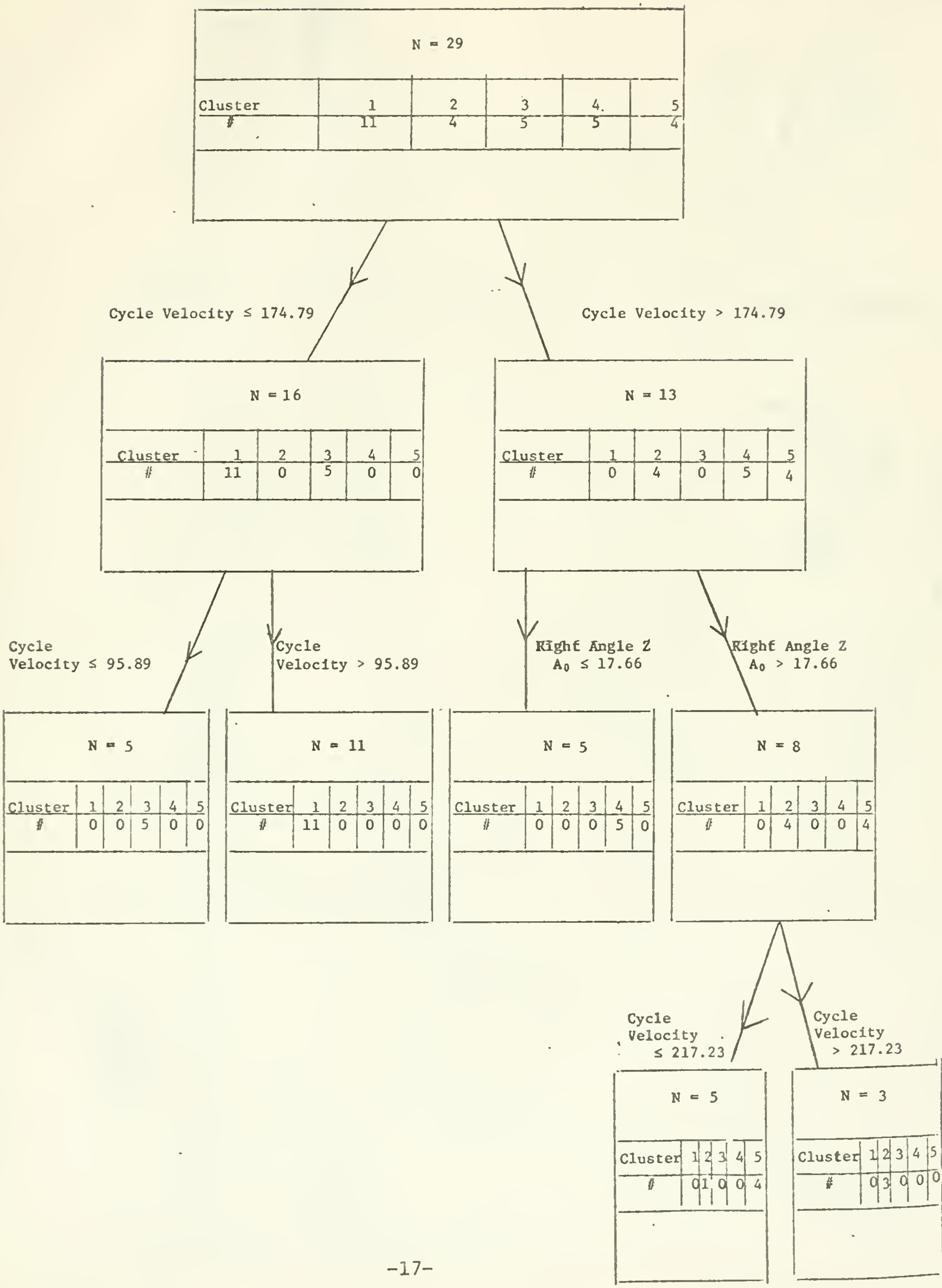
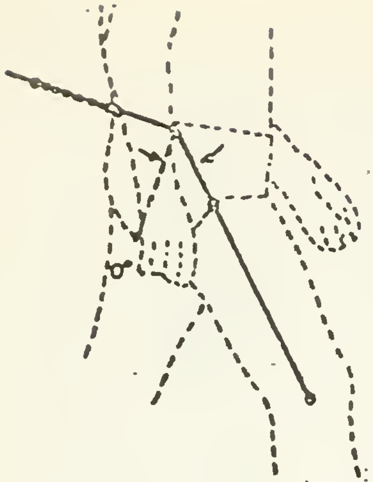
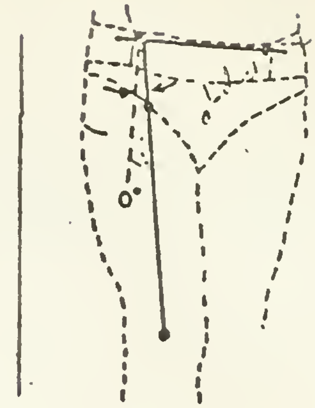


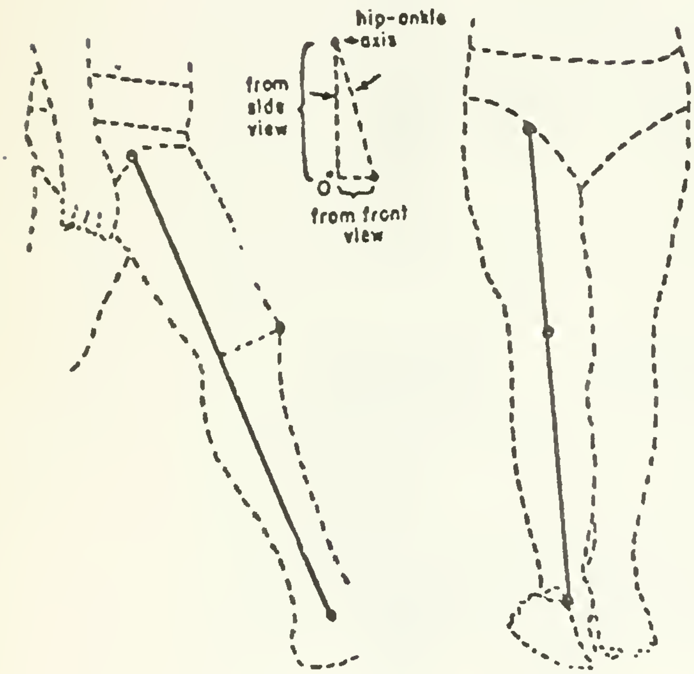
FIGURE A ANGULAR MEASUREMENTS OF LEG MOTION



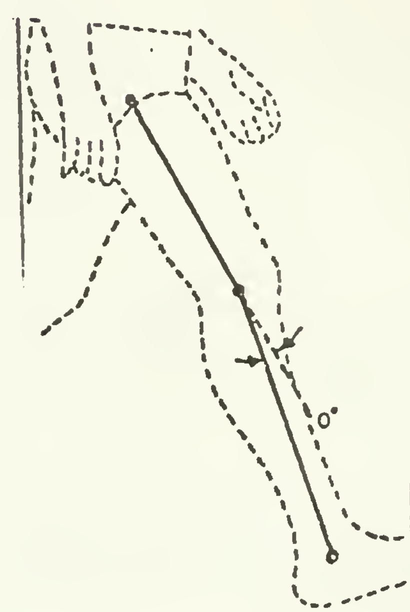
(a)
Hip Motion, x-direction



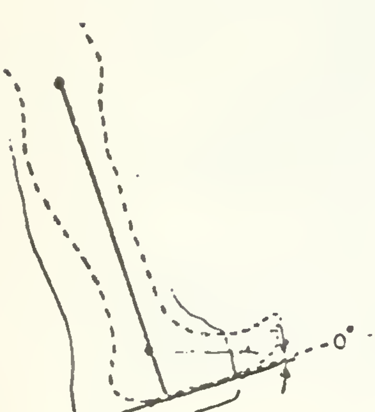
(b)
Hip Motion, y-direction



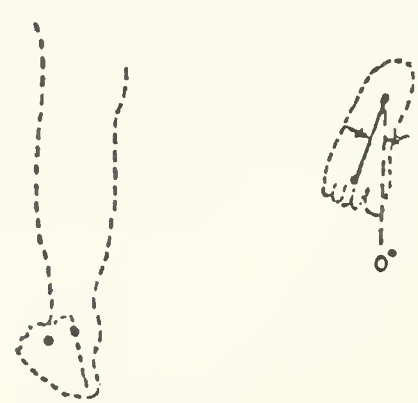
(c)
Hip Motion, z-direction



(d)
Knee Motion, x-direction

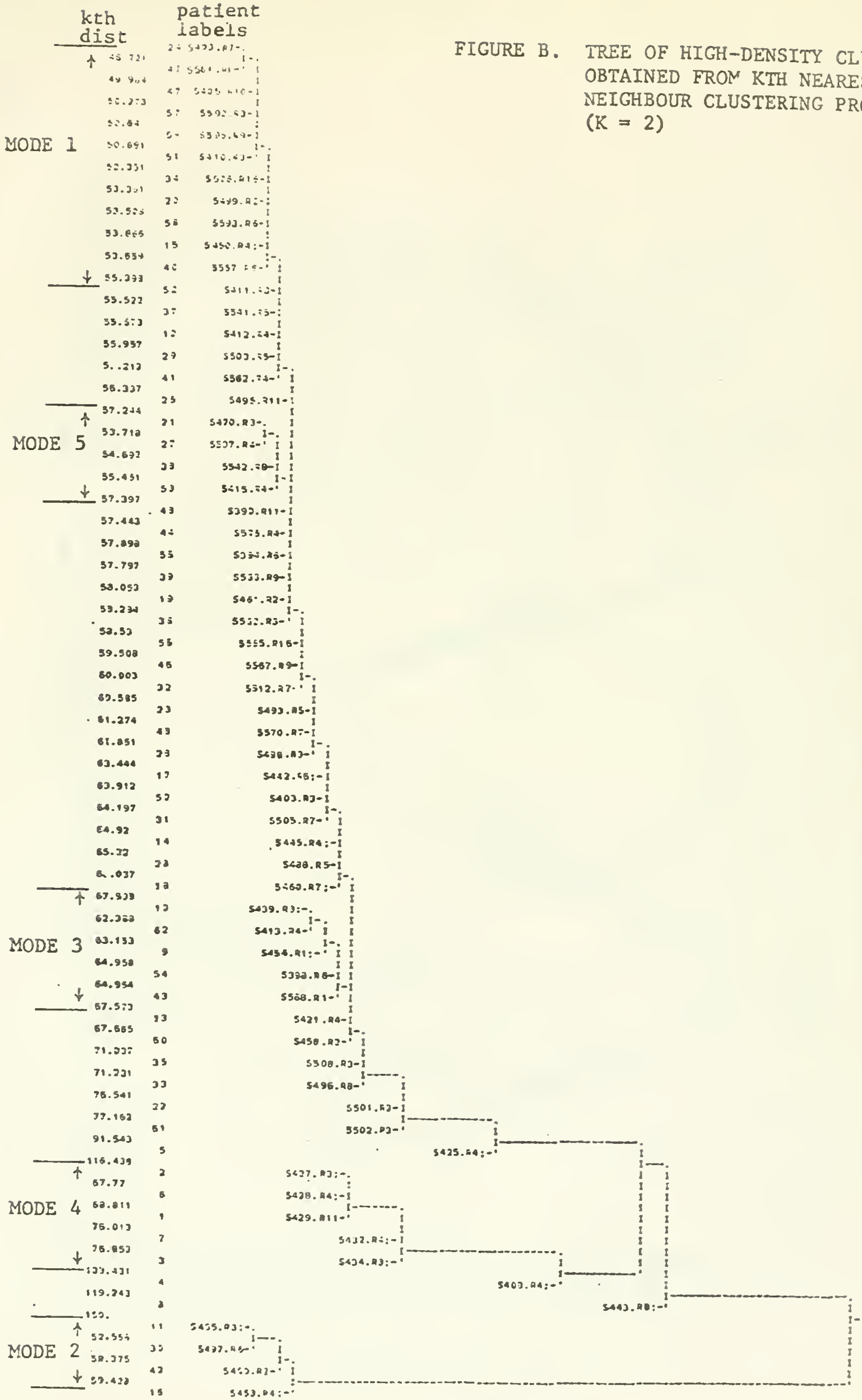


(e)
Ankle Motion, x-direction



(f)
Ankle Motion, z-direction

FIGURE B. TREE OF HIGH-DENSITY CLUSTERS OBTAINED FROM KTH NEAREST NEIGHBOUR CLUSTERING PROCEDURE (K = 2)



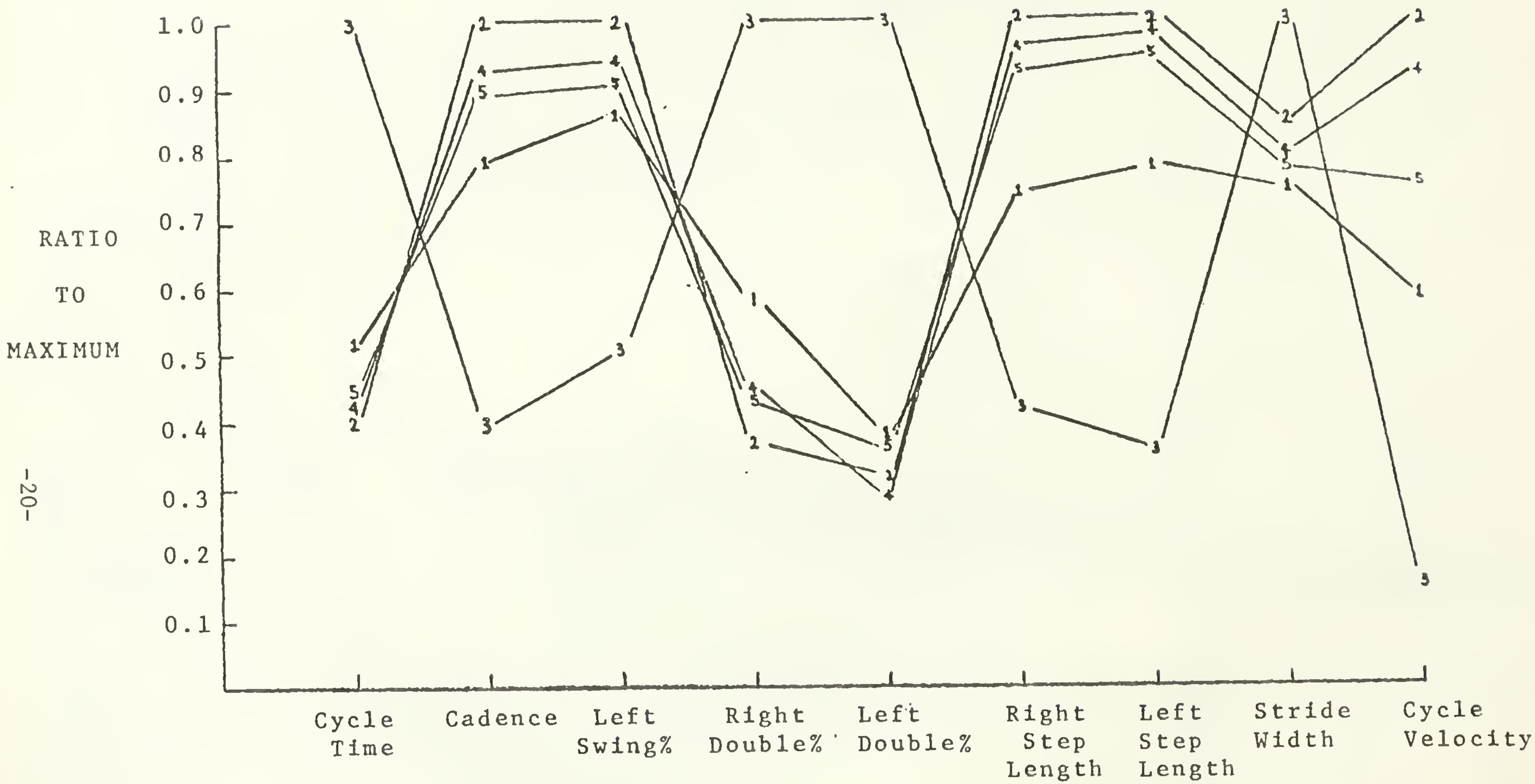


FIGURE C: COMPARISON OF CLUSTER PROFILES (STRENGTH MEASUREMENTS)

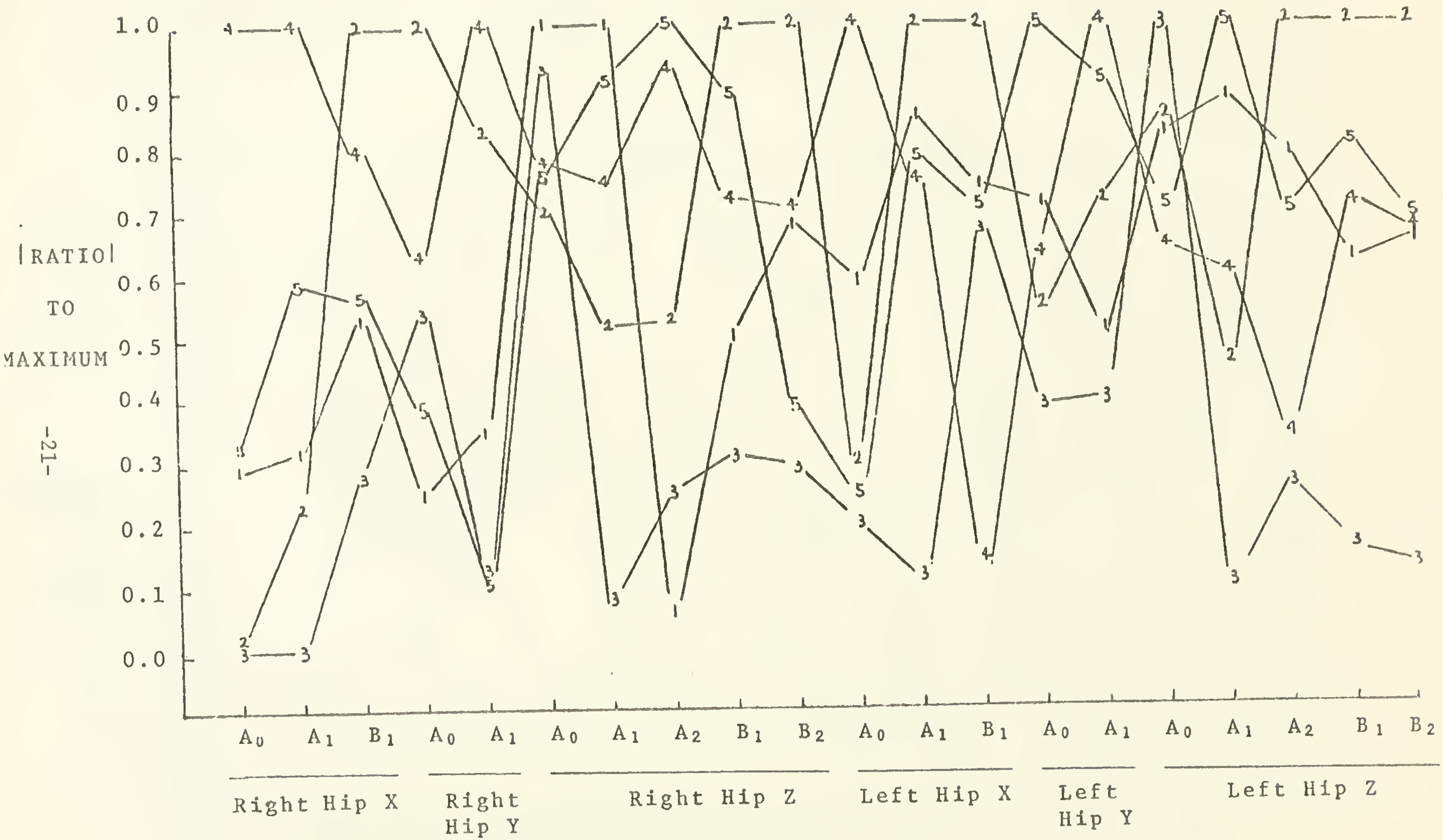


FIGURE D : COMPARISON OF CLUSTER PROFILES (HIP MOVEMENT)

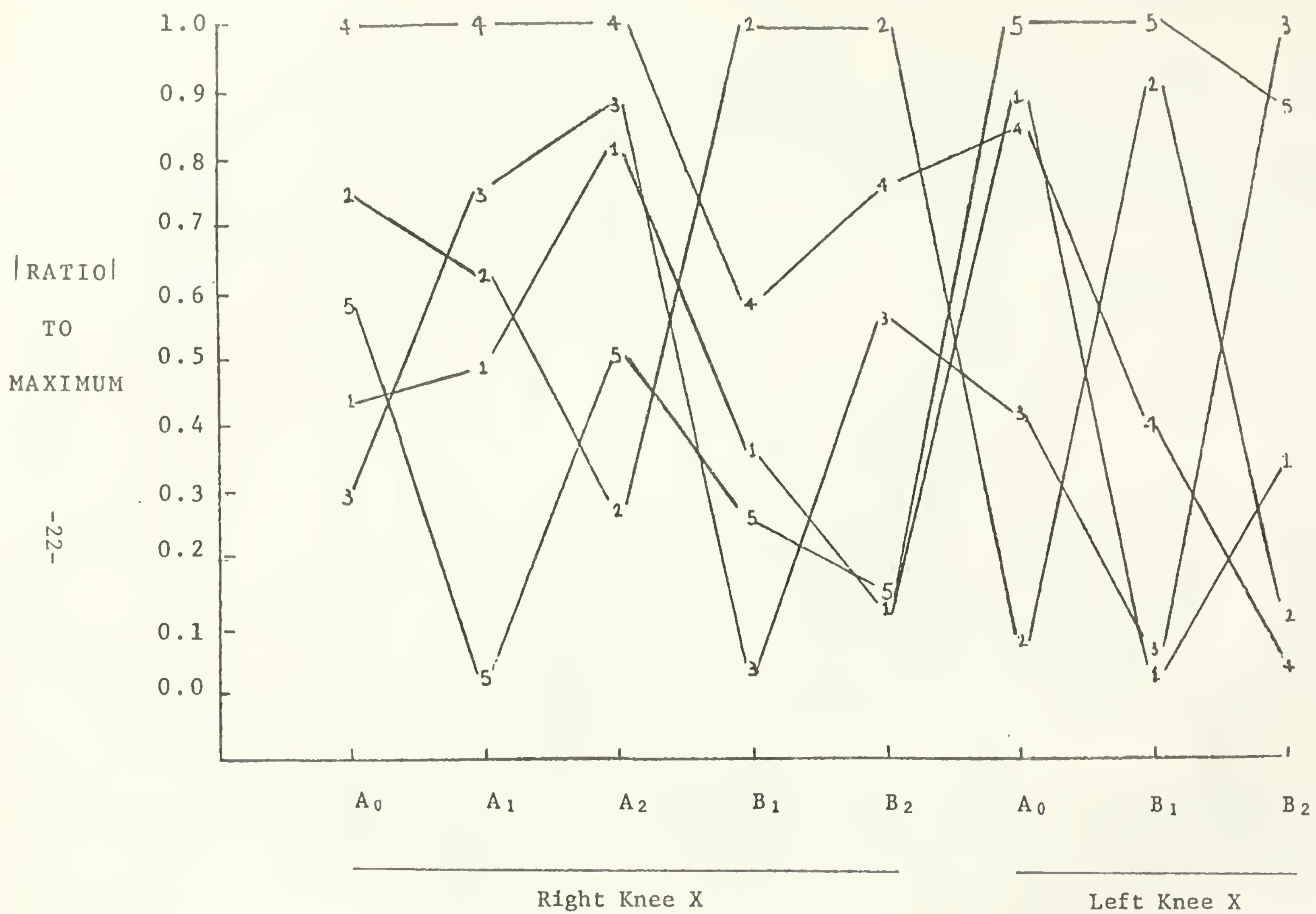


FIGURE E COMPARISON OF CLUSTER PROFILES (KNEE MOVEMENT)

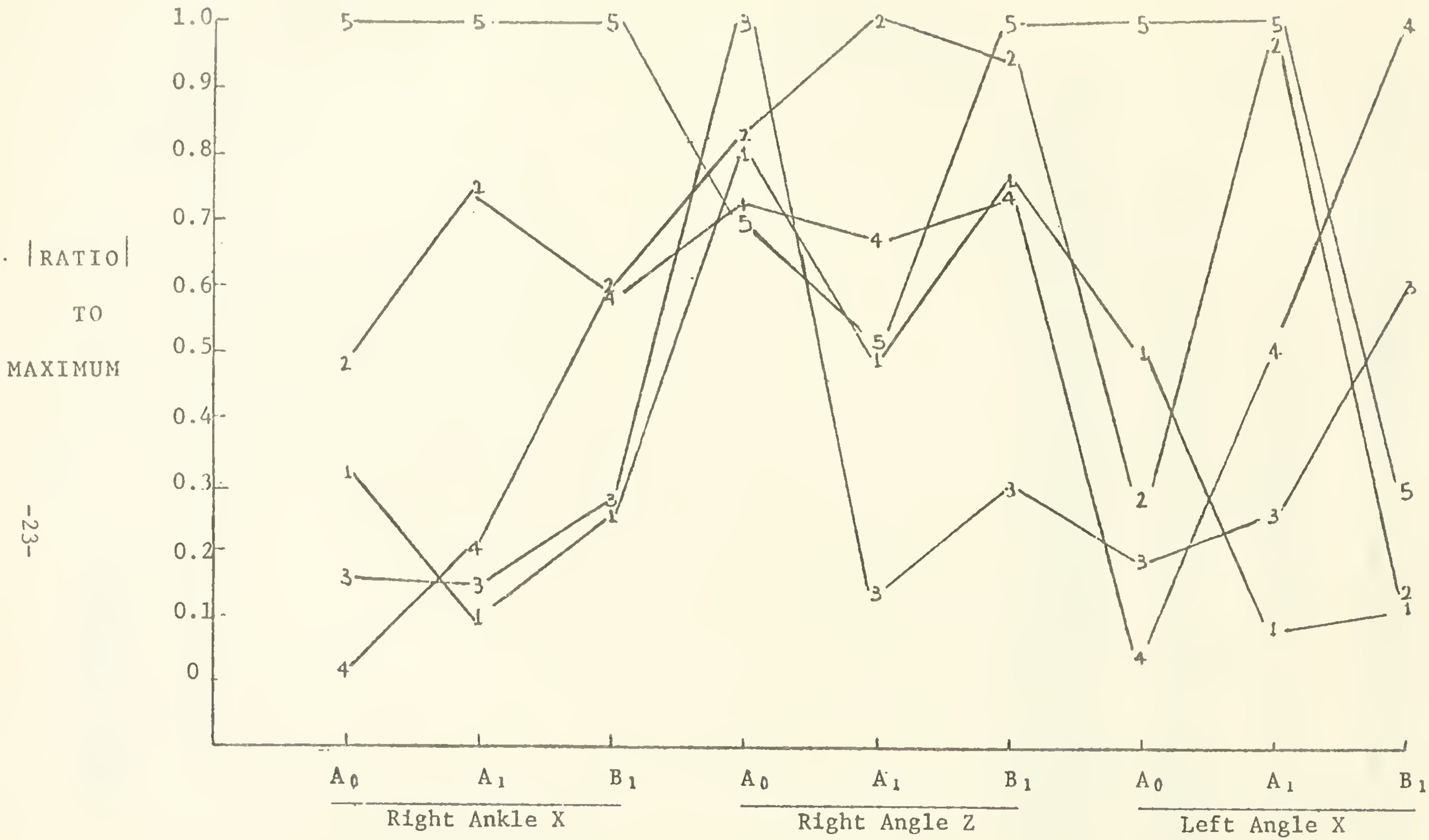


FIGURE F COMPARISON OF CLUSTER PROFILES (ANKLE MOVEMENT)

REFERENCES

Friedman, J.H. (1977), "A Recursive Partitioning Decision Rule for Nonparametric Classification," IEEE Trans. Computers, C-26, 404-408.

Hartigan, J.A. (1975), Clustering Algorithms, New York: John Wiley & Sons.

Sutherland, D.H., Olshen, R., Cooper, L., and Woo, S. (1980), "The Development of Mature Gait," J. Bone and Joint Surgery, 62-A, 336-353.

Wong, M.A. (1981), "A kth Nearest Neighbour Clustering Procedure", Sloan School of Management Working Paper No. 1213-81, M.I.T. Cambridge. (To appear in the Proceedings of the 13th Interface Symposium on Computer Science and Statistics, May 1981.)