IDENTIFICATION OF CLINICALLY SIGNIFICANT MEASUREMENTS FOR HUMAN GAIT EVALUATION AND DIAGNOSIS

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Summary

To date, clinical evaluation has, for the most part, remained subjective in nature. Over the last three decades, quite a number of basic studies have been carried out in an attempt to isolate and quantify the events that occur during gait, both normal and pathological. To this end, walkways have been developed with the instrumentation necessary for measuring the dynamic variables of gait. Considerable data has been generated. Little success has been achieved, however, in the reduction of this data to a clinically relevant form. In a number of different studies, small numbers of measurements were subjectively selected and evaluated for diagnosis of specific gait anomalies. Investigations of larger sets of parameters have not resulted in significant conclusions, vis a vis broad clinical application.

In this study over sixty parameters derived from locomotion studies on approximately 130 subjects were used to generate a minimized number of necessary measurements while maximizing the diagnostic information available from this data. The parameters were based on age, anthropometric measurements, and on both static and dynamic biomechanical measurements of joint motion and torque and foot/floor reaction forces. Techniques based on dimensional analysis, information theory, correlation analysis and principal component analysis were used to find an optimal set of measurements.

The results indicate that reduction of parameters to a manageable number is feasible. These features were rank ordered in terms of their information content. This should enable the use of different sets of parameters depending on the environment (clinical, lab or street) and on the intent of the clinician or investigator. Our goal has been to find a better mechanism of defining "normal" gait and of measuring deviations from this norm. The work herein described is part of a more encompassing study to derive a performance index or composite describing normal and pathological gait based on a novel approach derived from multidimensional pattern recognition.

Introduction

Achieving a better understanding of gait requires the study of many parameters and their interaction during the gait process. Nevertheless for the evaluation of gait and diagnosis of pathology, some relatively small set of measurements ought to distinguish gait anomalies and serve as a basis for clinical work.

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To derive an "optimal" number of significant parameters it is necessary to eliminate parameters which are redundant, those which do not add to the diagnosis, or worse, those that obscure the results. It is necessary to distinguish measurements which are significant to evaluation from those that are merely incidental. Isolating these parameters and minimizing their number is the focus of this paper.

Parameters that have been investigated in the past include: the range and pattern of joint motion, floor reaction forces, timing of foot/floor contact, gait speeds, cadences, stride lengths, swing to stance phase relations, and phasic muscular activities.

The techniques used in measurement of gait are varied. The methods used are generally a function of the intended application. Various factors affect the decision of which method to choose. These factors are simplicity of use, price, accuracy and repeatability, the accessibility of measurements, the transducers' effect on gait, the quantity of data that can be processed and the speed with which this data can be processed. Techniques that have been used for kinematic variables are motion picture photography, electrogoniometers, videophotography, strobelight photography and more recently the "Selspot" motion measurement system. Some of these techniques are reviewed in [9]. Additional methods not widely used include ultrasonics, fluxgate magnetometry, and accelerometry. Of all these systems, the "Selspot" seems to present the most potential for future computer integrated biomechanical measurement systems. For investigative foot/floor interaction, strain gauge or piezoelectric force plates, instrumented shoes and foot switches have been employed to study reaction forces and floor contact patterns.

Data

The data used in this study was collected from 1974 to 1977 in the Orthopaedic Biomechanics Laboratory of the Mayo Clinic. One hundred and twenty nine subjects were used in this study. Seventy subjects — 32 males and 38 females had normal gait as assessed by the laboratory staff, and ranged in age from 25 to 76. The patient population was comprised of 21 males and 38 females ranging in age from 17 to 83. Of this latter group (59 subjects), fifty seven had had at least unilateral total knee arthroplasty (TKA). Many of these patients had further complicating factors in their gait. A number of patients had had total hip anthroplasty, while many patients exhibited varying stages of osteo- or rheumatoid arthritis in other joints. A few subjects used a cane, but during the gait tests, a cane was not used.

A detailed description of the gait measurement instrumentation and of the experimental procedure can be found in Chao [2]. Three dimensional electrical goniometers were used to measure the joint angles during motion, foot switches provided stance and cadence information while a force plate measured the foot/floor reaction forces. A custom made device was developed to measure the isometric torque that can be applied at the knee in flexion and in extension. This enabled measurement of the maximum single effort isometric torque for the quadriceps and hamstrings.

In all instances, the force and angle data was not averaged or smoothed despite some particularly noisy signals.

Initial Selection of Features

Based on the literature and the biomechanics of gait, sixty one parameters were initially selected for study (See Table 1). Some of these were intentionally redundant (e.g., cadence and stride length define gait velocity, yet all three were included) as a check on the methods and also for determining which of these is most or more significant to clinical diagnosis.

Angular information was limited to that of the knee. This was done for two reasons. (1) Data for the trajectory of more than one joint taken concurrently was available only for a very limited population size; and (2) the patient population available for study had a pathological condition of the knee joint. Sex, age, height and weight are important in gait evaluation and thus were included. Clinical information such as pain, joint instability, joint tenderness and swelling, subject maneuverability and radiographic information such as articular surface regularity and joint spacing can contribute to proper diagnosis. However, due to the subjective nature of these assessments, they were not considered here. This is not to say that such parameters might not be investigated at a later date.

At an earlier stage in this study, harmonic analysis was performed on the data in the search for significant gait features. The likely value of a spectrum analysis may be to gain new insight into the gait dynamic process or to somehow reduce the dimensionality of temporal measurements to a smaller number of measures. There has been indications e.g. Chao [2], that the severity of the pathology might be indicated by higher harmonics of the knee joint information. Nevertheless, since temporal waveforms may be more readily interpretable and since neither of the two prospects for harmonic analysis were evident in this study, this technique was not explored further. There was no need to develop data transformations when the original data was significant, and sufficient of itself.

Symmetry measures have been proposed by Kljajic, Tadej and Stanic [7] and Chao [2]. These measures compare the dynamics of the right and left limb. The motivation is to reference the affected limb gait to that of the intact limb either for evaluation, or for control as Darling [3] and Grimes [6] have proposed. This might be an adequate procedure if the overall performance of the intact limb could be considered normal, but this is not usually the case. To overcome a diability on one side, the other limb adapts its gait to improve stability, comfort, posture, etc. Comparing gait of one limb to the other is a relative measure only and not necessarily a measure of gait in absolute terms. For this reason, symmetry measures were not considered here.

Most parameters were non-dimensionalized in order to eliminate some of the effect of parameter units. A rigorous description of the technique can be found in Taylor [10]. In essence, the method involves dividing and/or multiplying parameters to derive dimensionless numbers which may be associated with a particular phenomenon. For example, in fluid mechanics, Reynold's number is associated with distinguishing turbulent from laminar flow. In the case of gait, a number of anthropometric measures were developed: lower extremity length/height, and thigh diameter/height representing the somatotype of the individual; stride length/height, a standardized stride length accounting for height; maximum single effort isometric torque/(height x weight), a standardized torque accounting for body build; age/gait period, a standardized gait period accounting for the effect of age, and so on. The complete list is in Table 1. A number of other features were explored as well but were found to be too random to have any significance for classification.

Table 1. Listing of Features

CODE NUMBER	FEATURE
	PHYSICAL:
100	Age (yrs)
200	Height (cm)
300	Weight (N)
658	Thigh circumference/height
659	Extremity length/height
	GAIT PARTICULARS
601	Gait period (sec)
602	Stride length (cm)
603	Velocity (m/sec)
604	Double support time[1] (% gait period)
651	Age/gait period (yrs/sec)
652	Stride length/height
660	Stance phase (normalized by gait period)
	AVERAGE ANGULAR VELOCITY DURING
607	Knee flexion in stance (radians/sec)
608	Knee extension prior to swing (radians/sec)
609	Knee flexion in swing (radians/sec)
610	Knee extension in swing (radians/sec)
	VERTICAL FORCES[2] ON FLOOR
631, 641	Maximum in 1st 40% stance, & associated time (% stance)
632, 642	Minimum between f_{631} & f_{633}, & associated time (% stance)
633, 643	Maximum in last 40% of stance, & associated time (% stance)
	FOREAFT SHEAR FORCES[2] ON FLOOR
634, 644	1st local minimum (before f_{635}), & associated time (% stance)
635, 645	Maximum, & associated time (% stance)
636, 646	Minimum, & associated time (% stance)
	MEDIOLATERAL SHEAR FORCES[2] ON FLOOR
637, 647	Maximum in 1st half of stance, & associated time (% stance)
638, 648	Minimum in 1st half of stance, & associated time (% stance)
639, 649	Minimum in 2nd half of stance, & associated time (% stance)
	MAXIMUM SINGLE EFFORT ISOMETRIC TORQUE
640	Hamstrings (N · m)
650	Quadraceps (N · m)
656	Hamstring torque/(height x weight)
657	Quadraceps torque (height x weight)
	PASSIVE RANGE OF MOTION OF KNEE
653	Passive range in flexion (radians)
654	Passive range in extension (radians)
655	Total passive range (radians)

CODE NUMBER	FEATURE
	SAGITTAL KNEE ANGLE (radians)
661	At maximum extension at about heel contact[3]
662	1st local maximum knee flexion[4] during stance
663	Knee extension prior to swing[4]
664	Maximum knee flexion during swing[4]
	FOR SAGITTAL KNEE ANGLE, TIME FROM MAXIMUM EXTENSION (Normalized by gait period)
665	To heel contact
666	To 1st local maximum flexion
667	To extension prior to swing
668	To maximum flexion during swing
	RANGE OF KNEE MOTION IN OTHER PLANES (radians)
669	Coronal plane
670	Transverse plane
	BASED ON VERTICAL LOAD
671	Rate of load application; f_{631}/f_{641} (% weight/%stance)
672	Rate of load relief; $f_{633}/(1-f_{643})$ (% weight/%stance)
673	Ratio: Initial maximum to minimum; f_{631}/f_{632}
674	Ratio: Final maximum to minimum; f_{633}/f_{632}
	BASED ON FOREAFT SHEAR FORCES
675	Diff. Between Maximum and Init. Min.; f_{635}/f_{634} (% weight)
676	Ratio: Max to ABS (Min); $f_{675}/\|f_{636}\|$
677	Rate of Force Change: Max. to Min.; $(f_{636}-f_{675})/(f_{646}-f_{645})$
	BASED ON MEDIOLATERAL SHEAR FORCES
678	Ratio: Max to ABS[1st Min]; $f_{637}/\|f_{638}\|$
679	Ratio: 1st Min to 2nd Min; f_{638}/f_{639}
680	Rate of Force Change: Max to 1st Min.; $(f_{638}-f_{637})/(f_{648}-f_{647})$

[1] Temporal intersection of force signal of one leg with foot switch of other.
[2] Ratio of force to weight of individual.
[3] As measured from nominal zero (set when mounting goniometers on subject).
[4] Measured from maximum extension (i.e., from feature 661).

Analysis

Identifying those measurements which best contribute to gait diagnosis may be associated with determining how much information is contributed by a measurement to the differentiation between normal and pathological gait.

Shannon [8] first proposed the idea that information is a statistical concept in the context of a communications system. Shannon further proposed that information can be measured and this measure is essentially a unique function of the statistical frequency distribution (i.e. the histogram). Since then, further developments have taken placing in applying this concept to evaluating the information derived from an experiment.

The average information associated with the occurance of a number of events is a function of the a priori probabilities

$$H = \sum_i P(\omega_i) \log \left[\frac{1}{P(\omega_i)}\right]$$

for i events (the Shannon-Wiener Law). The greater the probability of events occuring, the less the information derived from that event.

When additional information is made available, e.g., a measurement, X_j regarding an event ω_1, the probability that event ω_1 will occur, $P(\omega_1)$, increases to the probability that event occurs given that measurement, $P(\omega_i|X_j)$. This increase in probability is equivalent to a decrease in the information derived from the occurrence of event. This information decrease about event ω_i is equal to the information contributed by measurement X_j regarding ω_i.

When evaluated over k intervals of measurement X_j; Donath [4] has shown that

$$I(X_j;\omega) = \sum_i P(\omega_i) \log \left[\frac{1}{P(\omega_i)}\right] - \sum_k p(X_k) \sum_i P(\omega_i|X_k) \log \left[\frac{1}{P(\omega_i|X_k)}\right]$$

where $I(X_j; \omega_i)$ is defined as the average mutual information per event. This equation represents the information contributed by a measurement X_j to differentiating between i events. Information gained from the occurance of an event can be considered equivalent to the uncertainty prior to that event occuring. Thus the mutual information contributed by a measurement represents a decrease from the a priori uncertainty to the a posteriori uncertainty; i.e. a decrease in uncertainty is equal to an increase in information regarding the events due to that measurement.

In our case, the events are the occurence of normal or pathological gait. The a priori probability may be estimated from the data,leading to a sample dependent result, or may simply be assumed equal, i.e. for two classes, $P(\omega_1) = P(\omega_2) = .5$. The latter assumption was made with the first term of the above equation then equal to one bit (log base = 2). The smaller the second term, the greater the average mutual. This second term is proportional to the relative size of the overlap between event histograms for a given measurement. By evaluating the information, it is possible to rank order parameters in terms of their relative contribution.

The above is developed to indicate the information given about an event by the measurement of a single parameter. It stands to reason that it should be possible to evaluate the information contributed by measurement of several parameters. The result would better indicate the overall contribution of several parameters taking into account their interdependencies (i.e. correlation). Such a generalized result for the joint information was developed in [4]. The difficulty in applying the result is its unwieldiness. The calculations call for a solution over a multivariate histogram with a reasonable number of intervals for each variable. The data requirement is quite large; at least far larger than presently available. A limited solution for two parameter sets is also presented in [4].

In the above development, no account was taken of the interdependency of the variables. Certainly if only the univariate information measure is considered for evaluating features, there will be parameters highly correlated to one another which both contribute information regarding the class discrimination. If features are dependent there is little reason to consider them both for diagnosis purposes. The solution is to consider only uncorrelated features. To achieve this, a correlation analysis on the features was performed on the two separate sets of data — the normals and the set of TKA patients.

Missing data was ignored in the analysis with the sample size adjusted accordingly. For the smallest considered sample size of a featured pair, a sample correlation coefficient of $|r| > .45$ indicated correlation at the .01 level of significance. Features were then eliminated if they were correlated (in both data sets) with a feature having a greater information contribution to discrimination.

RESULTS

Two feature sets resulted, one based on feature #603, the gait velocity, and the other based on feature #652, the ratio of stride length to height (See Table 2). Both these parameters are correlated, but confidence in results based on feature #603 (f_{603}) is not as great, since the available sample size for features paired with f_{603} is relative smaller. This results from the way f_{603} is calculated. The stride length[1], f_{602}, was divided by the gait period[1], f_{601}, to result in gait velocity, f_{603}. If either the stride length was not available or the gait period could not be calculated, no resultant velocity could be derived.

The feature set included all non-correlated parameters with a relatively high univariate information. A cutoff was chosen after f_{660}, the ratio of stance phase to full gait cycle (analogous to the swing to stance ratio often used in other studies). Physical parameters such as age (f_{100}), height (f_{200}), weight (f_{300}), thigh circumference/height (f_{658}) and extremity length/height (f_{659}) were included despite their low information content. It must be remembered that the information function measures the contribution of the parameter to distinguishing normal from abnormal gait. These anthropometric parameters are not meant to do so of themselves. As part of a multivariate parameter set, they may help contribute to diagnosis of gait and as such, they are included for further study. For example, age of itself will not discriminate whether an individual has normal or abnormal gait. When considered together with other parameters, it might, for example, assist in distinguishing between an older individual walking normally and a young person with pathological gait. The fact that these measurements do not individually contribute to the information measures indicates that the data is relatively well distributed over these features.

The two feature sets shown in Table 2 may be further analyzed. Principal component analysis (also known as the Karhunen-Loéve expansion) is a transformation which results in a lower-dimensional representation while accounting for

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[1] Defined from heel contact of the same leg.

Table 2. Rank Ordering of Features

	FEATURE #	I(ω;x) (bit)	Feature with which sample Correlation, r > .45	Resultant Feature Set #1 (based on f_{603}) 21 Features	Resultant Feature Set #2 (based on f_{652}) 21 Features
1.	603	0.7406		603(1)	
2.	653	0.7343		653(2)	653(1)
3.	655	0.7152	653		
4.	674	0.5852	603		674(2)
5.	673	0.5692	674/603		
6.	652	0.5644	603		652(3)
7.	602	0.5396	652/603		
8.	609	0.5365		609(3)	609(4)
9.	677	0.4918	652	677(4)	
10.	633	0.4872		633(5)	633(5)
11.	631	0.4543	633		
12.	632	0.4297	633		
13.	662	0.4276		662(6)	662(6)
14.	671	0.4209	603/652		
15.	610	0.3982		610(7)	610(7)
16.	635	0.3922		635(8)	635(8)
17.	672	0.3863	633		
18.	607	0.3838	662		
19.	656	0.3837		656(9)	656(9)
20.	636	0.3799	652/77		
21.	664	0.3764	610		
22.	608	0.3494		608(10)	608(10)
23.	601	0.3474		601(11)	601(11)
24.	675	0.3361	635		
25.	648	0.3237		648(12)	648(12)
26.	650	0.3212	656		
27.	667	0.3047	609		
28.	604	0.3024		604(13)	604(13)
29.	640	0.2939	656		
30.	641	0.2931		641(14)	641(14)
31.	657	0.2525	656		
32.	643	0.2485		643(15)	643(15)
33.	100	0.2426		100(16)	100(16)
34.	660	0.2282		660(17)	660(17)
				Cutoff Point for Using Information Measure	
35.	654	0.2230			
36.	645	0.2113			
37.	638	0.2011			
38.	637	0.1885			
39.	639	0.1814	638		
40.	200	0.1757		200(18)	200(18)
41.	663	0.1756	662		
42.	668	0.1644			
43.	669	0.1607			
44.	642	0.1602			
45.	666	0.1590			
46.	651	0.1587	100		
47.	659	0.1558		659(19)	659(19)
48.	646	0.1483			
49.	670	0.1465			
50.	649	0.1458			
51.	676	0.1376			
52.	658	0.1274		658(20)	658(20)
53.	644	0.1270			
54.	661	0.1210	662		
55.	647	0.1147			
56.	634	0.1055			
57.	300	0.1017	200	300(21)	300(21)
58.	678	0.0997	637		
59.	680	0.0734	638		
60.	679	0.0569			
61.	665	0.0504	637		

the original variance of the features [5]. A major drawback of this method is that transformation results in a loss of the significance of the original parameters. Nevertheless, principal component analysis for a two class data set indicates that it should be possible to eliminate even more parameters from consideration with minimal representation error. This was in fact done using pattern recognition based on a quadratic discriminant error estimator. The results indicated that a four parameter set (f_{652}, f_{653}, f_{662}, f_{674}) was sufficient to differentiate between normal and TKA subjects with a 2.3% error [4].

Conclusions

These results further emphasize the limitations imposed by considering one parameter (i.e. feature) at a time. Two issues are at stake here. Information from sets of uncorrelated measures may not be helpful if they interact in such a way as to cloud the issue. At the same time though, correlated measurements may be useful by providing a degree of redundancy. This is similar to explaining a concept several ways in order to increase the liklihood that it will be understood.

Examination of the results in Table 2, (especially Set #2) indicates the importance of such features as the passive range of motion of knee flexion (f_{653}), the ratio of the final maximum vertical force to the minimum force during stance (f_{674}), the stride length/height ratio (f_{652}) and others as indicators of normal gait. The first of these indicates limited motion for the disabled knee, and the second, the desire not to load the leg with high forces thereby causing pain. This latter point is significant. It indicates a smaller amplitude of vertical oscillation of the center of gravity. The third mentioned feature simply represents a smaller stride for subjects with gait disability. Other features in feature set #2 (Table 2) may be explained as well.

The methods described here provides a mechanism for isolating those measurements which contribute information to the diagnosis of gait disability. Certainly the population chosen for study affects the result. By selecting patient populations with other pathologies, more general parameter sets may be found. The quandary then, may be that an overly general result will not be as useful to a particular problem. However, the methods presented should allow derivation of significant parameter sets for the particular situation under study.

The work presented here was part of a more encompassing study to derive a performance index delineating normal gait in terms of measurable quantities [4].

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