Transpn. Res.-A Vol. 19A, No. 4, pp. 279–296, 1985
Printed in the U.S.A.

0191–2607/85 $3.00+.00

TRAVEL/ACTIVITY ANALYSIS: PATTERN RECOGNITION, CLASSIFICATION AND INTERPRETATION

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(*Received* 9 *October* 1984; *in revised form* 27 *November* 1984)

Abstract—This paper presents a methodology for the analysis of travel/activity patterns based on a classification procedure in which the set of measurements that define human movement is represented by a pattern vector. Transformation techniques are then applied to the pattern vectors to develop a taxonomy for the pattern space. Subsequent inversion of the transformed patterns yields representative activity patterns that can be related to socioeconomic and urban form characteristics. Pattern recognition theory is demonstrated to be an effective means by which complex travel/activity patterns can be transformed into a structurally simpler space for purposes of planning and analysis.

1. INTRODUCTION

The analysis of activity patterns can be viewed as a classification problem in which the input is a set of measurements that define human movement and the output is the classification of this movement into a set of either "natural" or predetermined categories. In the time-geographic approach to human movement (Hägerstrand, 1974), the depiction of human activity is adapted as a continuous, piecewise smooth surface in the space/time continuum. Since the attendant dimensionality of such a space/time/activity representation is quite large, reduction of the complexity of the measurement vector while maintaining the corresponding information content for pattern comparison is a necessary element of practical applications of this approach.

A technique that holds particular promise in operationalizing the activity approach to analyzing travel behavior is pattern recognition theory, which has been used successfully in several fields as a method of image analysis and character recognition (Andrews, 1971). The basic process can be conceptualized as being comprised of three successive stages: (1) pattern specification, (2) feature extraction and (3) pattern classification. Detailed, formal treatment of these (and other) procedures is presented by Young and Calvert (1974). In its application to activity pattern analysis, the set of measurements that define human movement is represented by a vector that is labeled the "pattern vector." The components of the pattern vector are the measurements that define the movement. The taxonomy of activity patterns into "natural" categories depends both on the vector and on the decision function used to segment the set of all possible values that the pattern vector may assume (i.e. the activity pattern space) into a set of decision regions. For example, the activity pattern space may comprise all points in time and space that an individual could reach from some arbitrary starting point during a continuous 24-hr period. Activity pattern analysis may then be described as finding a rule that divides the pattern space into a set of distinct regions that typify certain specific travel behaviors.

In activity pattern analysis, the dimensionality of the measurement vector will, in general, be large (e.g. the pattern vector may consist of the spatial location and activity type participation of the individual at each 10-min interval throughout a 24-hr period) and may span information superfluous to efficient classification of activity patterns. Consequently, it is advantageous to reduce the complexity of the measurement vector while retaining as much of the information content of the activity pattern relevant to its classification as possible. This is accomplished by dividing activity pattern analysis into two sequential stages—feature extraction and classification.

The feature extractor may be either a linear or nonlinear transformation that maps the activity pattern vector into a corresponding vector of lower dimensionality. As a result of this simplification, some information is lost in the feature extraction process. Correspondingly the selection of the transform must be based on some combination of preserving the information content of the original pattern vector while decreasing its dimensionality.

The simplest type of feature extractor is the linear transformation. A systematic way of selecting this transformation is to minimize the mean square error in approximating the original activity pattern vector by the set of spanning vectors associated with the transformation. For example, this can be achieved by the expansion of the pattern vector in terms of a set of eigenvectors associated with the covariance matrix, known as the Karhunen–Loeve expansion (see e.g. Young and Calvert, 1974).

While the linear extractor based on the Karhunen-Loeve expansion is optimal in the sense of maintaining the information content of the original pattern, vector implementation is hindered by the need to diagonalize rather large covariance matrices. Eigenvectors defined by other systems may be useful in defining a feature selection rotation matrix and are readily implementable. Two such transforms, Fourier and Walsh, are promising as feature extractors in activity pattern analysis for several reasons: (1) rapid implementation algorithms are available—fast Fourier (Cooley and Tukey, 1956) and fast Walsh (Whelchel and Guinn, 1968) transform algorithms; (2) an information theoretic justification has been advanced (Pearl, 1971) based on rate distortion theory; and (3) the transforms can be applied to continuous functions.

The well-known Fourier sinusoidal transforms are based on transformations in terms of an infinite series of orthogonal trigonometric functions. The feature vector in this case would have as components the first M coefficients of the Fourier trigonometric expansion.

Alternatively, the Walsh–Hadamard transform is based on binary functions (known as Walsh functions), which form a complete basis. The corresponding feature vector in this case would have as components the first M coefficients of the Fourier–Walsh expansion.

In the application that is the subject of this paper, the Walsh–Hadamard transformation is used to transform a three-dimensional representation of human travel/activity decisions into a simple feature space with reduced dimensionality. Pattern classification is then performed in the more-efficient, high-information, reduced space. Subsequent inversion of the classification results leads to the identification of representative travel/activity patterns that are related to key socioeconomic and urban form indicators. An example of the potential application of this approach to the evaluation of transportation policy options is provided in Recker et al. (1981).

2. APPLICATION OF PATTERN RECOGNITION TECHNIQUES

The three-dimensional (time/space/activity type) activity pattern can be depicted by two corresponding images in two-dimensional space. A space/time continuum and an activity/time continuum detail individual location and activity participation over time and become complementary pattern vectors for feature extraction.

An example of such a representation for a hypothetical activity pattern is shown in Fig. 1, where the activity pattern is decomposed into its projections on the time/space and time/activity continua. It is noted that activity types are nominally scaled; no metric is implied. This nominal scale presents no analytic problem since the associated pattern recognition problem is basically one of label identification rather than measurement. The transformation decomposes each label into corresponding "transform building blocks."

Performance of an activity incurs no spatial displacement throughout its duration; thus, the measurement vector $\mathbf{x}(t)$ remains constant. For the activity/time continua, $\mathbf{x}(t)$ is a pure "step function." However, nonzero slope segments link sequential activities in the space/time continua, corresponding to spatial displacement during travel. The nature of this decomposition provides a potential

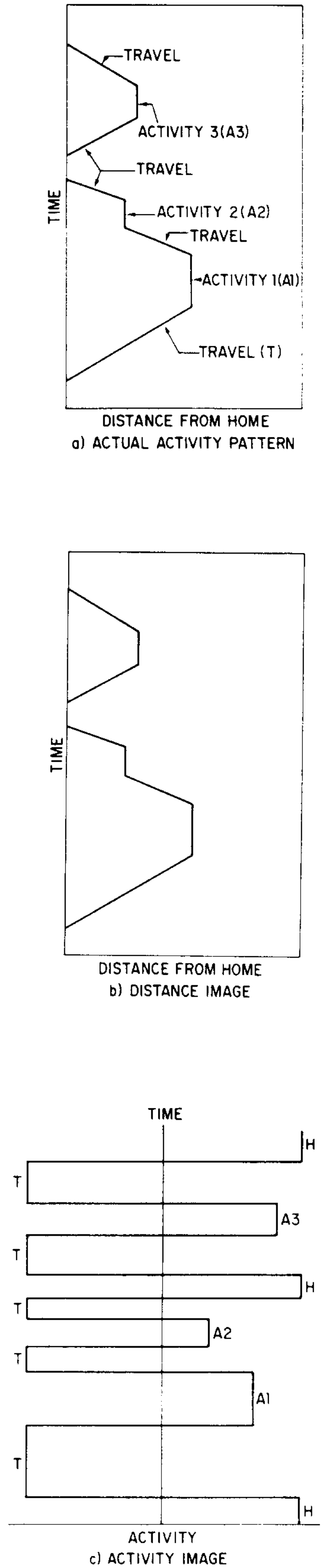

Fig. 1. Hypothetical activity pattern.

advantage of the Walsh over the Fourier transform, as the binary Walsh functions better represent the piecewise constant characteristic of the pattern vectors. Alternatively, with the Fourier sinusoidal transformation, transitions between travel and activity participation become less distinguishable in the feature space then in the pattern space.

As an example of this technique, a modified Walsh–Hadamard transformation algorithm was developed and applied to a dual-pattern vector representation of the sample activity patterns drawn from travel/activity diaries of 664 individuals from Orange County, California, randomly selected from the 1976 Southern California Association of Governments (SCAG) and California Department of Transportation (CALTRANS) Urban and Rural Travel Survey. The three-dimensional (time/space/activity) image characterizing each individual's behavior was split into two interrelated, two-dimensional images—the temporal variations of distance from home and of activity participation. The dual-pattern vectors were constructed by sampling the temporal variation in patterns over a 19-hr analysis day (5:30 A.M. to 12:30 A.M.) at ~9-min intervals, a value determined by the transformation algorithm's restriction of 2^N sample points and computational efficiency (yielding 128 sample points at 8.9-min intervals).

Activities were classified into five major categories (including travel), of which two were further divided into subcategories of similar activities (Table 1). The categories were ordinally ranked (subjectively) according to assumed temporal/spatial characteristics, with the total distance between subcategories equal to half that between categories. This apparent interval scaling constitutes an attempt to minimize classification errors after transformation. The purpose of the pattern recognition formulation is simply to distinguish among labels, and no further meaning in scale is implied. Travel is positioned at the extreme opposite of the scale to emphasize its dissimilar nature.

As a preliminary, a random sample of images was selected for transformation into Walsh–Hadamard space. These transformed images were subsequently inverted, retaining only a subset of the complete set of transform coefficients, and the mean square error between the inverted image and the original image was calculated. The mean of the mean square errors for random samples of various numbers of coefficients retained was plotted for both the "distance" and "activity" images. Results indicate that with 30–50 coefficients, the original image can be reconstructed to within limits of error that are tolerable. On the basis of these experimental findings, 50 transform coefficients were retained for each image.

Table 1. Activity classification

Category	Activity	Scale Value
1.	Home	9.0
2a.	Work	7.0
2b.	Work related	6.5
2c.	Education	6.0
3.	Shopping	4.0
4a.	Social/Entertainment	2.0
4b.	Recreation	1.5
4c.	Other	1.0
5.	Travel	−9.0

The dual-feature vectors, composed of the first 50 coefficients of each of the pattern vectors, were cluster analyzed in Walsh–Hadamard transformation space. The results (pseudo F ratio) indicated that the respondents were best classified into nine distinct groups in transformed space.

The transformed images associated with the coefficients centroids were inverted by Walsh–Hadamard inversion formulas to reconstruct the actual activity patterns that are representative of the travel/activity behavior of individuals in each group. The resulting activity patterns represent distinct sets of behavior by which the study population can be classified. Because these patterns are aggregated mean responses, the definition of the representative patterns necessarily is somewhat less than that of the original individual patterns. Correspondingly, there is some latitude in the interpretation of the results. Results in the form of the temporal distributions of the group members' distance from home and activity participation during the 19-hr analysis day were then combined to produce the representative activity pattern (RAP) of the group.

For example, Figs. 2–5 illustrate the results for two of the cluster groupings. The representative pattern associated with Group A (Fig. 2) is indicative of 8.4% of the respondents. Characterized by a traditional work activity approximately 7 mi from home and an evening shopping activity within 3 mi of home, respondents in Group A are primarily employed male heads of household (Fig. 3).

The corresponding patterns for Group B (Fig. 4), representing 12.5% of the respondents, differ significantly from those of Group A. This group is evenly distributed by sex and consists primarily of school-aged children and spouses of household heads (Fig. 5). The representative pattern reflects the proximity to home of both schools and the employed spouse's workplace. An evening sojourn to social/entertainment and/or recreational activities completes the representative pattern.

The temporal distributions of distance from home and activity participation together with the associated socioeconomic profiles for the remaining seven groups are shown in Figs. 6–17. The reconstructed activity pattern for Group C (Fig. 6), which is representative of ~5% of the population, depicts an activity pattern characterized by a lengthy early morning trip (approximately 25 mi) from home to work followed by a return trip home in the early evening. These individuals typically stay at home for the remainder of the day. The socioeconomic characteristics of individuals in Group C (Fig. 7) indicate that the composition is predominantly employed male heads of household between the ages of 25 and 34 years.

The most striking feature of the pattern for Group D is the absence of work/school activity (Fig. 8). The pattern is characterized by a high level of participation in social/recreation and shopping activities during the late morning to midafternoon hours. These activities take place

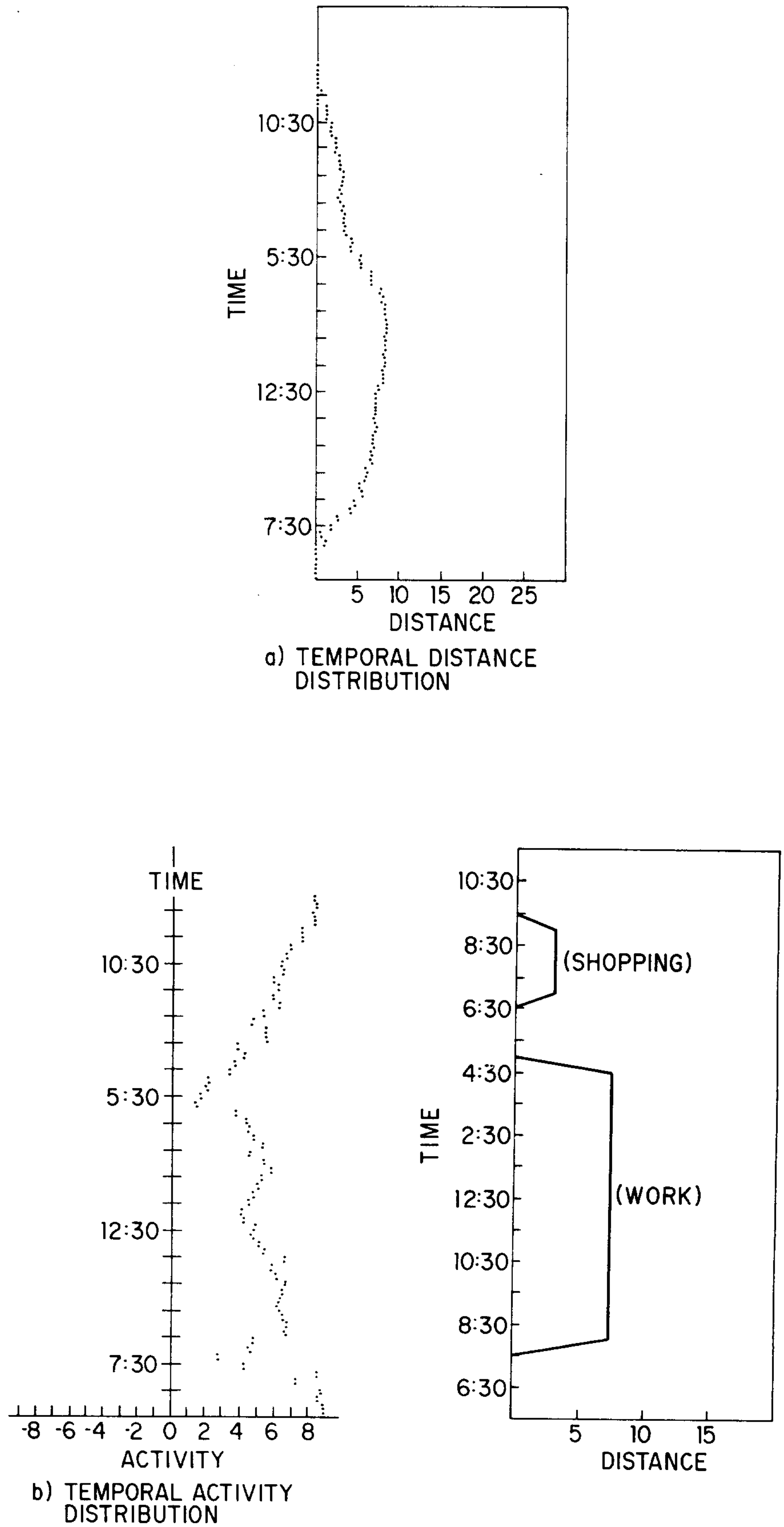

Fig. 2. Representative activity pattern for Group A.

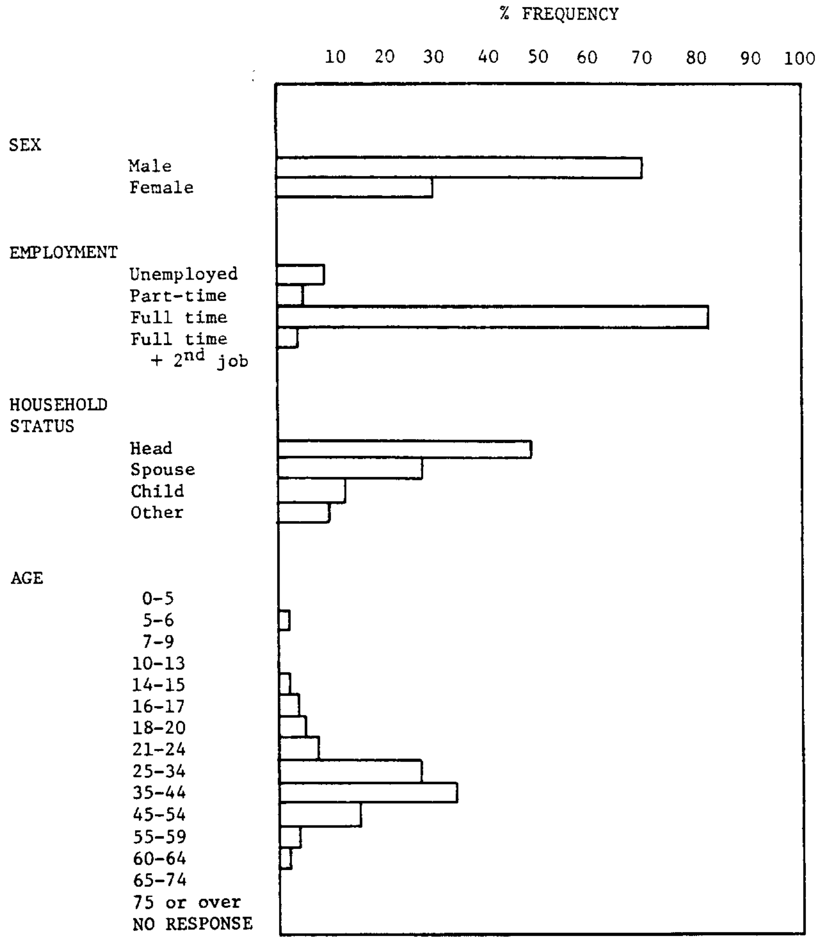

Fig. 3. Socioeconomic characteristics of Group A.

relatively close to home (within 5 mi) and are completed by approximately 5:30 P.M. with no subsequent travel. The population characterized by this RAP (~10% of the sample population) is comprised primarily of older, unemployed female heads of household or spouses of heads of household (Fig. 9).

Approximately 7% of the respondents are characterized by the activity pattern profile associated with Group E (Fig. 10). The principal components of this pattern are participation in fulltime work activities located approximately 15 mi from home during daytime working hours and a much shorter trip (approximately 2 mi) following dinner to participate in either school or work-related business. Individuals with this activity pattern are older, employed male heads of household (Fig. 11). The education component is a manifestation of the flourishing, free night school programs in the community college system in the region.

The representative pattern corresponding to Group F (Fig. 12) is associated with approximately 2% of the respondents. This pattern features a work activity within 2 mi of home followed by a sequence of social/entertainment and/or recreational activities in the evening, some of which involve extensive travel. This profile of activities is the only pattern identified that does not feature a final return trip home during the analysis day. This group is composed of employed males. (The size of this group was not sufficiently large to detail meaningful socioeconomic profiles.)

The travel/activity behavior of the largest segment of the sample population (46%) is characterized by Group G (Fig. 13). The activity pattern is extremely simple, consisting of a single school or work activity located very close (within 1 mi) to home. This group is composed of school-aged children (52%), heads of household and spouses of heads of household (Fig. 14). Employment levels are high among adults, and the group is evenly distributed according to sex.

The features of Group H (Fig. 15) are similar to those associated with Group G; the major differences involve the distance to/from the workplace and the exclusion of school activities. Individuals represented by Group H travel about 7 mi for the work trip. This pattern is characteristic of about 10% of the sample population (Fig. 16).

The last of the activity pattern profiles to be identified was that associated with Group I (Fig. 17). However, because of limited representation (<1% of the total respondents), Group I's characteristics could not be determined with confidence. The main feature of this pattern

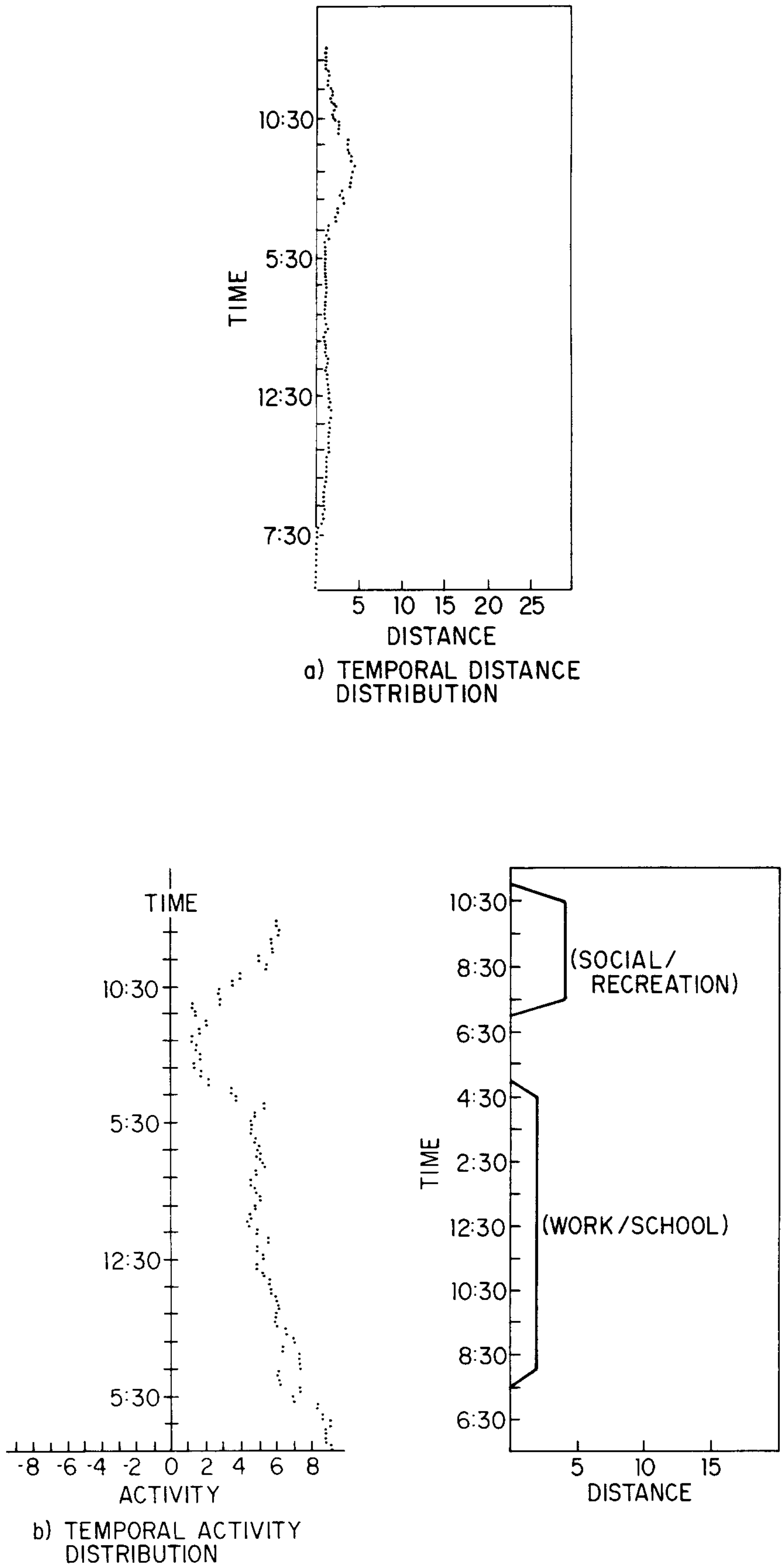

Fig. 4. Representative activity pattern for Group B.

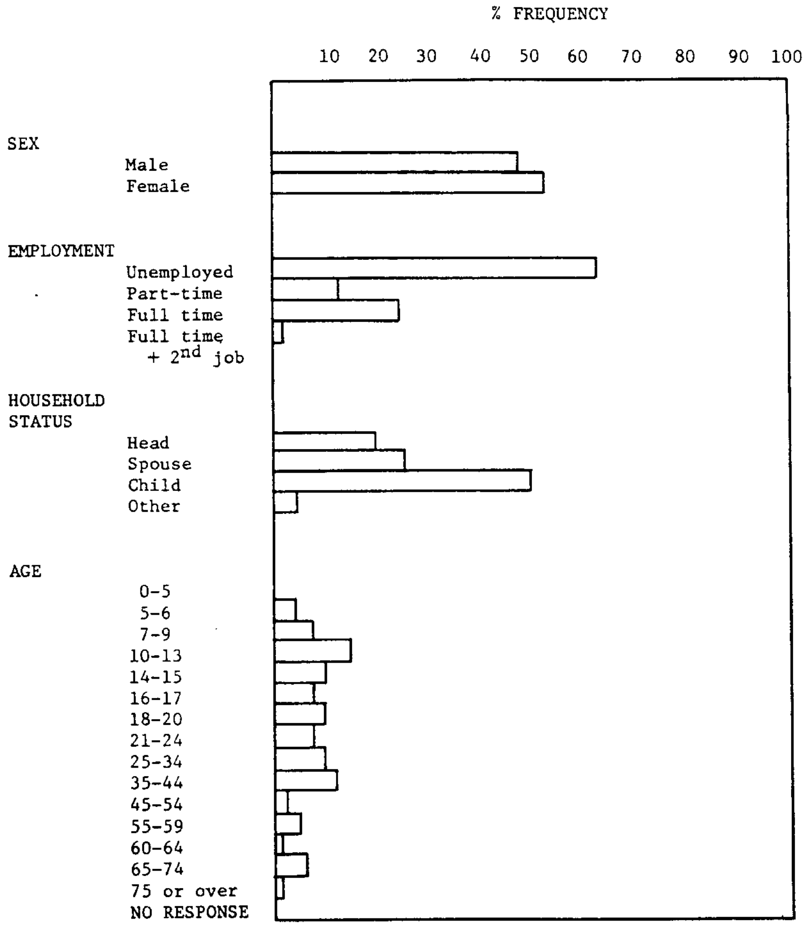

Fig. 5. Socioeconomic characteristics of Group B.

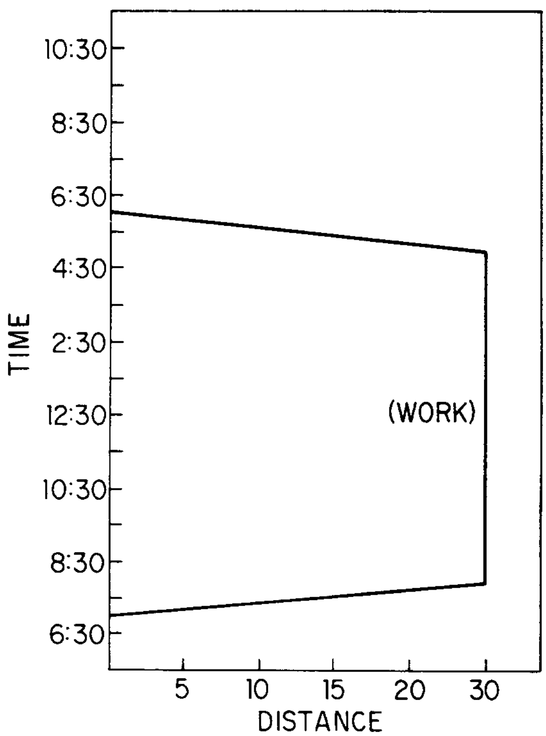

Fig. 6. Representative activity pattern for Group C.

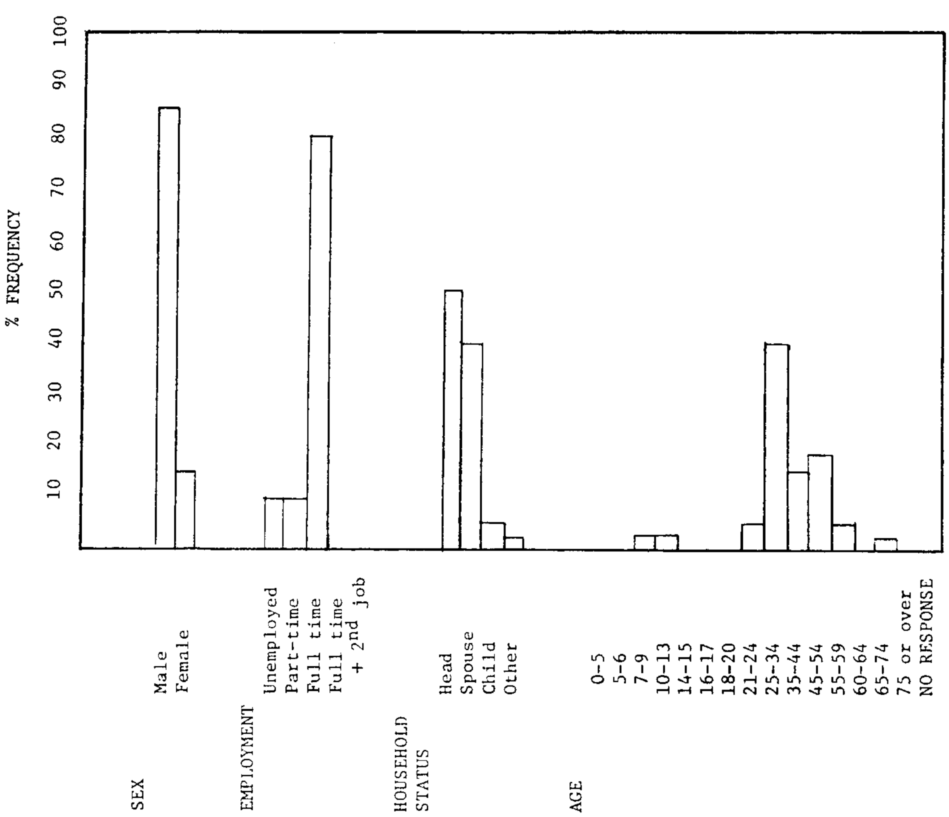

Fig. 7. Socioeconomic characteristics of Group C.

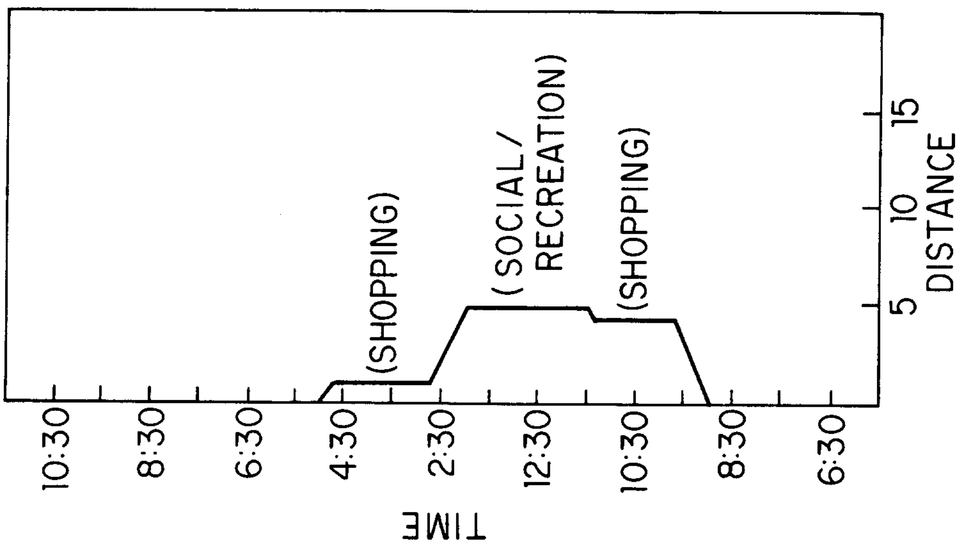

Fig. 8. Representative activity pattern for Group D.

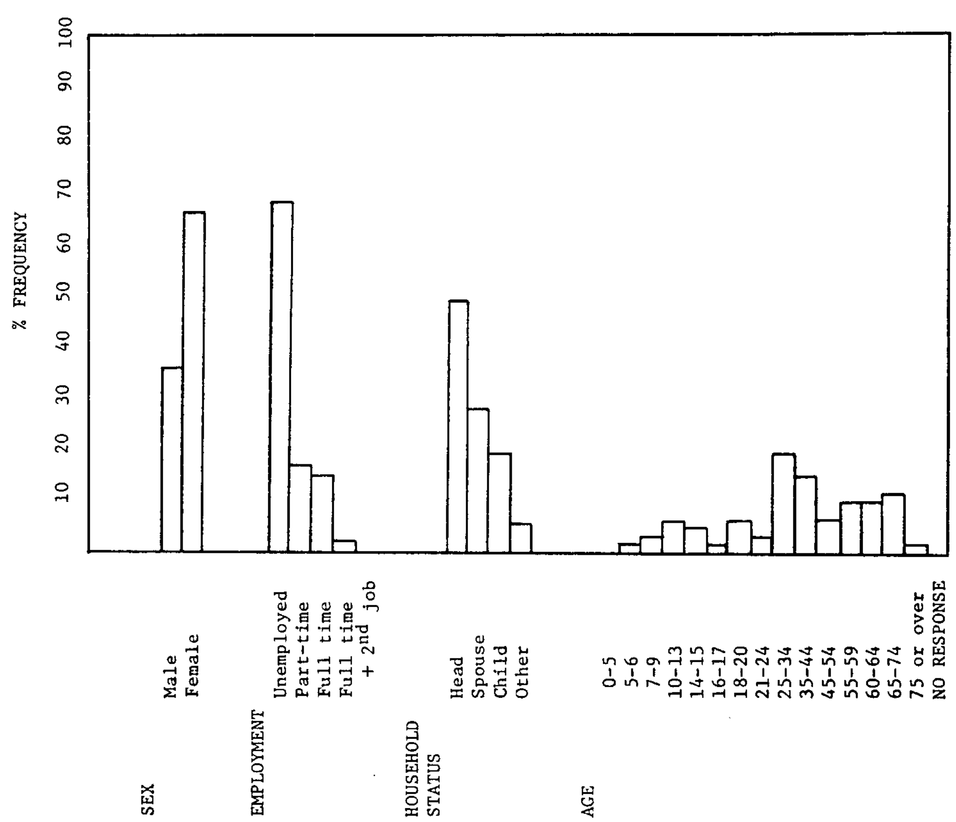

Fig. 9. Socioeconomic characteristics of Group D.

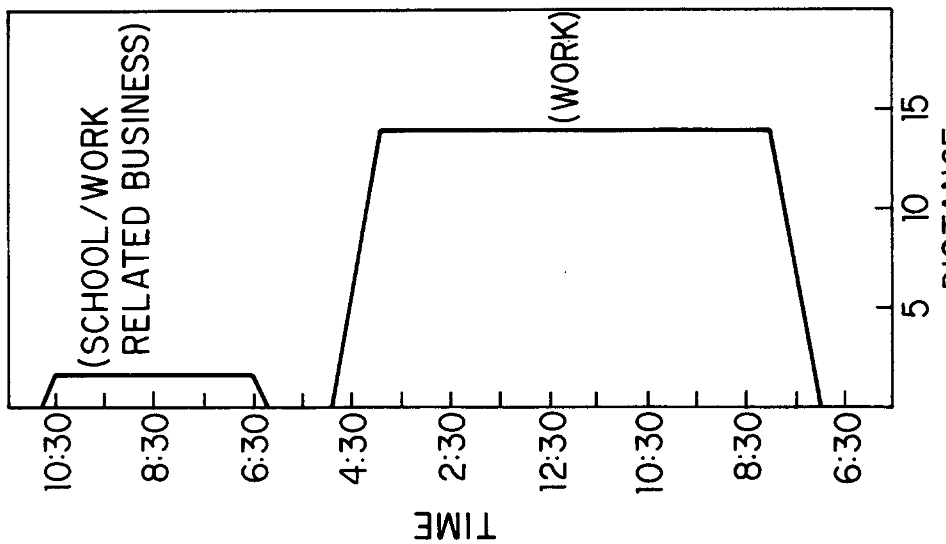

Fig. 10. Representative activity pattern for Group E.

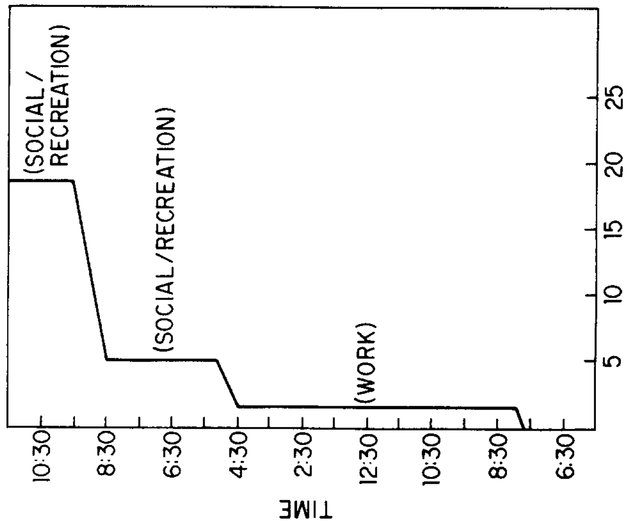

Fig. 12. Representative activity pattern for Group F.

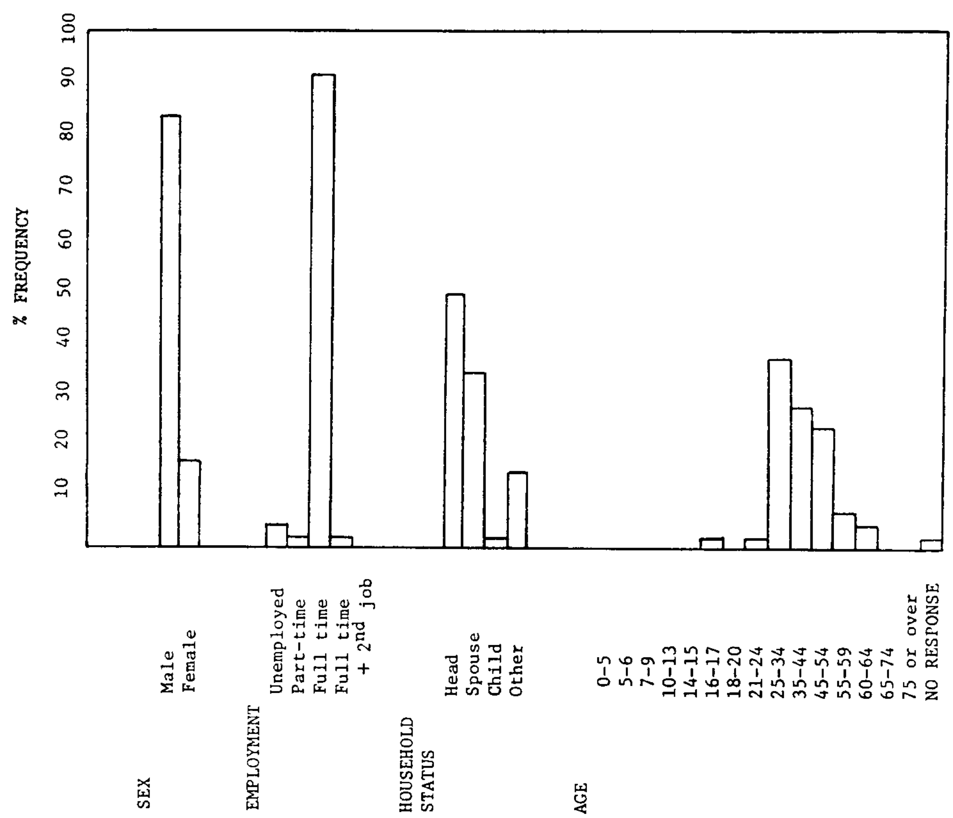

Fig. 11. Socioeconomic characteristics of Group E.

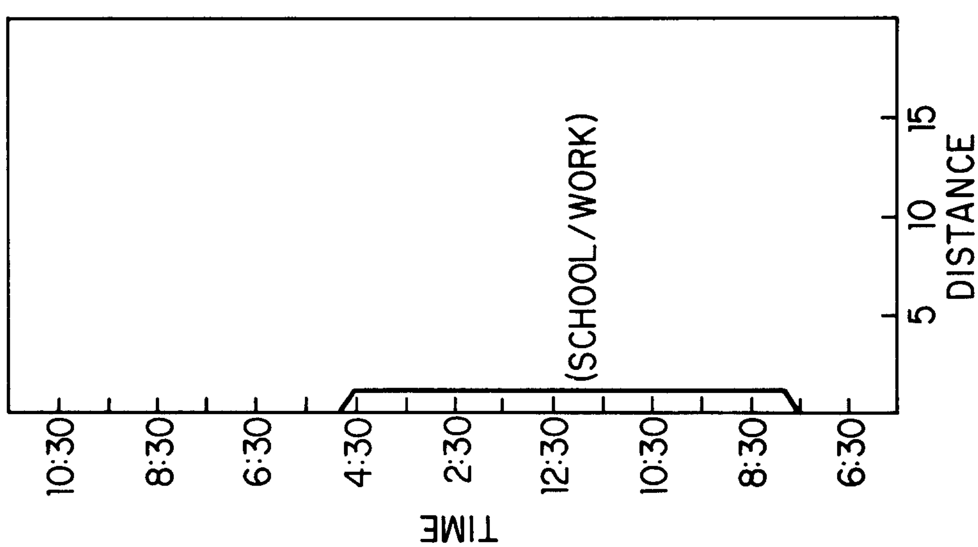

Fig. 13. Representative activity pattern for Group G.

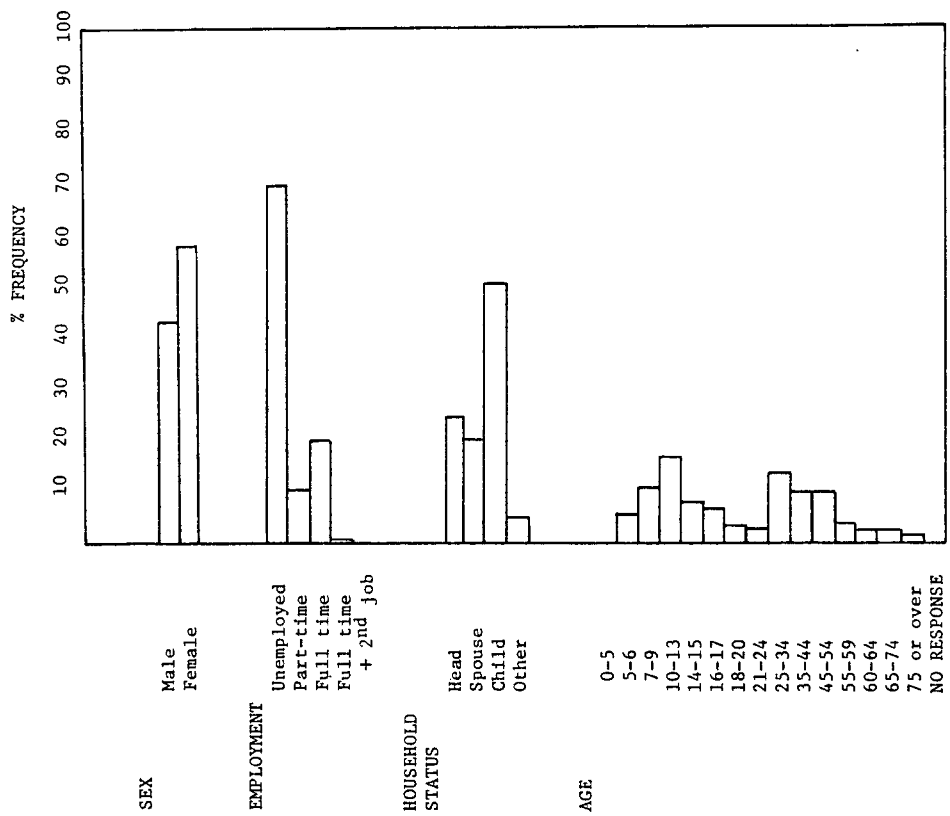

Fig. 14. Socioeconomic characteristics of Group G.

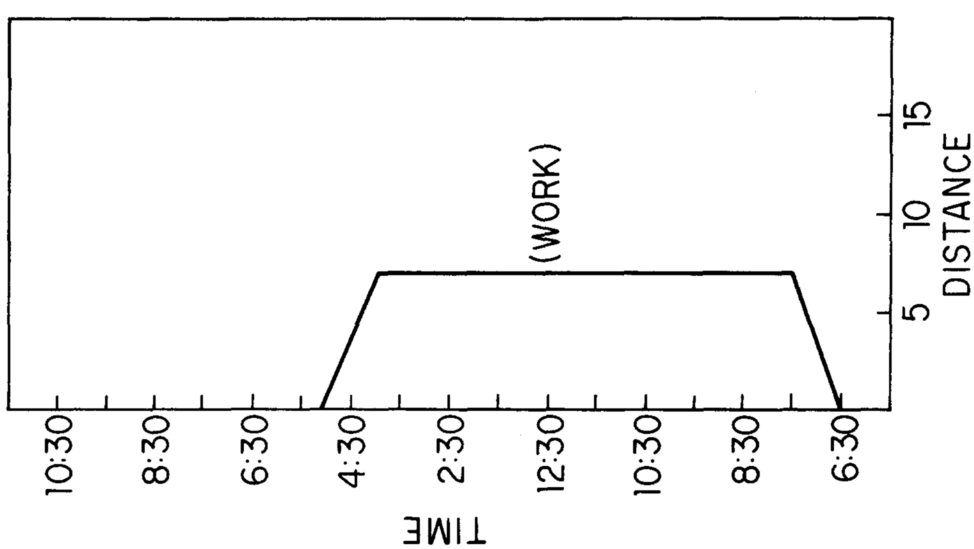

Fig. 15. Representative activity pattern for Group H.

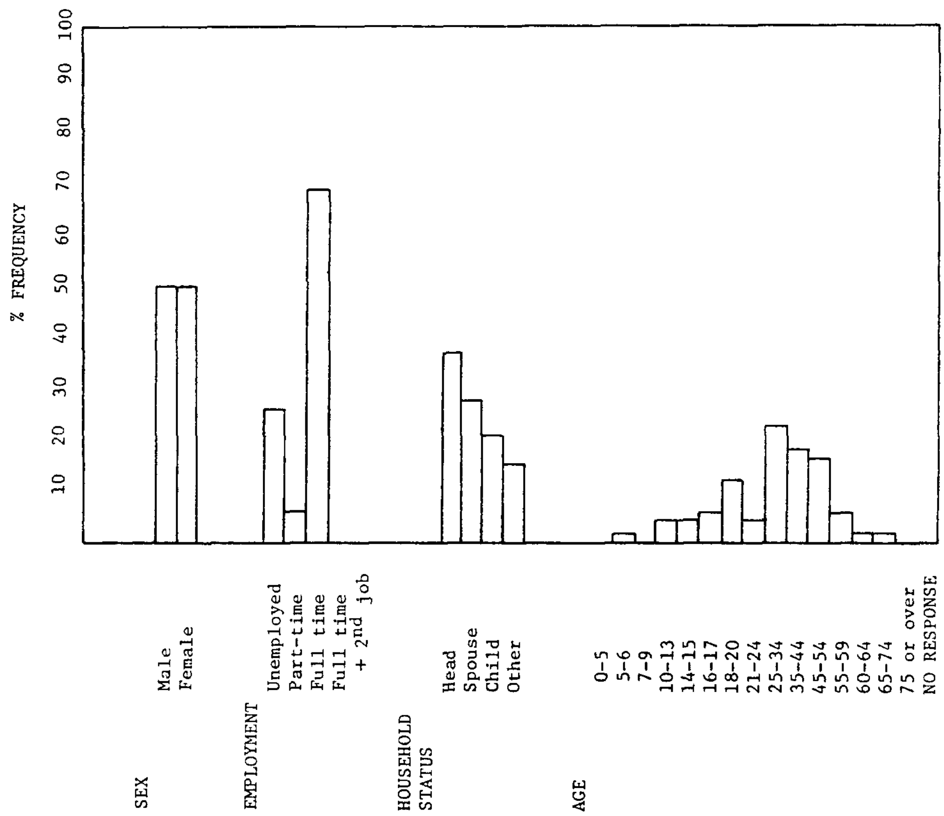

Fig. 16. Socioeconomic characteristics of Group H.

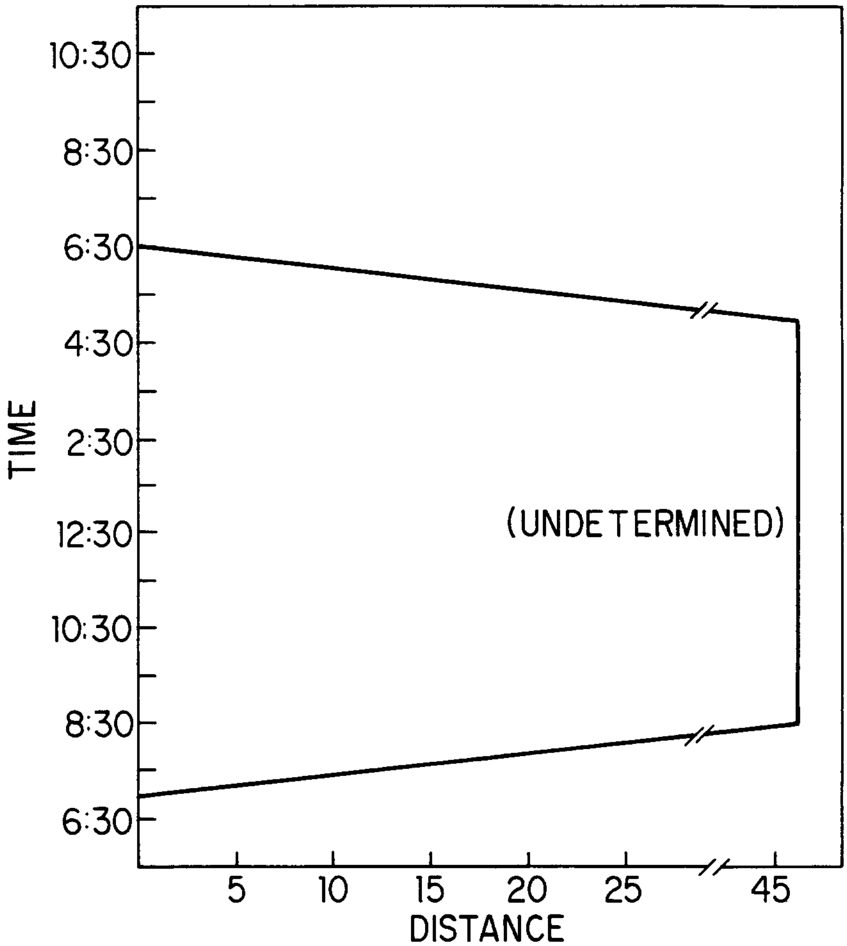

Fig. 17. Representative activity pattern for Group I.

profile is an extremely long travel distance to an undetermined activity of series of activities.

3. CLASSIFICATION OF ACTIVITY PATTERNS WITH CHARACTERISTICS OF HOUSEHOLDS AND URBAN FORM

If the activity pattern generalization process is to be useful in transportation planning contexts, it must be possible to specify the RAPs in terms of characteristics of both the households and the urban area in which the activity patterns are executed. To demonstrate one approach in this regard, variables that describe the household (e.g. auto ownership, household size, income) together with those that describe the urban area (e.g. economic activity, land use pattern) were used as discriminatory variables in a multiple discriminant analysis of the pattern profiles:†

$$\text{RAP}_k = f_{\text{DISC}}\,(\text{household characteristics, urban form indicators}), \quad (4)$$

where RAP_k represents the association of an activity pattern profile with the kth typical pattern (as determined by the pattern recognition analysis) and f_{DISC} represents the discriminant function.

The discriminant analysis of activity pattern profiles is presented in three distinct phases. The first details only the influence of household characteristics as discriminatory variables. The second provides the same analysis and discussion for the variables that are representative of urban form. The last phase is a presentation of the results of discriminant analysis when both sets of variables are combined. A subsample of 7 groups was formed from the 9-group cluster results by (1) deleting 2 groups containing only 6 members each and (2) randomly sampling the remaining 7 groups such that each contained approximately the same number of respondents (i.e. about 50 respondents each).

†The reader interested in a technical discussion is referred to Caculoos (1973) or Lachenbruc (1975).

Table 2. Household characteristics

Variable	Description	Categorization
HHSTATUS	Household of role of respondent	1 = head, 2 = spouse, 3 = child, 4 = other
AGE	Age of respondent	
EMP	Employment status	0 = unemployed, 1 = employed part-time 2 = employed full-time 3 = employed more than one job
LIC	Possession of driver's license	1 = yes, 0 = no
OCC	Occupation type	0 = non-compensatory 1 = compensatory
VEH	Vehicles available to household	
HHS	Household size	No. of individuals
H	Housing status	1 = own, 0 = rent
MRC	Monthly rent code	
HVC	Home value code	
HHI	Household income	
HTYPE	Housing type	1 = single family, 0 = other
RACE	Race of respondent	0 = white, 1 = other
INCHHS	Income/household size	
SEX	Sex of respondent	1 = female, 0 = male
VEHHHS	Vehicles/household size	

Household characteristics

The socioeconomic and demographic information used included those variables that *a priori* seem likely to have discriminatory power or have been investigated previously (Table 2). The results of the discriminant analysis indicated that satisfactory discrimination of group profiles can be obtained on the basis of eqns (5) and (6):

$$D_1 = -0.72(\mathrm{EMP}) - 0.24(\mathrm{OCC}) + 0.14(\mathrm{SEX}) \quad (5)$$

$$D_2 = 0.82(\mathrm{SEX}) + 0.61(\mathrm{HHSTATUS}) + 0.63(\mathrm{OCC}). \quad (6)$$

The first discriminant function is composed of three variables—employment (EMP), occupation (OCC) and sex. The equation illustrates that unemployed persons and female respondents will have much higher scores on this function than employed (or parttime employed) male respondents. Further, individuals with high scores on D_1 will make few (if any) work trips, while individuals with low scores on D_1 will be expected to make more work-related trips. This function is interpreted as an employment dimension.

The second discriminant function consists of the sex, household status (HHSTATUS) and occupation variables. Female spouses or children will have higher scores on D_2 than male heads of household who receive monetary compensation for work performed. D_2 is therefore interpreted as a household status/role dimension.

The group centroids defined by D_1 and D_2 are represented in Fig. 18. The first function (employment) discriminates between Groups B, D and G (unemployed respondents) and Groups A, C, E and H (employed respondents). These findings are supported by the cluster analysis results discussed previously. The RAPs of Groups A, C, E and H all contain work trips, while the RAPs of Groups B, D and G contain primarily nonwork trips.

The second function (household status/role) separates Groups B and H (supporting household roles) from Groups C, D, E and G (household heads). Approximately half of the respondents in Group A were heads of household, while the remaining respondents were spouses or non-heads of household. This equal split makes it difficult to classify Group A on the basis of household status.

The derivation of two significant discriminant functions in the analysis indicates that the RAPs are quadripolar in nature. The first grouping (A, C and E) consists primarily of employed heads of household who are ex-

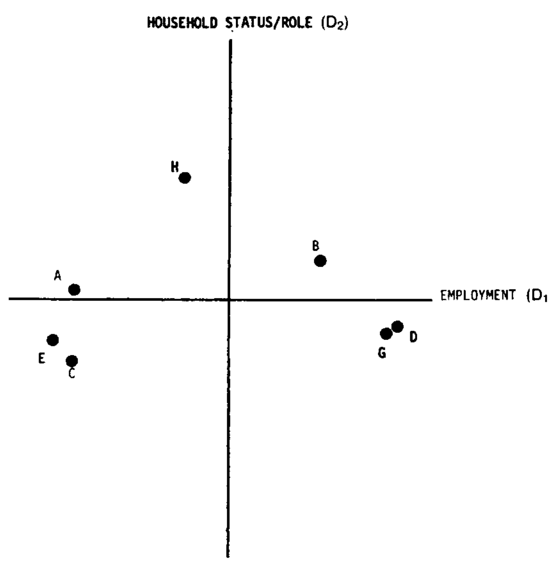

Fig. 18. Group centriods for discriminant analysis using household characteristics.

Table 3. Discriminant analysis classification results based on household characteristics

	Predicted Group Membership						
	A %	B %	C %	D %	E %	G %	H %
A	20.0	0.0	32.0	4.0	24.0	4.0	16.0
B	2.0	10.0	10.0	18.0	16.0	30.0	14.0
C	18.8	3.1	37.5	3.1	25.0	3.1	9.4
D	4.0	6.0	10.0	50.0	6.0	18.0	6.0
E	17.0	0.0	34.0	2.1	31.9	4.3	10.6
G	2.0	4.0	4.0	26.0	12.0	44.0	8.0
H	8.0	2.0	14.0	14.0	18.0	12.0	32.0

pected to make work trips. The second group (B) contains unemployed household members who make predominantly shorter nonwork related trips. The third group (D and G) is made up primarily of unemployed, female respondents who make nonwork-related trips. The fourth group (H) is characterized by heads of household, some of whom work on a parttime basis. These work trips are expected to be few in number.

The classification results associated with this discriminant analysis are summarized in Table 3. Members of Groups D and G were most easily classified correctly with 50.0 and 44.0%, respectively. The most difficult respondents to classify were members of Groups A and B or those groups that the discriminant analysis revealed to be most similar. For example, 10% of the actual members of Group B were classified correctly. The rest were assigned incorrectly to other groups. Similarly, more members of Group A were assigned incorrectly to Groups C and E than correctly.

The discriminant analysis exhibited a limited ability to discriminate between groups on the basis of household characteristics. The results indicate that there are factors in addition to household characteristics that influence the activity/travel behavior of an individual.

Urban form indicators

The second analysis details the impact of urban form indicators in the discrimination of activity pattern profiles. The set of indicators chosen for consideration is shown in Table 4. This information was compiled in 1976 as part of the Multi-Modal Transportation Study in Orange County, California, and was made available by the Orange County Transportation Commission.

Discrimination of group profiles can be achieved on the basis of eqn (7):

$$D_1 = -0.94(\mathrm{SDUDEN}) + 0.31(\mathrm{TEMPDEN}). \quad (7)$$

This function is interpreted as a housing/employment density dimension. The numbers of single dwelling units per acre (SDUDEN) and total employment per acre (TEMPDEN) are inversely related in determining the value of the discriminant function D_1.

The single function indicates that activity pattern profiles are bipolar with respect to urban form. The corresponing group centroids are presented in Fig. 19. The first cluster grouping is comprised of Groups A, B, C, E and G. Groups D and H are treated as outliers.

The classification results are contained in Table 5. The overall prediction rate of only 25% and the derivation of only one discriminant function imply that there are obvious shortcomings when attempting to characterize respondents on the basis of urban form indicators. Orange County is a fairly homogeneous area with 26 city centers that are all < 200,000 persons in size. This factor, perhaps, contributed to the rather poor discrimination.

Household characteristics with urban form indicators

The third analysis describes the ability to discriminate among group activity pattern profiles on the basis of household characteristics and urban form indicators. The results indicate that two discriminant functions satisfactorily discriminate between the RAPs:

$$D_1 = 0.72(\mathrm{EMP}) - 0.22(\mathrm{TEMPDEN}) + 0.21(\mathrm{OCC}) \quad (8)$$

$$D_2 = 0.70(\mathrm{SDUDEN}) - 0.66(\mathrm{HIDUDEN}) + 0.48(\mathrm{HHSTATUS}). \quad (9)$$

The first discriminant function is primarily an employment (EMP) dimension with smaller contributions coming from the total employment density (TEMPDEN) and occupation variables. The coefficients indicate that

Table 4. Urban form indicators

Variable	Description
WRKRDEN	Workers residing in zone per acre
MEDINC	Zonal median income
HIDUDEN	High income dwelling units per acre
SDUDEN	Single dwelling units per acre
TEMPDEN	Total employment per acre
AREA	Land area in acres
POPDEN	Population per acre
REMPDEN	Retail employment per acre
LIDUDEN	Low income dwelling units per acre
MDUDEN	Multiple dwelling units per acre
MIDUDEN	Middle income dwelling units per acre
QTDEN	Population in group quarters per acre

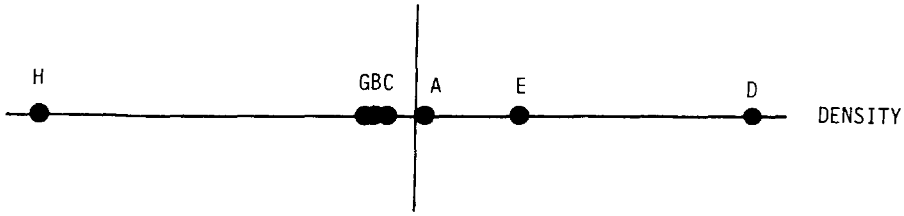

Fig. 19. Group centriods for discriminant analysis using urban form indicators.

an individual who is employed fulltime and lives in an area that has a low level of total employment will have a much higher score on this discriminant function than an unemployed individual who lives in an area of high total employment. Individuals with high scores on D_1 are expected to make long trips to work, whereas those with low scores are expected to make few work trips (if any) that are short in length.

The second function is composed of three variables—single-family dwelling unit density, high-income dwelling unit density (HIDUDEN) and household status. Individuals living in an area characterized by a high density of single-family dwelling units and a low density of high-income dwelling units who also have a supporting role in the household (a role other than the head of the household) will have a high score on this function. Conversely, those individuals who are heads of households located in areas characterized by a low density of single-family dwelling units and a high density of high-income dwelling units will have a low score on this dimension. This function is therefore interpreted as a housing density/household status dimension. It is expected that individuals in the former category tend to make shorter trips than those in the latter because of the relative proximity of activity sites.

An examination of the plot of the group centroids in the (reduced) space defined by the two discriminant functions reveals additional information about the relationships among the groups, the RAPs and the discriminant functions (Fig. 20). The first discriminant function (the employment dimension) discriminates between Groups A, C, E and H (employed respondents) and Groups B, D and G (unemployed respondents). As discussed previously, Groups A, C, E and H all have RAPs that contain a work trip, while Groups B, D and G have RAPs containing primarily nonwork trips. The second discriminant function (the housing density/household status dimension) differentiates Groups A, C, D and E from Groups B, G and H. All groups in the first set are composed primarily of heads of households who have RAPs involving large total distances traveled. The second set of groups is comprised of spouses and children who have RAPs involving less total distances traveled.

The analysis indicates that the activity pattern profiles are quadripolar in nature. The first grouping (A, C and E) is composed of working heads of households living in areas dominated by the presence of large, high-income, single-dwelling units and the absence of employment centers.. The separation of residence and employment site results in long-distance, work-related travel by these individuals. The second grouping (H) is also characterized by employed heads of household, but, unlike the previous groups, these individuals reside in areas characterized by lower-income, single-dwelling units of smaller size and more employment centers. The distances associated with these trips are much less than in the other groups because of the relative proximity of employment centers to residential locations.

The third grouping (B and G) is composed of unemployed spouses and children who live in the same areas as Group H. The predominance of short-distance school/work trips in RAPs B and G is a consequence of both the absence of workers and the increased availability of nearby school/work sites. The last group (D) is made up of older, unemployed females living in high-income, large, single-family dwelling units. More traditional roles associated with gender result in a large number of shopping and social/recreation travel. A summary of the relationships between the discriminant functions and the RAPs is presented in Table 6.

The classification results based on this discriminant analysis are summarized in Table 7. Again, the majority of the incorrect classifications were associated with those groups the discriminant analysis determined to be aligned closely to the group in question. For example, 49.1% of the individuals classified into Group C actually belong to Groups A and E, which, according to the plot of the group centroids (Fig. 20), are most similar to Group C.

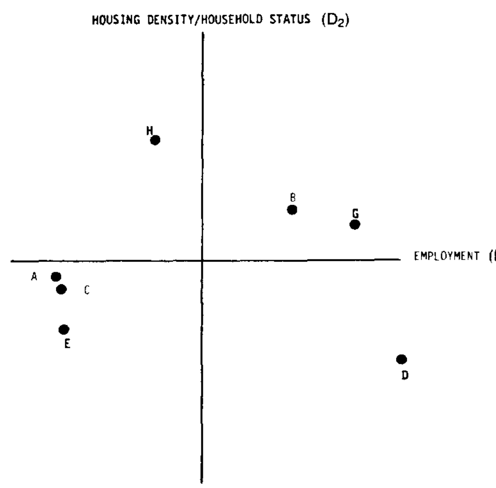

Fig. 20. Group centroids for discriminant analysis using household characteristics and urban form indicators.

Table 5. Discriminant analysis classification results based on urban form indicators

	Predicted Group Membership						
	A %	B %	C %	D %	E %	G %	H %
A	30.0	2.0	8.0	16.0	18.0	0.0	26.0
B	14.0	2.0	8.0	16.0	22.0	6.0	32.0
C	31.3	0.0	6.3	15.6	18.8	6.3	21.9
D	14.0	0.0	4.0	40.0	18.0	8.0	16.0
E	12.8	0.0	0.0	23.4	34.0	0.0	29.8
G	14.0	4.0	2.0	22.0	24.0	6.0	28.0
H	6.0	4.0	2.0	8.0	26.0	2.0	52.0

Table 6. Relationship between discriminant results and RAPs

Unemployed Non-Head of Household	SOCIO-ECONOMIC CHARACTERISTICS DIMENSION	Employed Head of Household	
GROUPS C, G		GROUP H	HIGH DENSITY SINGLE D.U. LOW DENSITY
School Trips (short distance)		Full-time	HIGH INCOME D.U.
Work Trips (short distance)		Worktrips (short distance)	
GROUP D		GROUPS A, C, E	RESIDENTIAL AREA DIMENSION
Shopping/Social Recreation trips (long distance)		Full-time Worktrips (long distance)	LOW DENSITY SINGLE D.U. HIGH DENSITY HIGH INCOME D.U.

Table 7. Discriminant analysis classification results

	Predicted Group Membership						
	A %	B %	C %	D %	E %	G %	H %
A	34.0	0.0	30.0	2.0	12.0	6.0	16.0
B	12.0	16.0	8.0	14.0	8.0	30.0	12.0
C	18.8	0.0	34.4	6.3	25.0	6.3	9.4
D	2.0	10.0	2.0	58.0	8.0	18.0	2.0
E	14.1	0.0	19.1	4.3	38.3	4.3	14.9
G	0.0	10.0	4.0	10.0	10.0	56.0	10.0
H	12.0	4.0	8.0	6.0	16.0	16.0	38.0

Those groups (D, G and H) that experienced the greatest percentage of correct classifications were, expectedly, also the groups whose centroids were located farthest from the other group centroids.

4. CONCLUSIONS

Travel behavior research has entered the "third generation" of transportation demand analysis, characterized by the integration of the full individual activity pattern into the decision-making process. The transforms discussed and their application to behavioral research represent a significant departure from conventional methods of transportation analysis.

The techniques examined in this study form an initial framework for the quantitative analysis of complex travel behavior in the form of individual activity patterns. No attempt was made to synthesize a definitive theory of movement behavior.

The goal of this study was to develop alternative techniques to quantitatively depict individual activity patterns facilitating classification of pattern profiles within the population as a means of identifying common travel behavior. The techniques presented should not be considered an alternative theoretical formulation of travel behavior, but rather as tools to describe and explain complex movement.

The tradeoffs between resolution of representative patterns and complexity of analysis must be examined in detail. An increase in information efficiency in image construction would allow the incorporation of additional image characteristic vectors without added computation requirements in addition to reducing the loss of information involving short-duration activities during transformation.

The prospect for utilizing transform elements as building blocks for activity patterns in transform space is promising. This extension enables the transition of the graphical representation of activity patterns to functional analysis, greatly simplifying analysis of complex behavior.

Theoretical models of pattern responses are dependent on significant advances in the descriptive and explanatory power of pattern recognition, classification and analysis techniques. Those proposed herein represent a starting point for such further research.

Acknowledgement—This research was supported in part by a contract with the U.S. Department of Transportation.

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