Statistical Designation of Traffic Control Subareas

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ABSTRACT

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A method for identifying control subareas in traffic signal networks has been developed and tested with data from the Miami, Florida business district. The procedure combines the use of cluster analysis and discriminant analysis to group signalized intersections. Unlike existing procedures which use degrees of association between adjacent signals, the multivariate procedures used in this method allow for consideration of degrees of association amongst all signals in the original network.

Model tests used the flow ratio for each intersection approach as the vector of intersection attributes. The resulting subareas were compact, well defined and slightly different for a.m. and mid-day traffic conditions. The procedure appears to have considerable utility in defining control subgroups in signal system design.

KEYWORDS: Signals, statistical analysis, traffic
I. INTRODUCTION

Traffic signals in urban areas were first controlled by digital computer in the mid 1960's (1). One principal attribute of large computerized traffic signal networks is the need to partition them into smaller control subareas. The selection of subareas recognizes explicitly that several different control problems can exist in a large signal network: traffic flow levels may vary in intensity in different parts of the network; differing geometric characteristics may require different control parameters (e.g. cycle length, split, offset); and traffic may vary differently with time of day throughout the network, requiring changes in timing plans with different frequency.

Most of the major traffic control systems developed during the 1970's and early 1980's use the concept of control subareas. The Urban Traffic Control System (UTCS) tested three different traffic control algorithms in Washington D.C. during the mid 1970's (9). While each algorithm had slightly different procedures for selecting cycle length, split and offset all three shared the common attribute of using control subareas for timing plan implementation. Advanced traffic signal control schemes developed in the early 1980's in England (10) and in the late 1970's in Australia (16) also used definable subareas for control.

While control subareas appear to be a common characteristic of nearly all advanced signal control systems, there has been very limited research conducted on procedures to identify control subareas. Typical of the procedures available for partitioning networks are those outlined in the National Cooperative Highway Research Program's Project No. 3-18(3), An Approach for Selecting Traffic Control Systems. Essentially, the document suggests relying on any obvious physical or topographical features in order to identify network regions of limited interaction, thus determining coarse boundaries for separate control areas. It is asserted that these coarse boundaries could then be refined by indexing quantitative temporal variations in link flows and using that information as a basis for qualitative control subarea designations. It seems that such a procedure might group signals based on arterial movements, but the report does not address this possibility.

Other existing methodologies relate characteristics of adjacent intersections, but make no attempt to relate the characteristics of nonadjacent intersections. The current literature tends to identify the relationship between adjacent intersections in terms of the desirability of coordinating their operations. The interconnection desirability index developed by Whitson, et al., (18) is a prime example:

\[ I = 0.5 \left( \frac{q_{max}}{q_1 + q_2 + \ldots + q_x} - 1 \right) / (1+t) \]  

where:

- **I** = interconnection destination desirability index (range 0 to 1.0);
- **t** = link travel time = link length divided by average speed, expressed in minutes;
- **x** = number of departure lanes from upstream intersection;
- \( q_{max} \) = straight through flow from upstream intersection; and
- \( q_1 + q_2 + \ldots + q_x \) = total flow exiting the upstream approach.
In the context of this index, a score of zero indicates that the signals in question are isolated from one another and should be operated independently, while maximally coordinated operations are warranted by a score of one.

Similar to this index, but somewhat simpler and less data intensive is Yagoda's intersection coupling index (19):

\[ I = \frac{V}{L} \]  \hspace{1cm} (21)

where:

- \( V \) = total link volume between adjacent intersections in both directions; and
- \( L \) = intervening link length.

The coupling index is intended to capture the degree of benefit available from coordination, and ranges from zero to arbitrarily large values. Unlike the interconnection desirability index, the coupling index was conceived specifically for the purpose of identifying control subareas. Index values for all network links are computed, and those links whose values do not exceed some minimum threshold level are eliminated from the network map. If no distinct signal subareas are determined by this process of elimination, then the threshold level is incrementally increased until the continued elimination of links eventually identifies a network partition.

There are some problems with this approach. Quite often, one of the contiguous subareas identified by Yagoda's procedure consists of a single, isolated intersection. Though such a signal might well be a candidate for isolated operation, such a result does not contribute to the identification of a useful set of control subareas. Thus, Yagoda's approach implies the use of very ad hoc halting rules in order to produce meaningful results.

If the coordination of traffic signals within a given subarea is to be prevented from degrading efforts to coordinate signal operations within surrounding subareas, then it is generally desirable for the subareas involved to be mutually convex, or at least reasonably compact. In terms of their physical configurations on a plane, a cord drawn between any pair of intersections within the same subarea should be contained strictly within the region defined by that subarea.

If this convexity requirement is significantly violated, then adjustments in the control parameter values associated with the signals in a given subarea could induce changes in the coordination needs of adjacent but possibly nonconvex subareas. Resultant changes in the control parameter values associated with the nonconvex control regions could then, in turn, induce changes in the coordination needs of the original subarea. The anticipated result is intensified feedback between control subarea operations and oscillation in regard to the appropriate values for their control parameters; thus creating a lack of any real coordination within either subareas due to an inability to coordinate between subareas. Experimentation with Yagoda's procedure indicates that his method has, at best, only a limited tendency to produce network partitions that are convex on the plane.

A more empirical approach is illustrated by Ferguson's attempt to use regression analysis on TRANSYT simulation results in order to develop a model for estimating the delay on links with different upstream and downstream signal cycle times (1), i.e., links connecting signals located in different subareas. With this information, Ferguson develops a TRANSYT based procedure for estimating the difference in the total delay associated with the separate optimization of two interconnected signal subareas with different cycle times versus the total delay associated with optimizing the two subareas as a single
network with a single cycle time. Ferguson's method, however, requires 2n
subarea simulations for every candidate pair of adjacent subareas, where n is
the number of connecting links between a given pair of adjacent subareas.
Since the number of candidate pairs of adjacent subareas is a combinatorially
large function of the number of signals in the network, even a contrived
network partitioning problem would require a great deal of simulation time and
effort if all reasonable subgroup configurations were to be investigated with
this approach. Still, if the specific topography of a given network were to
place some convenient constraint on the number of partitioning options
available, then the expense associated with Ferguson's procedure could be
significantly reduced, and its use justifiable.

II STATISTICAL BACKGROUND

If rational control subareas are to be identified within networks, then
some reasonable means of describing degrees of association between
intersections, both adjacent and nonadjacent, must be determined. The indices
noted in the preceding section have been applied to adjacent intersections
only, and hence impose an implicit zero degree of association between
nonadjacent intersections. If this simplifying assumption could be relaxed,
the result could only mean an improved set of criteria for the partitioning of
traffic networks, and thus the designation of rational control subareas.

In statistical contexts, levels of association amongst observations are
measured in terms of their Mahalanobis distances from one another. The
Mahalanobis distance is a generalized metric derived from the variables on
which the observations are measured. By treating each intersection within a
given network as an observation, it becomes possible to associate with each
signal a vector of variables whose values characterize that particular

signal's operating environment. A Mahalanobis distance between any pair of
coordinate positions defined by such signal vectors is thus generated (13) and
may be interpreted as an inverse measure of the statistical degree of
association between the corresponding signal's operating environments. Thus,
rather than relying on a measure of association that is only defined for the
case of physically adjacent intersections, a measure of association between
signals has been defined that applies to every pair of signals in the network.

The advantage of this perspective lies with the statistical techniques
that may be used to examine the information contained in appropriately defined
observations. It is desirable to assign signalized intersections to control
subareas such that, for a given subarea, the sum of the Mahalanobis distances
between the coordinates corresponding to each member intersection's vector is
minimized; and the Mahalanobis distances between intersection coordinates
defined for different subareas is maximized. That is, control subareas should
be established so as to encompass signals with maximally similar operating
environments while simultaneously separating signals with very dissimilar
operating environments. A set of minimum Mahalanobis distances within control
subareas thus minimizes the multivariate sum of squares for the vectors
associated with that subarea's membership; within group variance is minimized
while between group variance is maximized.

Three general classes of statistical procedures can be used to group
observations: hierarchical cluster analysis; nonhierarchical cluster
analysis; and, discriminant analysis. Cluster analysis denotes a set of
heuristic algorithms designed to reduce the enormous computational burden
associated with identifying clusters of observations whose members are
statistically similar enough to be treated together (2). The hierarchical
approaches utilize greedy adding or greedy adding and substitution algorithms
in order to sequentially classify observations into groups such that the increment in total within group variance due to the classification of the most recently examined observation is minimized. Nonhierarchical methods iterate to convergence through a process involving the allocation of observations to initial seed points, i.e., coordinates identified in the variable space on which observations are measured. Seed point values are updated by calculating group centroids; the observations are then reallocated to the updated seed points. Thus, the nonhierarchical methods require some a priori notion of the number of groups to be formed; and of appropriate, representative variable space locations for those groups, i.e., the initial seed points (6). The hierarchical clustering techniques are more popular, have more existing computer software associated with them, work well on small problems, and have been much investigated in the statistical literature as to their convergence properties and dependence on initial conditions. There has been limited experience with the nonhierarchical techniques.

Cluster analysis algorithms are mathematically analogous to the discrete space location/allocation heuristics that are applied to p-median and maximum coverage type problems, i.e., problems that involve locating facilities on network nodes that will serve demands originating at other nodes (3). In the context of maximum coverage problems, greedy algorithms have been used to try to minimize the number and/or location costs of facilities required in order to serve a given set of network demands, locating facilities sequentially such that each new facility serves the largest possible portion of the remaining demands. Since demand nodes are assumed to be serviced by exactly one facility, these algorithms ultimately produce clusters of network demand nodes. These procedures are thus specialized cases of greedy hierarchical clustering algorithms (4).

The location/allocation center-of-gravity methods, such as the faranzana algorithms, analogously constitute specialized cases of nonhierarchical clustering procedures (12). In such applications, the number of facilities to be allocated to a network is assumed known, and thus the number of demand clusters is known. Facilities are initially located at arbitrarily selected nodes (seed points) and the demands from the remaining nodes are allocated to the nearest facility. A new center-of-gravity (an updated seed point) is determined for each resulting cluster of nodes. That is, the node within each cluster that would minimize the total travel or other generalized cost required to service all demands within that cluster were a facility to be located there is identified. Facilities are assumed to be relocated at these new centers-of-gravity, and demands are reallocated to these new locations. Iteration continues until no further relocation of facilities is indicated, and thus no changes in the configurations of the demand node clusters are warranted.

In contrast to cluster analysis, discriminant analysis focuses on the classification of new observations into existing groups or clusters, and on the improvement of existing group membership designations. In short, the procedure extracts a function or set of functions from the existing observations and their group designations such that, when evaluated in terms of the variables on which new observations are measured, the resulting values of the function(s) identifies those observations' most probable group designations (5). This manipulation is especially important in that it permits the existing observations from which the discriminant function was extracted to be simulated against that discriminant function and possibly reclassified into a statistically more likely group.
The usage of the word "simulation" in the literature surrounding this procedure is nonstandard relative to its usage in the context of stochastic systems and their related computer models. "Simulation" in the context of discriminant analysis refers to an evaluation of the discriminant function in terms of the variable values associated with the existing observations in an effort to improve the observations' group membership designations. This contrasts with an evaluation of the discriminant function in terms of the variable values associated with new observations for the purpose of providing those observations with initial classifications. In the former case, new observations are, in a sense, being simulated by existing observations; and the discriminant function is being used to simulate existing group designations. Given the results of a discriminant analysis simulation, an updated version of the discriminant function can be calculated on the basis of the improved group designations, and the improved designations simulated against that updated function. This process has been shown to eventually converge to stable group memberships (12).

A graphical interpretation of discriminant analysis is illustrated in Figure 1 (5). A discriminant function has been extracted from the information associated with the known memberships of groups A and B. The information in each observation is measured in terms of the variables X and Y. The discriminant function, a linear combination of the variables X and Y, constitutes a decision rule that minimizes the total number of existing observations misclassified into either group A or group B when the rule is applied. The number of linear discriminant functions that can be extracted from any given data set is constrained by both the number of variables on which the observations are measured and by the number of groups assumed. Note that the centile contours for groups A and B are identical, implying that those groups' memberships are equivariant in terms of X and Y.
Figure 2 (5) demonstrates the importance of equivariance across groups in regard to the generation of meaningful linear discriminant functions. If the equivariance assumption is violated, then the appropriate discriminant function is nonlinear. If a linear function is extracted from such a data set, then observations in the neighborhood of the linear function will be misclassified if simulated against that function. In general, the number of observations misclassified into any group with an excessive variance will exceed the number of observations misclassified into any group with a smaller associated variance (17). Similarly, linear discriminant functions classify new observations into excessively variant groups with a frequency exceeding that implied by the true likelihood of such memberships, and too infrequently classify into groups exhibiting relatively smaller variances. No general algorithms for the extraction of nonlinear discriminant functions are currently available in the literature.

A null hypothesis of equal variances across groups is testable via Box's M statistic. The M statistic has a strictly positive distribution that can be transformed, for the sake of convenience, into either a corresponding Chi-square distribution of an approximate F distribution. Rejection of the null indicates that the assumption of equivariant groups has been violated. Rejection of the equivariance assumption is not, however, unusual in discriminant analysis applications, and the procedure is generally considered to be robust enough to absorb this violation without serious analytical consequences (12).

It is also possible to test the null hypothesis that the extracted discriminant function does not discriminate between the groups involved. The appropriate test statistics are the Wilks-Lambda statistic and, again, a Chi-square distributed statistic. Either construct is ultimately based on the

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Figure 2: Effects of a Violation of the Equivariance Assumption on the Appropriate of a Linear Discriminant Function
ratio of the within group variance and the total variance in the data. Rejection of a null hypothesis in this case indicates that the discriminant function extracted from the data and group designations successfully discriminates between those groups.

Computer statistics packages vary as to the analysis options they offer. The Bio-Medical Diagnostic Package (BMEDP) includes cluster analysis capabilities (6), while the Statistical Package for the Social Sciences (SPSS) does not (15). Thus, the cluster analyses referred to below were executed via the BMEDP software, while all discriminant analyses were completed using the SPSS programs.

III THE APPROACH

This research relies on a vector of incident approach flow ratios, i.e., volume/saturation flow in order to characterize the operating environment of any given signal. Volume is expressed in vehicles per hour while saturation flow is in vehicles per hour of green. It is reasonable to expect that clustering on the flow ratios associated with each intersection will designate control subareas that are largely homogenous in regard to their cycle length and timing requirements within each group, and significantly different in regard to their requirements across groups. The flow ratio has a basic role in the determination of intersection timing requirements; in the critical movement method it is used to determine the green time/cycle time ratio (1).

Given that traffic flow intensities vary throughout any network, and given that flows are movements, then the traffic flow intensity associated with any specific location on the network must necessarily influence and be influenced by the intensities associated with proximal locations on that network. It is this perspective that makes the partitioning of a traffic grid into compact control subareas theoretically reasonable. The designation of subareas permits the analyst to manage locally related traffic flow characteristics with appropriate subarea specific signal timing and cycle length policies. The approach in this paper relies on a relatively more robust, more generalized version of each signal's neighborhood than exists in the current literature. The association of any signal with any (contiguous) subarea, the subsequent operating policies imposed on that signal, and the degree to which the subarea control policies are adjusted to accommodate that signal's operations are thus a function of that signal environment's similarity to the operating environments of the several candidate control subareas. This is as opposed to some simpler measure of association defined only between the given signal's operation and those of its physically immediate neighbors.

The procedure begins with a cluster analysis in order to generate initial signal control subareas (Figure 3). Several different types of cluster analysis methods have been tested; experience with an actual network is described in section IV. Discriminant functions are then extracted from these initial groupings (step 2); individual observations are then simulated against the discriminant functions (step 3) and the number of misclassified observations is determined (step 4). These misclassified observations are candidates for reassignment to alternative groups. The analyst then manually selects the observations to be reclassified based upon a desire to improve the compactness (i.e., the physical convexity) of the subareas (step 5).
A new discriminant function is then calculated and the process iterates until one of the stopping criteria are met. The stopping criteria are:

1. The analyst perceives no convenient, subjective configuration that further reclassifies any signals misclassified by the discriminant function simulation step so as to produce subareas of a more compact contiguous nature; or
2. The analyst's reclassification efforts are not affecting the results of subsequent discriminant analyses.

Of these two possibilities, the latter is the most probable. If all the signals misclassified by each discriminant function simulation were to be reclassified so as to conform to the results of the simulation at every iteration, then as has been identified, the procedure would converge to stable, perfectly classifiable group memberships in a finite number of steps (12). However, at each iteration, the analyst reclassifies only those signals whose locations relative to their new subareas contributes to the compactness and contiguity of all subareas. Consequently, it is possible for the procedure to effectively halt at a point at which the discriminant function simulation step is continuing to misclassify some small percentage of the signals, but for which no subjective improvements are apparent.

IV AN APPLICATION

A. The Test Network

A number of cluster analyses were executed in an effort to explore a 79 member subset of the Miami, Florida CBD's 103 signalized intersections (Figure 4). A vector of clustering variables consisting of the incident
approach flow ratios was associated with each intersection (observation) in the subset. The 79 member subset was selected by default, as intersections for which defined data was incomplete were omitted from the analyses. The omitted data included the intersections between West 2nd & 3rd Avenues and North 10th, 11th, and 14th Streets; the intersections between North 8th Street and the Interstate-95 access ramps; the intersections between Biscayne Avenue and North 13th, 14th, and 15th Streets; the intersection between Interstate-95 parallel to South 3rd Street and Biscayne Avenue, and the interchange between Interstate-95 and Flagler Street. All of the intersections noted are positioned on, or are adjacent to, the outer boundaries of the network.

The first set of analyses were based on observations consisting of eight-vectors, each vector representing an intersection. Each vector element is a noon or a.m. peak flow ratio for each of any given intersection's (typically) four incident approaches. Subsequent analyses treat the a.m. peak and noon data sets separately rather than simultaneously, reducing all observations to four-vectors and extracting two sets of control subareas; one set for the a.m. case and one set for the noon case. An important issue in the context of this information is how to legitimately represent and compare intersections with different right-of-way configurations. Due to the presence of one-way movements on the Miami grid, some flow ratios are not defined for some approaches.

B. Representation of the Data and Selection of a Clustering Algorithm

It was necessary to search for the best of the several cluster analysis algorithms available. Given the size of the sample involved, options included

Figure 4: 79 Signalized Intersections in the Miami, Florida CBD
the execution of two or three group hierarchical and nonhierarchical cluster analyses as well as analyst designation of selected intersections as initial seed points in the event of a nonhierarchical analysis.

An initial set of exploratory, two and three group hierarchical and nonhierarchical cluster analyses constitute the first attempt to confront the problem of approaches with undefined flow ratios. Undefined vector entries were consistently assigned values of either zero or one within each analysis. Also, the effect of designating initial cluster seed points (initial cluster centers) versus the option of using software selected seed points in the case of nonhierarchical clusters was examined.

Setting undefined vector elements equal to zero tends to drive both the hierarchical and nonhierarchical analysis to cluster on one-way North/South movements, while imposing a value of one analogously tends to force clusters on one-way East/West movements. In no case does the analysis produce contiguous, much less compact clusters. Thus, there is definite evidence that any values imposed on undefined vector elements will tend to strongly drive the analysis.

Since several of the streets in the Miami grid, a total of 15 out of 27, are one-way, assumed values enter the clustering algorithm's calculations many times before those calculations are complete, i.e., convergent. If fewer one-way streets were present in the grid and hence more of the approach flow ratios were defined, then the procedure's existing tendency to cluster on N/S or E/W movements might well disappear.

The designation of seed points for nonhierarchical clusters has a definite effect on the results of such analyses, but not in a theoretically predictable way. The seed points selected for these applications are largely arbitrary, but physically distant from one another. Thus there is a good chance that they should be allocated to different clusters if those resulting clusters are reasonably compact. However, though the designation of physically distant intersections as cluster seeds might tend to drive the analysis toward the result of compact groups, there is no constraint imposed that the initial seed points will ultimately be assigned to different clusters. Fortunately, it is not necessary to rely solely on analyst judgment for the selection of nonhierarchical cluster seed points. Rather, the software itself can search for and heuristically select likely observations. In general, since it is unlikely that any strong theoretical justification will exist, a priori, for imposing the different initial cluster memberships on seed intersections associated with the analyst designation of such seed points, it is quite reasonable to leave the selection of initial seeds to the search component of the nonhierarchical clustering algorithm.

The effects of analyst designation of initial seed points in the case of nonhierarchical three cluster results were found to be exceptionally divergent from the results associated with algorithm selected centers. In either case, however, the third cluster in a three cluster application tends to accumulate arterial movements perpendicular to the other two clusters.

C. Results for A.M. Peak Period

Applying the same set of hierarchical and nonhierarchical procedures to the data for the a.m. peak produces results analogous to the preceding. It was again made apparent that values imposed for undefined vector elements drive the results of the analyses, and that they do so in a fashion similar to that which was noted previously, especially in the case of N/S movements.

However, in the case of the nonhierarchical procedure, an analysis has been completed for which the undefined approach flow ratios have all been
omitted from their associated intersection's vectors (Figure 5). This procedure results in far more compact, less arterially oriented clusters of signals; even though one of these groups (group two) is not self contiguous and hence, by definition, not convex. This specific result is the output of a three cluster analysis. It was found that designating a third cluster resulted in two large clusters and one small cluster, but that the two largest clusters tended to be more equally sized and compact than those that resulted from a two cluster designation. The option of omitting vector elements without imposing substitute values is specific to the nonhierarchal procedure. There is no analogous manipulation for the hierarchical algorithms.

A discriminant analysis was completed for the compact, nonhierarchal clusters displayed in Figure 5. These initial cluster memberships were then simulated against their extracted discriminant function and the misassigned signals, 19.0 percent of all observations, recorded in Figure 6. Given this information, two candidate configurations for upgraded signal clusters, i.e., clusters with both a greater degree of compactness and intended to yield improved discriminant analysis results, were subjectively determined by reassigning selected signals that had been misassigned by the discriminant simulation. In the first case, intersections 9, 10, 11, 19, 23, 30, and 64 only were reassigned from group one to group two, while intersections 16, 31, 32, and 48 were reassigned from group two to group one. These two candidate configurations are summarized in Figure 7.

A second discriminant analysis completed for each of the two candidate configurations resulted in a greater degree of improved discrimination in the first case relative to the second case: only 15.2% of all signals being misassigned from the former configuration versus 20.3% of all signals being

Figure 5: A.M. Data, Initial Nonhierarchal Three Group Clusters (Collapsed into Two)
64 signals correctly assigned.

8 Group 1 signals misassigned to Group 2.

7 Group 2 signals misassigned to Group 1.

1st candidate for upgraded Group 1, 22 signals.

1st candidate for upgraded Group 2, 57 signals.

2nd candidate for upgraded Group 1, 29 signals.

2nd candidate for upgraded Group 2, 50 signals.

Figure 6: Misassigned Signals for the First Discriminant Analysis and Simulation Executed for the A.M., Nonhierarchical Clusters

Figure 7: Two Candidate Configurations for Upgraded A.M., Nonhierarchical Clusters
misassigned from the latter configuration. Thus, attempts to further upgrade the signal group designations proceeded from the first candidate configuration. Updated clusters were again generated subjectively given the results of a second discriminant analysis and simulation. A third discriminant analysis executed for these further upgraded groups indicated that, with only 12.7% of all signals being misassigned by the discriminant simulation, further improvement was unlikely. The final subarea configurations are illustrated in Figure 8.

In these and all subsequent discriminant analyses, the specific Chi-square statistics associated with the null hypothesis that the extracted discriminant functions are not discriminating between their respective groups can be rejected with four degrees of freedom at some significance level greater than .0001. It is apparent that significantly different subareas can be identified for both the a.m. and the noon data sets. Unfortunately, tests of the hypothesis that the two clusters being treated are of equivariance also lead to a rejection of their null. In the case of the noon data, Box's M statistic indicates that the null hypothesis of equivariance can be rejected at some significance beyond the .0001 level. The situation is better in the case of the a.m. data, as the same test procedure indicates a rejection of the null only at significances lower than the .2352 level. Thus, in the case of the a.m. data, the hypothesis of assumed equivariance across groups cannot be rejected at conventionally accepted levels of statistical significance, i.e., the .05 level or greater.

It is still quite probable, however, that the linear discriminant functions extracted by the discriminant analysis algorithms are not entirely appropriate for these data sets. This is especially true in the case of the noon analyses. The true discriminant functions are most probably nonlinear.

Figure 8: Final A.M., Nonhierarchical Clusters
Thus some of the intersections that each of the discriminant functions' simulations are noting as correctly classified are actually being misclassified. A few of the intersections located in the variable space neighborhood of the linear discriminant functions are not being placed in their most likely subareas even though the results of their discriminant function simulation indicates that they are. Given that there are no currently implemented computer procedures for extracting nonlinear discriminant functions from data sets, there is little to be done other than to note the situation and hope that those few signals that the final linear discriminant function simulation cannot seem to classify into a group in such a fashion as to produce physically compact, contiguous control subareas capture the aberrations generated by the linearity of the procedures components.

v. Results for mid-day

Cluster analyses based on the four-vector observations associated with the noon approach flow ratios produced results consistent with the preceding. Again, omitting undefined values from the nonhierarchical analysis results in the most physically compact signal groups. In this case, however, the two cluster designation provides better results than does the three cluster effort. As before, the analysis providing the best results included algorithms generated seed points (Figure 9).

Discriminant analysis was again used to upgrade the initial nonhierarchical cluster analysis results. Only a single application was required in this case. Intersections 23, 53, 55, 69, 70, and 71 were reassigned from group one to group two, while intersections 48, 49, and 51 were reassigned from group two to group one, and a second discriminant

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Figure 9: Noon Data, Initial Nonhierarchical Two Group Clusters
analysis performed. With these upgraded group memberships, observations
missassigned by the discriminant simulation dropped from 11.9 percent to 9.0
percent, while the corresponding signal subareas became significantly more
compact. Given the positions of the existing missassignments, no further
improvements are apparent; Figure 10 illustrates the final group designations.

It is worth noting that these mid-day subareas are different from those
identified for the AM peak. This is not surprising since network traffic flow
patterns are likely to be very different during these two time periods. These
findings are consistent with the attempt to allow variable subarea
definitions in operating first and second generation control systems.

V. CONCLUSIONS AND EXTENSIONS

Cluster and discriminant analysis procedures can be used to extract
reasonably compact, contiguous signal subareas from data based on approach
flow ratios. If one accepts the contention that these flow ratios represent,
in a general way, the operating environment of any traffic signal at a given
point in time, then the signal subareas designated by this procedure should be
strong candidates for separate cycle times and operating policies. Such
subareas are defined by their collective set of statistical similarities. The
subareas individually represent collections of signals that are both
physically proximal, and proximal in terms of the variable space in which each
intersection is defined. Such high internal proximity takes into account the
relationships between each signal and the entire network, as opposed to a
perspective that accounts only for relationships between physically adjacent
intersections. Statistical methods are relied on in order to (heuristically)
process the information required, with the analyst’s intervention permitted in
order to ensure the identification of operationally sound area control

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configurations. In essence, the careful, well defined application of the analyst's judgment displaces a considerable mass of network specific computer code.

The flow ratio characterizes the state of a supply and demand relationship for each (defined) intersection approach. It would be reasonable to consider including more facility-specific information in the vector representing each intersection, since such additional information might serve to further capture the (supply side) impact of any given signal's operations on the remainder of the network. An effort was made to include standardized longest (approach) link length information into each observation, but the outcome was not encouraging. Results were reasonable, but degraded relative to those obtained previously. If, however, the network's right-of-way configuration changes with the time of day, then the inclusion of more facility specific information in the definition of each observation would be expected to be more productive.

Additional candidates for facility specific information would include the standardized shortest approach length, the network (Manhattan) distance from each intersection to randomly or theoretically selected reference intersections, or perhaps even indices of intersection design levels. Additional clustering variables that might capture further demand and supply interactions might include approach speeds, or approach turning movement ratios. A logical extension of this paper would be to conduct simulations of the entire network and the subareas; network performance could then be assessed to see if improved traffic flow did result from the identified subareas. This test is the subject of a future paper.


