GRANULAR ANALYSIS OF TRAFFIC DATA FOR TURNING MOVEMENTS ESTIMATION

Andrzej Bargiela[1], Iisakki Kosonen[2], Matti Pursula[2] and Evtim Peytchev[1]

[1]*The Nottingham Trent University, Nottingham, NG1 4BU, UK*

[2]*Helsinki University of Technology, Espoo, FIN-02105 HUT, FINLAND*

andre@doc.ntu.ac.uk, iisakki.kosonen@hut.fi, matti.pursula@hut.fi, epe@doc.ntu.ac.uk

ABSTRACT

The paper proposes and evaluates a new framework for estimation of turning movements in urban traffic networks. Turning movements are essentially atomic descriptors of average driver intentions as they proceed through the road network. The advance knowledge of these intentions enables progression from the local optimisation of traffic on individual crossroads to the more holistic optimisation of traffic in a road network. Unfortunately the measurement of turning movements requires additional instrumentation, which can be quite expensive. In this paper we present a method for approximate estimation of turning movements based on granular analysis of stop-line queues. Information about stop-line queues is much more readily available as it is routinely used for adaptive tuning of signal lights on individual crossroads. However, individual readings of stop-line queues are too greatly influenced by the specific traffic situation at a given time instance and the statistical analysis of queue data is frequently impeded by the lack of valid statistical characterisation of traffic. We propose therefore a recursive information granulation approach based on the Fuzzy C-Means (FCM) algorithm that allows us to extract the essence of data and to disregard the irrelevant detail. The granulation algorithm has two distinctive features: (i) the information granules are formed by means of hierarchical optimisation of information density and (ii) the granules are created as hyperboxes thus being readily interpretable in the pattern space. The granular estimates of turning movements are calibrated using HUTSIM microsimulator.

Key Words: Knowledge and information management, Simulation, Transportation**.**

1. INTRODUCTION

Modelling of urban traffic represents a significant conceptual and computational challenge. This is because the atomic components of urban traffic, i.e. individual vehicles, are controlled by drivers who take into consideration both local traffic conditions and global intentions of their individual journeys. Although the local traffic situation can be measured to some degree, only the drivers generally know the global journey intentions. Furthermore, the driver intentions information is a dynamic entity that is not approximated well by some static characterisation such as an "origin-destination matrix". What is needed is a real-time estimation of journey intentions that is economical to deploy and does not compromise the privacy of individual drivers. The first requirement points to the use of the existing traffic telemetry and the second implies some statistical rather then vehicle-specific journey characterisation.

The estimation of dynamic origin-destination (O-D) matrices from traffic counts in a transportation network has received much attention in the last two decades. Conventionally, O-D flow matrices were considered only for certain period of interest and thus were estimated with the average traffic count data for that period (Chang G., *et al,* 1994). A comprehensive review of research along these lines has been presented by Cascetta E., *et al* (1988). Such methods were static in nature and relied on some prior O-D information as well as "standard" driver behaviour to produce a reasonable result. At the other end of the spectrum are the O-D estimation models that are based on statistical analysis of detailed traffic counts on individual approaches to the intersection. The O-D estimation problem is formulated in this case as a problem of minimisation of the prediction error evaluated as a discrepancy between the expected and actual traffic counts on all approaches (Nihan N. *et al*, 1987, Cremer M. *et al,* 1987, Peytchev E., 1999). Although this approach can, in principle, deliver accurate estimates of turning movements on the intersection, it depends critically on the extensive instrumentation of each intersection, i.e. real-time measurements of the incoming and outgoing traffic.

In this paper we propose an alternative method that preserves the benefits of real-time estimation of turning movements while avoiding the need for extensive instrumentation of intersections. We argue that the secondary effect of the right-turning traffic (in UK) on the traffic queue provides an adequate approximation of turning movements. The key to this analysis is the observation that the reduction of measurement information requires that the analysis be performed at a more aggregated (granular) level.

The rationale for information granulation is deeply rooted in human information processing which can be characterised as a constant endeavour to extract and organize knowledge about the external world. It is this very ability to abstract detailed information into more general information granules that enable humans to be successful in dealing with complex systems. Zadeh (1979; 1996; 1997; 1999) promoted a notion of information granulation in the framework of fuzzy sets that are particularly well suited for representing vague or imprecise data. However, other granulation frameworks such as sets (intervals) are quite appropriate in a broad range of situations and have long been used for representing physical reality (that is essentially analog) in digital computers. In a nutshell, information granules are treated as collections of entities (say numeric readings) that are grouped together because of their similarity, functional closeness or any other criterion that captures a feature of indistinguishability. Information granules give rise to hierarchies of cognitive entities. When forming information granules one needs to reconcile two aspects. On one hand information granules are conceptual constructs that do not need to have immediate physical counterpart. However, on the other hand they have to be anchored in the world of experimental data so as to reflect in some way the reality of the physical world. These two principles point to the algorithmic approach to information granulation.

In this paper we start by describing a detailed algorithm for constructing information granules from the experimental data. Subsequently, we show how the derived information granules can be combined even further via recursive application of the algorithm so as to arrive at the higher levels of data abstraction. In order to achieve information granules that are easily interpretable we adopt interval analysis as a formal framework for the description of the algorithm.

2. PRINCIPLES AND ALGORITHM OF INFORMATION GRANULATION

In the interest of generality we adopt a set-theoretic formalism for the description of information granules. In particular we focus on intervals and their multidimensional versions i.e. hyperboxes. The granular properties of sets are straightforward: the larger the size of interval, the lower its granularity. So, a suitable measure of granularity might be an inverse of the cardinality of a set. In other words the bigger the cardinality of the set, the lower its granularity.

2.1. Characterization of information granules

We shall follow here an approach to information granulation proposed in Bargiela & Pedrycz (2002b) which can be summarised as follows. Information granules are designed in two stages (phases). First, in the entire data set under consideration (in our case a time series data), we define a size of a segment (window of granulation), specify the elements (data points) within each segment and in sequel use these elements to construct a detailed form of the information granule. More formally, we define a mapping

$$\mathbf{X} \underset{\Omega}{\Rightarrow} A \tag{1}$$

In the above scheme, $\mathbf{X}$ denotes an original data set, Ω is a set of disjoined time periods Ω_k representing windows of observation, and A is a set of information granules.

Building interval-valued granules arises as a compromise between two evidently conflicting requirements

i) the interval should "embrace" as many elements of $\{x_j: j \in \Omega_k\}$ as possible (to be a sound representation of the window of observation)

ii) the interval should be highly specific. This translates into the requirement of a minimal length of this interval (set).

As far as the first requirement is concerned, a cardinality of the set covering elements of Ω_k is a suitable criterion, that is

$$\text{card}(I) = \sum_{x_j \in X} \chi_{[a,b]}(x_k) \tag{2}$$

where I = [a,b] denotes the interval we are about to construct and $\chi_{[a,b]}$ stands for its characteristic function, that is

$$\chi_{[a,b]}(x) = \begin{cases} 1, & \text{if } x \text{ is in } [a,b] \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

The specificity of the interval can be directly associated with its width,

$$\text{width}(I) = \text{width}([a,b]) = b-a \tag{4}$$

More precisely, the larger the width of the interval, the lower its specificity. While this definition is straightforward, we will be using its slightly enhanced version expressed as

$$\phi(\text{width}([a,b])) \tag{5}$$

where "ϕ" is monotonically increasing function of the original width and $\phi(0) = 1$ (with the boundary condition facilitating the uniformity of processing of data points and data intervals). For instance, a mapping of interest can assume the form

$$\phi(u) = \exp(u) \tag{6}$$

Bearing in mind a conflicting nature of the requirements (i) - (ii) that is captured in the form

$$\text{card}(I) \rightarrow \max \qquad \phi(\text{width}([a,b])) \rightarrow \min \tag{7}$$

it is legitimate to take a ratio of these expressions

$$\sigma = \frac{\text{card(I)}}{\phi(\text{width(I)})} \tag{8}$$

and determine the interval I so that it maximizes expression (8). In this way, we simultaneously cope with the two contributing optimization problems defined in (7). We refer to the optimization expressed by (8) as maximization of 'information density' of granules. This is to distinguish it from the concept of 'data density' that is typically represented as a ratio of cardinality of a given set over the volume of the pattern space containing this set. Consequently 'data density' is not defined for a single numeric data (zero volume in pattern space).

The choice of function $\phi(u)$ depends on the preference for large or small information granules. Figure 1 shows contour plots of the expression (8) obtained with $\phi(u)$ defined as in (6). It can be seen that the decrease of the gradient of the contours with the increase of the cardinality of the granules implies inherent preference for smaller granules. This is an advantageous feature as it gives us a possibility of avoiding undue influence of inherently local optimization on the more global view of data that is obtained through recursive application of the granulation algorithm. An alternative choice of $\phi(u)=1+u$ results in constant-gradient contours of (8) and is thus less appropriate in the context of our algorithm. A function $\phi(u)=(1+u)^2$ results in contour plots that are broadly similar to those obtained with $\phi(u)=\exp(u)$ but it is less convenient numerically.

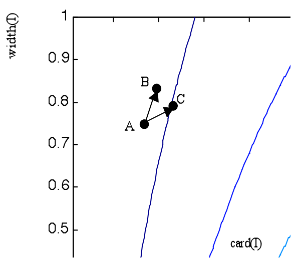

Figure 1. Contour plot of the information density function (8); $\sigma(I)$=const.. Transition from granule A to B represents a net decrease of information density and is therefore avoided. Transition from A to C represents formation of a granule with higher information density.

The above considerations generalize easily to multi-dimensional data. The maximization of information density, implied by the expression (8), can be performed for multi-dimensional hyperboxes. We consider in this case a ratio of the cardinality of the input data set contained in such hyperboxes to a function of volume of the hyperboxes. However, such a direct approach creates dependence of the information density measure on the dimensionality of the pattern space. So, in order to maintain comparability of granulation results obtained in pattern spaces of varying dimensions it is advantageous to consider a dimensionality-invariant version of mapping $\phi(u)$. This can be given as follows

$$\phi(u)= \exp(\max_i (u_i))*\exp(\max_i (u_i)-\min_j (u_j)) \quad (9)$$

where $u=(u_1\ u_2\ \dots\ u_n)$, $u_i = \text{width}([a_i,b_i])$ and $i,j=1,2,\dots,n$, is an index of the dimension of the pattern space. The first exponent function in (9) ensures that the specificity of information granules is maximized through the reduction of the maximum width of the hypercube along all dimensions in the pattern space. The second exponent in (9) ensures that the hyperboxes are as similar to hypercubes as possible. The above function can be expressed in a more compact form

$$\phi(u)= \exp(2*\max_i (u_i)-\min_j (u_j)) \quad (10)$$

where, $i,j=1,\dots,n$. It is clear that (10) is not affected by the dimensionality of the pattern space. The maximization of the width of the hyperbox (granule), over all dimensions of the pattern space, results in a scalar value that is of the same order regardless of the space dimension. Also, the function satisfies the original boundary condition $\phi(0) = 1$, since for the point-size data $\max_i (u_i) = \min_i (u_i) = 0$, $i=1,\dots,n$.

While, in general, the pattern space **X** can be any subset of $\mathbf{R}^n$, we restrict the operation of the optimization task (8) to a unit hypercube $[0, 1]^n$. Such a restriction does not imply any loss of generality of our approach while affording clear computational benefits (with regard to mapping $\phi(u)$).

2.2. The algorithm

The granulation of data based on maximisation of information density is carried out as a one-pass process:

a) Normalize data to a unit hypercube;
b) Initialize data structures representing cardinality and the width of individual data items (1 and 0 respectively for the point-data);
c) Calculate and store the value of 'information density' (as implied by (8)) of hypothetical granules formed by any two data items in the input data set. This forms an upper-diagonal matrix D of size NxN, where N is the cardinality of the input data set.
d) Find a maximum entry in D;
e) If the maximum corresponds to an off-diagonal element (i-th and j-th coord):
   - merge the two information items (identified by the i-th row and j-th column) into a single information granule, which has width defined by the maximum and minimum values of coordinates in each dimension from the two component granules
   - update the cardinality of the resulting granule to the sum of the cardinality counts of the component granules;
   - update the i-th row and column of D with the information pertinent to the newly formed information granule and remove the j-th row and column from D;
   - return to d)
f) If the maximum corresponds to a diagonal element (i=j):
   - copy the granule to an output list and remove the corresponding row and column from matrix D;
   - if the size of matrix D is greater than 1, return to d), otherwise terminate.

Computational complexity of this granulation algorithm is $O(N^2)$ owing to the computations of matrix D in step c). However, unlike the clustering techniques (such as FCM, (Bezdek, 1981)), the granulation process has an inherently local character and can be easily applied to a partitioned input data thus circumventing the high computational cost associated with large data sets. It is worth emphasizing that the size of matrix D is being reduced in every iterative step by one row and one column thus the number of steps equals N-1.

In contrast to "subtractive clustering" algorithms, the algorithm presented here does not make any assumptions about the maximum size of granules. Granules are allowed to grow as long as their local data density keeps increasing. Also, the algorithm does not require any arbitrary decision about the separation of cluster centres. The formation of closely separated granules is largely avoided by the very nature of maximization of information density, which tends to increase the size of granule if it means adding sufficiently large number of data items (another granule) without undue increase of its volume. If, on the other hand, the increase in volume would imply the reduction of information density, the granule does not expand and remains well separated from the neighbouring granules. Another distinguishing feature of our algorithm is that it allows processing both point-size and hyperbox data. This is an important characteristic that allows hierarchical granulation of data. It should be noted that hierarchical granulation enables overcoming the limitations of the 'local view' of data while supporting the application of the algorithm to a partitioned input data set.

It is worth noting that the number of granulation levels does not need to be defined in advance. The hierarchical granulation can simply be carried out until the number of granules identified at the subsequent granulation levels does not change. Of course, in any practical application the maximum size of granules is frequently pre-defined so that the granules map conveniently onto some linguistic entities. In this case the relative weighing of the two components in the expression (8) can be adjusted so as to achieve the required granularity.

2.3. Assessment and interpretation of information granules

In the description of the algorithm in the previous section we have relied on the implicit assumption that the information granules are topologically "compatible" with the original data. This assumption is necessary because after the first step of the algorithm we have a mix of data points and hyperboxes in the pattern space. However, it is clear that in the n-dimensional space a data point P is represented as $P=[x_1, \ldots, x_n]$ and a hyperbox H is represented as an ordered pair of minimum and maximum vertices, $H=[x^l_1, \ldots, x^l_n, x^u_1, \ldots, x^u_n]$. So, the two topological entities are in fact defined in $\mathbf{R}^n$ and $\mathbf{R}^{2n}$ respectively. It is necessary therefore to "generalise" the description of data points and make them compatible with hyperboxes by considering points as special cases of hyperboxes that have identical minimum and maximum vertices, i.e. $P=[x_1, \ldots, x_n, x_1, \ldots, x_n]$. As a preparation for the deployment of the granulation algorithm we double the dimensionality of the input space and make it compatible with hyperbox topology. It is important to note that since the hyperboxes are already defined in $\mathbf{R}^{2n}$ the computational load implied by the increase of the dimension of the data point is negligible.

While the information density associated with the resulting information granules increases quite significantly it is of fundamental interest whether this 'condensing' retains the essential characteristics of data. We can assess the quality of granulation by identifying a limited number of representatives of both the original numeric data and the constructed information granules. This is accomplished by clustering and identifying prototypes (representatives) of the granules, cf (Everitt, 1974). In particular, a fuzzy clustering method - a well-known FCM algorithm (Bezdek, 1981) is of interest here. As a result of this clustering mechanism, the method returns a partition matrix. This matrix captures all granules in the form of some generalized architecture of fuzzy sets formed over the family of the original information granules. However, in contrast to the standard clustering method we do not deal with data points but with hyperboxes as input data. As a consequence, the prototypes returned by FCM are also in the form of hyperboxes (information granules). In other words, the prototypes represent fully decomposable relations in the feature space in addition to representing, through the partition matrix, the fuzzy membership of data in clusters. The combination of the two aspects delivers a more comprehensive insight into the granular nature of information being summarized by the prototypes.

One important consequence of using granular prototypes is the ability to appreciate instantly the spatial dimensions of the original data. Something that is not possible with point-size prototypes of the standard FCM. Although the FCM partition matrix contains information that represents the area of influence of individual clusters its direct interpretation is quite difficult due to the complex topology of the contour plots of the partition matrix. In this sense, clustering of granular data affords a better insight into the nature of data.

Another important consequence is the ability to overcome the well-known bias of the FCM algorithm, that of under representing smaller groupings of data. Since the granulation reduces the number of information items in the high data density areas, the relative count of granules in large and smaller groupings of data evens out. In other words, granulation substitutes explicit enumeration (that unduly affects FCM) with an update of the cardinality attribute associated with individual granules (that is transparent to FCM).

3. EMPIRICAL ASSESSMENT OF TURNING MOVEMENTS

The recursive information granulation algorithm has been applied to real-life traffic queues data collected by the SCOOT – UTC system in Mansfield, Nottinghamshire, UK. While the Mansfield SCOOT system includes some 40 intersections we will limit ourselves to the discussion of a representative 3-way intersection illustrated in Figure 2.

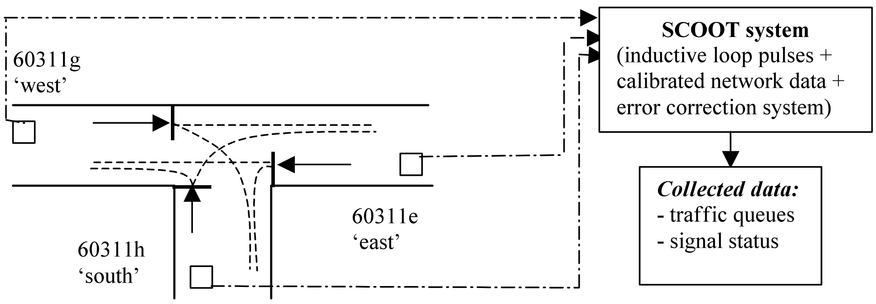

Figure 2. Junction "60311" in Mansfield (UK) with 3 measured traffic queues.

The three inductive loops are the measuring devices that count discrete pulses generated by cars passing over them. The number of pulses generated by a car is proportional to the length of the car and inversely proportional to its speed. So a small vehicle moving slowly and a large vehicle moving quickly may generate the same number of pulses. This is actually a very advantageous property of this type of measuring devices because it enables focusing on generic "road occupancy" rather than specific vehicles. The pulses are weighted on a sliding scale so as to ensure that the occasional inductive loop errors do not affect unduly the results. The weighted pulses are referred to as Link Profile Units (LPU). The inductive loop measurements are combined with real-time readings of traffic signal status and also the calibrated travel times between each inductive loop and its corresponding stop-line. On this basis SCOOT is able to estimate the number of vehicles that will arrive at the stop-line during the red signalling stage. This estimate, updated in real-time, is referred to as 'traffic queue measurement’ (in LPUs). Since the integration of inductive pulses is prone to systematic error, there are additional inductive loops (not shown on Figure 2), which are used to re-set this error to zero for some specific queue length. In effect, the SCOOT system has a built-in ‘safety net’ for the traffic queue measurements. By monitoring the ‘discharge flows’ from the stop-line during the green signalling stage, SCOOT accounts also for the queue remaining from the previous signalling stage in the derived traffic queue measurements.

The original time series consist of 705 discrete measurements for each inductive loop taken every 4 seconds. The readings are time-aligned and form a 3-dimensional vector of system states for 705 time instances (2820 seconds) as illustrated in Figure 3.

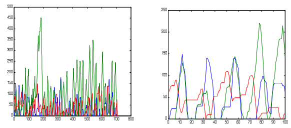

Figure 3. Traffic queue data in LPUs. Complete set (705) and a subset (100) readings.

The state vector is normalised so that the maximum value of any coordinate of the vector is 1.0 and the minimum value is 0.0. A small extract from the 3-dimensional state vector is given in Table 1.

Table 1. Normalised state vector for time instances 185 through to 195.

State vector	Queue - east	Queue - west	Queue - south
…			
x(185)	0.4536	0.4731	0.4848
x(186)	0.4536	0.4731	0.4848
x(187)	0.4536	0.6774	0.4848
x(188)	0.4536	0.5054	0.4848
x(189)	0.4536	0.5914	0.4848
x(190)	0.4536	0.5591	0.4848
x(191)	0.5979	0.6022	0.5758
x(192)	0.4948	0.5806	0.3939
x(193)	0.4536	0.4731	0.2424
x(194)	0.4536	0.4731	0.2727
x(195)	0.2680	0.3548	0.4848
…			

In the first instance we analyse a 3-dimensional time series of changes of traffic queues in the links ‘60311g’, ‘60311e’ and ‘60311h’. We will refer to these links as ‘west’, ‘east’ and ‘south’ respectively. Clearly the expectation is that the relative changes of traffic queues in consecutive time periods recorded in east and west links will reveal the information about the right-turning traffic from the west link (into south link).

At the start of the granulation algorithm the state vector for each time instance represents a point-value of queues on the corresponding approaches to the intersection. However, as the granulation proceeds, the original point-values are expanded into intervals specifying minimum and maximum queues for each granule on each of the three approaches. This is accommodated by the increase of the dimensionality of the state vector from 3 to 6, which corresponds to specifying hyperboxes in the 3-dimensional pattern space. An extract from the 6-dimensional state vector is given in Table 2.

Table 2. Normalised 6-dimensional state vector for time instances 185 through to 195 at the start of the granulation process.

State vector	Min Queue - east	Min Queue - west	Min Queue - south	Max Queue - east	Max Queue - west	Max Queue - south
…						
x(185)	0.4536	0.4731	0.4848	0.4536	0.4731	0.4848
x(186)	0.4536	0.4731	0.4848	0.4536	0.4731	0.4848
x(187)	0.4536	0.6774	0.4848	0.4536	0.6774	0.4848
x(188)	0.4536	0.5054	0.4848	0.4536	0.5054	0.4848
x(189)	0.4536	0.5914	0.4848	0.4536	0.5914	0.4848
x(190)	0.4536	0.5591	0.4848	0.4536	0.5591	0.4848
x(191)	0.5979	0.6022	0.5758	0.5979	0.6022	0.5758
x(192)	0.4948	0.5806	0.3939	0.4948	0.5806	0.3939
x(193)	0.4536	0.4731	0.2424	0.4536	0.4731	0.2424
x(194)	0.4536	0.4731	0.2727	0.4536	0.4731	0.2727
x(195)	0.2680	0.3548	0.4848	0.2680	0.3548	0.4848
…						

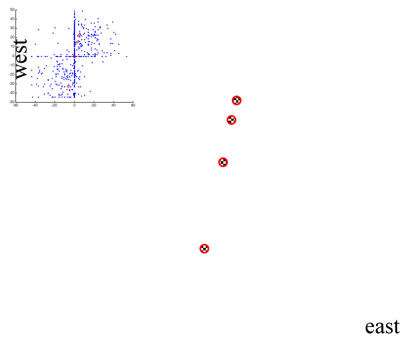

Figure 4. FCM prototypes identified for original measurements of changes of traffic queues on “east” and “west” links.

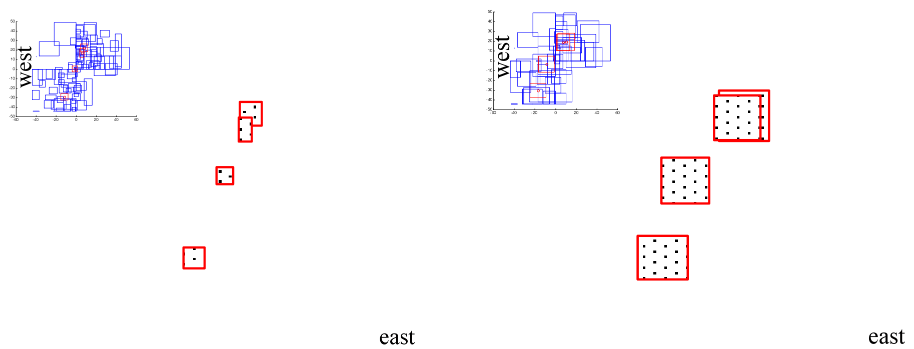

Figure 5. FCM prototypes identified for level-one and level-two granulated measurements of changes of traffic queues on “east” and “west” links.

We apply the granulation and FCM-based identification of granular prototypes to this 6-dimensional state vector and visualise the results by projecting them onto the 2-D "east-west" space. The FCM prototypes identified for the original data are illustrated in Figure 4 and the level-one and level-two granular prototypes are illustrated in Figure 5. The exact numerical coordinates of the FCM prototypes in the normalised space for level-one and level-two granulation are given in Table 3 and Table 4 respectively.

Table 3. Coordinates of the minimum and maximum vertices of FCM prototypes (hyperboxes) evaluated for level-one granulation.

FCM Prototype	Min - east	Min - west	Min - south	Max - east	Max - west	Max - south
1	0.2950	0.1246	0.5222	0.3686	0.1968	0.5729
2	0.4983	0.6706	0.5135	0.5724	0.7577	0.5943
3	0.4886	0.6071	0.1073	0.5348	0.7063	0.1802
4	0.4135	0.4428	0.5125	0.4695	0.5096	0.5697

Table 4. Coordinates of the minimum and maximum vertices of FCM prototypes (hyperboxes) evaluated for level-two granulation.

FCM Prototype	Min - east	Min - west	Min - south	Max - east	Max - west	Max - south
1	0.4647	0.5852	0.0945	0.5948	0.7686	0.2951
2	0.4753	0.5882	0.5059	0.6433	0.7791	0.6882
3	0.1964	0.0717	0.4970	0.3568	0.2250	0.6088
4	0.2852	0.3485	0.5085	0.4416	0.5267	0.6744

We highlight here the coordinates of the prototype 4 as it contains information pertinent to the turning movement estimation. The "min-east" and "max-east" values for this prototype are below the average value of 0.5 indicating that the queue length on the "east" approach is decreasing. However, the "west" approach, as characterised by the prototype 4, is different in that the queue can be either decreasing ("min-west" < 0.5) or increasing ("max-west" > 0.5). The reason for the increasing queue length on the "west" approach is that the right-turning traffic can be impeded by the traffic from the "east" approach. Consequently the ratio: ("max-west" – 0.5) / ("max-west" – "min-west") becomes a measure of the right-turning traffic (denoted here as $T_{w\text{-}s}$, where the subscript w-s means traffic from "west" to "south" direction).

In order to verify the robustness of the above turning movement estimate, we evaluate it for level-one and level-two FCM prototypes as detailed in Table 3 and 4. For level-one granulation we obtain

$$T_{w\text{-}s} = (0.5096 - 0.5) / (0.5096 - 0.4428) = 0.1437$$

and for level-two granulation we have

$$T_{w\text{-}s} = (0.5267 - 0.5) / (0.5267 - 0.3485) = 0.1498$$

It is clear from the above that the turning movement estimate does not depend significantly on the level of granulation of data and that the inherent information about the right-turning traffic is preserved in the information granules. In other words, the granular data analysis provides a good basis for the interpretation of traffic queues data. However, in order to make a link between the $T_{w\text{-}s}$ index and the percentage of right-turning traffic on this intersection one has to take into account driver behaviour in terms of acceleration and gap-acceptance parameters. If the average driver behaviour is more dynamic (smaller gaps accepted and higher acceleration) the index T_{w-s} will translate into higher percentage of right-turning traffic. Conversely, if the average driver behaviour is less dynamic, the index T_{w-s} will translate into a lower percentage of the right-turning traffic.

The quantification of the drivers' behaviour is in itself a complex problem mainly because of the lack of direct measurement data that would support such quantification. However, we have already reported in our earlier publications (Kosonen *et al,* 1998, 2000) that it is possible to derive information about average driver behaviour from real-time traffic simulations; i.e. simulations that receive actual lane occupancy data as its input and compare the simulated and actual traffic readings.

4. CONCLUSION

Granular analysis of data offers a powerful tool for creation of information abstractions in the context of data that cannot be easily characterised by statistical relationships. Granulation is based on the intuitive concept of data similarity/proximity without making any reference to such statistical descriptors as mean/variance/probability distribution etc. We have shown, using the example of urban traffic data, that the essential characteristics of data are preserved in the process of information granulation and that the quantification of these characteristic features does not depend significantly on the level of information granulation (abstraction).

In the context of traffic data analysis, the work reported here gives basis for a new approach to urban traffic monitoring and control; one that is based on the use of real-time traffic simulations coupled with granular analysis of detailed traffic readings. By focusing on the formation of semantically rich and robust information abstractions the granular analysis can be used as a basis for the development of large-scale system models.

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