Location Aware Resource Management in Smart Homes

Abhishek Roy, Soumya K. Das Bhaumik, Amiya Bhattacharya, Kalyan Basu, Diane J. Cook and Sajal K. Das
CReWMaN Lab, Computer Science and Engineering Department
The University of Texas at Arlington
{aroy, sdas, bhatt, basu, cook, das}@cse.uta.edu

Abstract— **The rapid advances in a wide range of wireless access technologies along with the efficient use of smart spaces have already set the stage for development of smart homes. Context-awareness is perhaps the most salient feature in these intelligent computing platforms. The "location" information of the users plays a vital role in defining this context. To extract the best performance and efficacy of such smart computing environments, one needs a scalable, technology-independent location service. In this paper we have developed a predictive framework for location-aware resource optimization in smart homes. The underlying compression mechanism helps in efficient learning of an inhabitant's movement (location) profiles in the symbolic domain. The concept of Asymptotic Equipartition Property (AEP) in information theory helps to predict the inhabitant's future location as well as most likely path-segments with good accuracy. Successful prediction helps in pro-active resource management and on-demand operations of automated devices along the inhabitant's future paths and locations — thus providing the necessary comfort at a near-optimal cost. Simulation results on a typical smart home floor plans corroborate this high prediction success and demonstrate sufficient reduction in daily energy-consumption, manual operations and time spent by the inhabitant which are considered as a fair measure of his/her comfort.**

I. Introduction

The essence of Weiser's *ubiquitous computing* vision [20] lies in the creation of smart environments saturated with computing and communication capabilities, yet gracefully integrated with human users. The two distinctive characteristics of ubiquitous computing are: (i) the noticeable migration of computing from general-purpose computers to smaller customized mobile terminals, and (ii) the pro-active interaction and inherent *sentience* [11] of the computing devices with their surrounding network infrastructure. "Context-awareness" is perhaps the key characteristic of next-generation intelligent networks and associated applications. *Location awareness* is the most important "context" for the vast majority of ubiquitous computing scenarios, since the information needed by users depend strongly on their current or near future location. A quick look into different such applications like Advanced Traveler Information Systems (ATIS) [19], electronic tourist guides [1] and fleet management systems [21] reveal that the prime objective of all these prototypes is to improve the convenience of the visitors.

This vision of ubiquitous computing has already given birth to a new research area: 'intelligent location management in smart indoor environments.' In such an environment the technology needs to be weaved into the fabric of our everyday life such that it becomes "technology that disappears" [20]. Over the past few years, there has been an upsurge of several innovative prototypes for indoor location-aware computing platforms. The Active Badge [8] is perhaps the first infra-red based location tracking system developed for indoor offices. Active Bat [9] takes the help of 'ultrasonic time-of-flight lateration technique' to improve the granularity of location-sensing offered by the badge system. On the other hand, MIT's Cricket Location Support System [18] delegates the responsibility of location reporting to the mobile object itself. RADAR [3], another RF-based indoor location support system uses signal strength and signal-to-noise ratio to compute 2-D positioning. The Motion Star [2] tracking system uses electromagnetic sensing and virtual reality to compute the required location information. Microsoft's Easyliving and Microsoft Home [13] projects use real-time 3D cameras to provide stereo-vision positioning capability in an indoor environment. In the Georgia Tech's Aware Home [17], the embedded pressure sensors capture inhabitant's footfalls, and the system uses this data for position tracking and pedestrian recognition. The Neural Network House project [16] of the University of Colorado focuses on the development of an adaptive control of home environments (ACHE) to anticipate the needs of the inhabitants. The Intelligent Home Project [14] at the University of Massachusetts explores the application of multi-agent systems technology to develop and maintain a smart indoor environment. MIT's Intelligent House_n [12] also focuses on developing excellent products and services to satisfy the needs of the people living in the future-generation houses. A careful insight into the features of these location services reveals that the ability to predict the inhabitant's future location often becomes the key to system's associated "smartness".

In this paper we have taken an *information-theoretic* approach to develop a *location-aware resource optimization* scheme in the smart home environments. The complexity of the indoor location management is related to *entropy*, a well-known measure for uncertainty of a probabilistic source. An analysis of inhabitant's daily routine reveals some patterns in his/her daily-life. Although the life style changes over time, but such changes are not frequent and random. This observation helps us to assume the inhabitant's mobility as a *piece-wise stationary, ergodic, stochastic process*. Exploiting this general, yet realistic assumption, the *LeZi update* [4], [5] provides an asymptotically optimal location information in the symbolic domain. Although, in a smart home, there exists a wide number of possible routes from one part of the room to the another, an inhabitant usually follows his/her most likely paths. A similar analogy, dealing with the *asymptotic equipartition property* (AEP) [22] in information theory, states that among all the long-range sequences consisting of random variables, there exists a fairly small *typical set* [22] which contains most of the probability mass and controls the average behavior of all such sequences. Using this concept, one can capture the inhabitant's *typical path segments*. We claim that reserving resources and activating the automated

This work was supported by NSF grants under EIA-0086260, EIA-0115885 and IIS-0121297 and Texas Telecommunications Engineering Consortium (TxTEC).

devices *only* along the typical paths, are sufficient to create an amicable, context-aware atmosphere in the house, yet attempting to minimize the overall energy consumption. The scheme being fast and efficient, is also well-suited for implementation.

The rest of the paper is organized as follows. In section II, we have taken a brief look into the architectural overview of our smart home project, named MavHome [7] at the University of Texas at Arlington. The new predictive framework for location-aware resource management is described in section III. Simulation environment, and experimental results in section IV delineates the efficiency of our predictive platform. Finally, section V concludes the paper with pointers to future research issues.

II. Architecture and Indoor Networking of MavHome

The MavHome (**M**anaging **A**n intelligent **V**ersatile **Home**) is a multi-disciplinary research project at the University of Texas at Arlington. It is focused on the creation of an intelligent home environment capable of perceiving its surroundings through the use of sensors, and thereby adopting suitable actions by using the actuators. The overall goal is to provide the inhabitant's comfort at an optimal cost. In such a smart computing platform there will be movements of inhabitants interacting with their surrounding environments through the hand-held devices. Intelligent networking technologies and protocols are necessary in development of indoor networking infrastructure for this smart home. Figure 1 gives a possible floorplan of MavHome together with the placement of motion-sensors along the inhabitant's routes. A broad overview of the home network for MavHome is shown in Figure 2. The entire house will be connected to the external network through a home access point (e.g.,a cable modem). This access point will be connected to a high-performance router, which in turn, acts as a bridge between the indoor home LANs at every room and the computing cluster dedicated for executing the location & route prediction algorithm and taking intelligent decisions regarding the activation of actuators. The gateways in the router will be having the ability to gather and communicate information as needed to manage and deliver services over the different home LANs. All the home LANs will in turn, be connected to a secondary cluster consisting of an ethernet switch and a small server for sensory-data acquisition. These ethernet switches will be connected to the wireless LANs and Bluetooth-enabled home-base-stations. The indoor robots will be communicating through the wireless LANs. On the other hand, the in-building sensors and actuators can communicate in either wired or wireless modes. One possibility is to connect all the wired sensors and actuators with the ethernet switch through another LAN dedicated for sensor networks only. The wireless sensors and actuators will be bluetooth equipped, thus communicating with the ethernet-switch through bluetooth-enabled home base-station.

A quick look into the floorplan reveals that the MavHome's coverage area can be partitioned into different *zones* or sectors. When the system needs to contact the inhabitant, it will initiate a prediction scheme to predict the inhabitant's location together with his/her most likely paths. In order to control the location uncertainty of the inhabitant, the system also relies on location information provided by the in-building sensors from

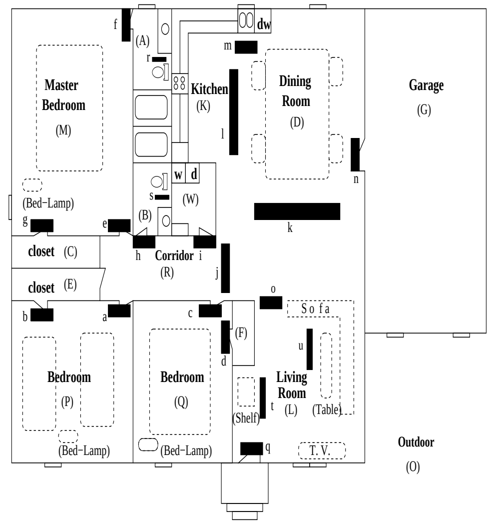
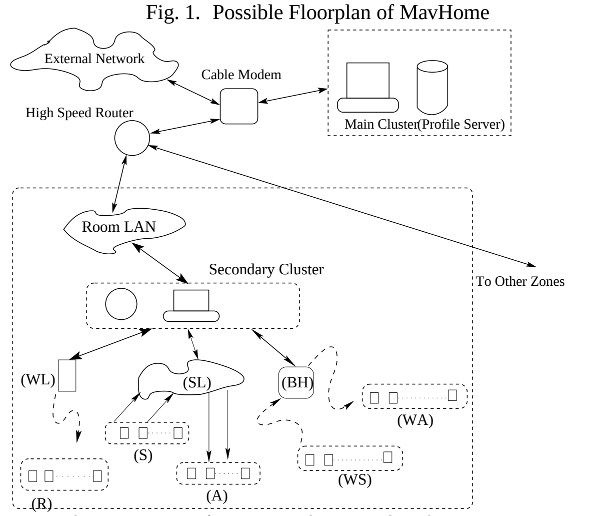


Fig. 1. Possible Floorplan of MavHome



WL = Wireless LAN, SL = LAN for Sensor Networking BH = Bluetooth Home Base Station
R = Robots . S = Wired Sensors . A = Wired ACtautors. WS = Wireless Sensors. WA = Wireless Actuators

Fig. 2. Overview of Network Architecture in MavHome

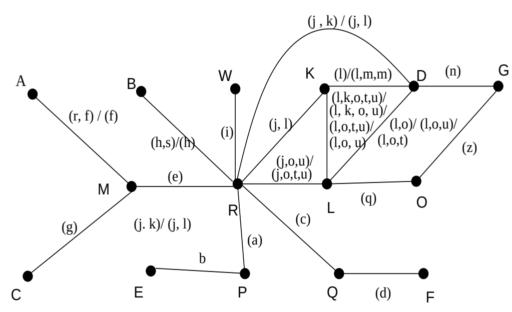


Fig. 3. Graph Representing the Connectivity of Zones/Locations

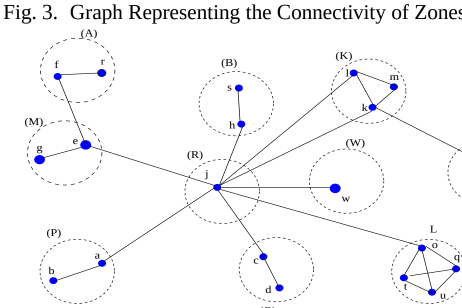


Fig. 4. Graph Representing the Connectivity of In-building Sensors

time to time. This helps in reducing the search space for the next prediction. The overall MavHome network can be represented by a connected graph $\mathbf{G} = (\mathbf{V}, \mathbf{E})$, where the node-set $\mathbf{V} = \{A, B, C, D, ...,\}$ represents the zones and edge-set $\mathbf{E}$ represents the neighborhood between a pair of zones. While moving from one zone to another the inhabitant goes through an array of sensors along the path. In other words, every edge of the graph actually consists of an array of sensors. Figure 3 depicts this scenario, where the possible paths between a pair of zones are represented by a single edge with different combinations of sensor-ids. For example, the movement from corridor R to dining-room D can be expressed by the collection of sensors $\{j, l\}$ or $\{j, k\}$.

The blessing of symbolic representation helps us to hierarchically abstract the indoor network infrastructure into different granularities. The graph represented in Figure 3 can be easily abstracted to represent the networking among different in-building sensors as shown in Figure 4. This graph represents the underlying sensor-network topology where the set of nodes $(\mathbf{V}' = \{a, b, c, d, ...,\})$ represents the set of sensors and the edge set represents the connectivity between individual sensors. Since, the prime focus of this paper is predictive resource utilization and comfort management in MavHome, we leave out the intimate details of the underlying sensor-technology and investigate into our proposed predictive framework.

III. Location Aware Resource Management in MavHome

The indoor location management problem can be formulated as an optimization problem, in terms of personal mobility profiles of individual inhabitants. The seminal work of Bhattacharya and Das [4], [5] is perhaps the first model-independent approach to characterize and solve this location management problem in PCS networks. However, this approach can be easily adapted to the MavHome scenario, as demonstrated below. From the information theoretic perspective the complexity of mobility tracking can be related to the location *uncertainty* and subsequently *entropy* [6] becomes a good choice for quantifying it. In fact, it is impossible for any algorithm to track down an inhabitant by exchanging any less information, on the average, than the uncertainty generated due to its mobility, and hence optimality is achieved when these two amounts are the same. This motivates us to develop a location-aware resource optimization framework for indoor environments.

Our proposed predictive framework is based on symbolic interpretation of the inhabitant's movement (mobility) inside the building, which is captured by sampling the in-building sensors (RF-id reader or pressure switches). Thus, the movement history of a inhabitant is assumed as a string "$v_1 v_2 v_3 \ldots$" of symbols (sensor-ids) where $v_i \in \vartheta$ (alphabet set). We argue that the inhabitant's current movement is merely a reflection of his/her movement history (profile), which can be learned over time in an on-line fashion. Characterizing such mobility as a probabilistic sequence suggests that it can be defined as a stochastic process $\mathcal{V} = \{V_i\}$, while the *repetitive* nature of *identifiable patterns* adds *stationarity* as an essential property, leading to $Pr[V_i = v_i] = Pr[V_{i+l} = v_i]$, for all $v_i \in \vartheta$ and for every shift l. Referring to our typical smart home in Figure 1, let "$ajlloojhhaajlloojaajlloojaajlm \ldots$" be such a movement history of an inhabitant at a particular time-frame. This scenario reveals that the inhabitant's movement generates an exponential number of strings representing the different path-segments followed by the inhabitant. However, we will show that only a small sub-set of all these set of paths are relevant for consideration. Also, a family of optimal text compression algorithms are suitable for efficient encoding of these variable length paths (strings) of mobility profiles in such a way that the overall entropy is minimized.

A. Location Uncertainty and Entropy

The traditional information-theoretic definitions of *entropy*, *relative entropy* and *conditional entropy* of random variables of a stochastic process are outlined here [6]. The entropy $H_b(X)$ of a discrete random variable X with probability mass function $p(x)$, $x \in \mathcal{X}$, is defined by: $H_b(X) = -\sum_{x \in \mathcal{X}} p(x) \log_b p(x)$. The limiting value "$\lim_{p \to 0} p \log_b p = 0$" is used in the expression when $p(x) = 0$. The *relative entropy* between two probability mass functions $p(x)$ and $q(x)$, $x \in \mathcal{X}$, is given by $D(p||q) = \sum_{x \in \mathcal{X}} p(x)\ log \frac{p(x)}{q(x)}$. This relative entropy is a fair measure of the inefficiency of assuming that the distribution is q, when the actual distribution is p. Also, *conditional entropy* is defined as $H(Y|X) = \sum_{x \in \mathcal{X}} p(x) H(Y|X = x)$. For any set $\{V_1, V_2, \ldots, V_k\}$ of k discrete random variables with distribution given by $p(v_1, v_2, \ldots, v_k) = \Pr[V_1 = v_1, V_2 = v_2, \ldots, V_k = v_k]$, where, $(v_i \in \vartheta)$, the joint entropy is given by $H(V_1, V_2, \ldots, V_k) = \sum_{i=1}^{k} H(V_i \mid V_1, V_2, \ldots, V_{i-1})$. The additive terms on the right-hand side carry necessary information which makes the higher-order context models more information-rich as compared to the lower-order ones. This motivates us to look for such higher order context models. The Lempel-Ziv [6], [24] type of text compression algorithms provides an elegant way to obtain these higher order models.

B. Probability Assignment of Path Segments

The optimal Lempel-Ziv text compression schemes helps to reduce the cost of sensory information acquisition by processing the symbols (sensor-ids) in chunks. The entire sequence of sampled symbols withheld since the last reporting is reported in an encoded form. Thus, the movement history "$v_1 v_2 v_3 \ldots$" reaches the profile-server (see Figure 2) as a sequence "$C(w_1)C(w_2)C(w_3)\ldots$," where the w_is are non-overlapping, distinct segments of the string "$v_1 v_2 v_3 \ldots$" and $C(w)$ is the encoding for segment w. For example, the input string "$ajlloojhhaajlloojaajlloojaajlm \ldots$" is parsed as distinct substrings "a, j, l, lo, o, jh, h, aa, jl, loo, ja, aj, ll, oo, jaa, jlm, $\ldots$,". Such a symbol wise context model can be efficiently stored in a dictionary implemented as a search trie. Figure 5 shows these different phrases with their frequencies, where the frequency of every symbol is incremented for *every prefix of every suffix* of each phrase [4], [5]. The incremental parsing accumulates larger and larger phrases in the dictionary, thereby accruing estimates of higher order conditional probabilities and asymptotically outperforming any finite order Markov Model. Essentially, the algorithm approaches optimality for stationary, ergodic sources.

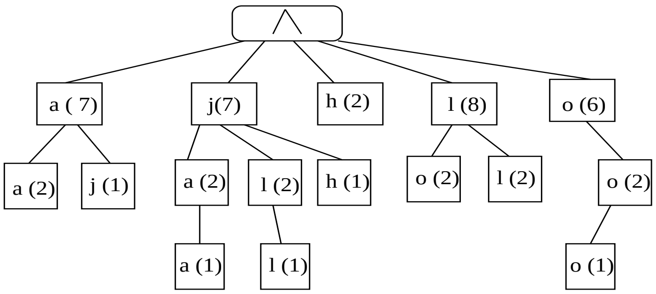


Fig. 5. Trie Representing the Symbols

Maintaining the inhabitant's context in such a trie helps in efficient computation of the probabilities of the different path segments. Following a PPM-style blending technique [5], our prediction mechanism starts from the highest order of context and *escape* to lower orders until order-0 is reached. If ξ, $N(\omega)$, $\mathcal{L}(\omega)$, $\mathcal{S}^k(\omega)$ and $\rho(\omega)$ denote the last updated phrase, number of occurrences of a phrase ω, its length, k-th suffix, and prefix respectively, the probability of any phrase ϕ can be estimated by the recursive formula: $Pr\,[\phi] = \frac{N(\phi|\rho(\mathcal{S}^k(\xi)))}{\sum_\omega N(\omega|\rho(\mathcal{S}^k(\xi)))} + \frac{N(\Lambda|\rho(\mathcal{S}^k(\xi)))}{\sum_\omega N(\omega|\rho(\mathcal{S}^k(\xi)))} \times \Pr\,[\mathcal{S}^1(\rho(\mathcal{S}^k(\xi)))]$, for all k, where $1 \leq k \leq \mathcal{L}(\xi)$. Thus, considering "$jll$" as the latest message updated in the profile-server, the usable contexts are "jl" (order-2), "j" (order-1) and "Λ"(order-0). A list of all predictable paths with frequencies at this context are shown in Table I. Subsequently, the probabilities associated with all such path segments are shown in Table II.

TABLE I

Phrases and their frequencies at contexts "jl," "j" and Λ

jl (order-2)	j (order-1)	Λ (order-0)		
$l \mid jl(1)$	$a \mid j(1)$	$a(4)$	$aa(2)$	$aj(1)$
$\Lambda \mid jl(1)$	$aa \mid j(1)$	$j(2)$	$ja(1)$	$jaa(1)$
	$l \mid j(1)$	$jl(1)$	$jh(1)$	$l(4)$
	$ll \mid j(1)$	$lo(1)$	$loo(1)$	$ll(2)$
	$h \mid j(1)$	$o(4)$	$oo(2)$	$h(2)$
	$\Lambda \mid j(2)$	$\Lambda(1)$		

TABLE II

Probabilistic prediction of symbols on path until next update

Path Segments	$Pr[Phrase]$	Path Segments	$Pr[Phrase]$
l	0.5905	oo	0.0095
ll	0.0809	h	0.0809
lo	0.0048	j	0.0095
loo	0.0048	jh	0.0048
o	0.0195	a	0.0905
ja	0.0048	jaa	0.0048
jl	0.0048	aa	0.0809
aj	0.0048		

C. Collection of Inhabitant's Typical Paths

It is true that a particular inhabitant typically follows only a small subset of all the paths stored in the Lempel-Ziv trie, which reflects his/her mobility profile in the long run. The concept of *asymptotic equipartition property* (AEP) from information theory helps in obtaining this *small set* of *highly probable* routes of a particular inhabitant. The *type* ($P_{\mathbf{v}}$) [6] of a sequence $\mathbf{v} = \{v_1, v_2, \ldots, v_n\}$ is the relative proportion of occurrences of each symbol. In other words, $P_{\mathbf{v}}(a) = \mathcal{N}(a|\mathbf{v})/n$, for all $a \in \vartheta$, where ϑ is the alphabet set and $\mathcal{N}(a|\mathbf{v})$ is the number of times the symbol occurs in the sequence. Let, $\mathbf{P}_n$ denotes the set of all types. If $P \in \mathbf{P}_n$, then the set of all sequences of length n and type P is referred as the *type class* $T(P) = \{\mathbf{v} : P_{\mathbf{v}} = P\}$ of P. The essential power of the method of types arises from the fact that the number of types is at-most *polynomial* in n, i.e. $|\mathbf{P}_n| \leq (n+1)^{|\mathbf{v}|}$ [22]. The crucial point to note here, is that there are polynomial number of types, but exponential number of sequences. Hence, there exists types consisting of exponentially many sequences in its type class. If $\mathcal{V}_1, \mathcal{V}_2, \ldots, \mathcal{V}_n$ denotes the set of sequences drawn according to the distribution $Q(v)$, then the probability of the sequence depends on its *type*. If $Q^n(\mathbf{v}) = \prod_{i=1}^{n} Q(v_i)$ denotes the the associated product distribution with Q then,

$$\begin{aligned} Q^n(v) &= 2^{-n(H(P_{\mathbf{v}})+D(P_{\mathbf{v}}||Q))} \\ Q^n(T(P)) &\leq 2^{-nD(P_{\mathbf{v}}||Q)} \end{aligned} \tag{1}$$

This result on the type class helps us to conclude that the probability of each type class and its sequences depend on the *relative entropy* between the type P and the original distribution Q. Hence, the type classes and the corresponding sequences that are far from Q have exponentially smaller probability. This leads to the concept of *typical set*: *"for a given $\epsilon > 0$, a typical set T_Q^ϵ of sequences for the distribution Q^n is defined as: $T_Q^\epsilon = \{\mathbf{v} : D(P_{\mathbf{v}}||Q) < \epsilon\}$"*. All we now need is the probabilistic estimation of these typical sequences. Fortunately, this is exactly what the *Shannon-McMillan-Brieman* theorem [6], [22] provides. According to this theorem, if $H(\mathcal{V})$ is the entropy rate of finite-valued stationary ergodic process $\{\mathcal{V}\}$, then

$$-\frac{1}{n}\, log\,[\, p\,(V_0, V_1, \ldots, V_{n-1})] \rightarrow H(\mathcal{V}) \tag{2}$$

Equation 2 provides the basis of *asymptotic equipartition property* (AEP) [22]. For any stationary, ergodic process, AEP states that "*for a fixed* $\epsilon > 0$, as $n \rightarrow \infty$, $Pr\{\mathcal{V} \in \mathcal{T}_Q^\epsilon\} \rightarrow \infty$". Thus, asymptotically almost all the probability mass of $\mathcal{V}$ is concentrated in the *typical set*, which encompasses the inhabitant's most likely paths and determines the *average nature of the large route-sequences*. If $Pr[\phi]$ denotes the probability of a particular phrase (route) of length $\mathcal{L}(\phi)$, the *probabilistic difference* (δ) is computed as: $\delta = |Pr[\phi] - 2^{-\mathcal{L}(\phi)H(\mathcal{V})}|$. Clearly, δ provides the gap between the ideal probability of typical phrases and the probability of a particular phrase stored in the trie. The value of this δ plays a critical role at this context. Choosing a high value of δ leads to the inclusion of a large number of *atypical* mobility-profiles and the framework starts deviating from capturing the typical routes. In our experiments, we have used $\delta \leq 0.03$.

Example: In order to derive the typical set of phrases from the list of all phrases, the entropy of the source is dynamically calculated as the running average. For a particular depth d of the Lempel-Ziv trie (shown in Figure 5): $H(\mathcal{V}) = \frac{1}{d}\sum_{i=1}^{i=d} [V_i\,|V_1, \ldots, V_{i-1}]$, where V_i represents the entropy at the i^{th} level of the trie. In our example we got $H(\mathcal{V}) = 1.789$.

Hence, the typical set of path-segments (phrases) consists of phrases having probabilities $Pr[\phi]$ in the interval $[2^{-1.789\mathcal{L}(\phi)} - \delta, 2^{-1.789\mathcal{L}(\phi)} + \delta]$. This results in typical set of phrases $T_Q^\epsilon = \{l, ll, loo, jaa, aa\}$, which reflects the behavior of inhabitant's movements at this context. Ideally, if the predicted set of sequence $\{\mathbf{v}\}$ falls in the exactly same type class as the original mobility distribution (Q) of the inhabitant, then we have, $D(P_{v^n}||Q) \to 0$. A sketch of the procedure for computing typical routes is highlighted in Figure 6.

Typical-Route Determination Algorithm

```
initialize trie := null;
initialize typical-set (T_Q^ε):= null;
loop
   wait for the next event;
   process the event to get symbols;
   incrementally parse the symbols to get new phrase;
   encode the phrase to keep it in compressed form;
   decode the phrase and update the trie;
   Wait until the inhabitant is about to leave a zone;
   compute the probabilities (Pr[φ]) of every phrase;
   calculate the per-symbol entropy (H(V));
   obtain the probabilities of typical-phrases as:
   Pr[T_Q^ε] = 2^(-L(φ) H(V));
   If(Pr[φ] - δ ≤ Pr[T_Q^ε] ≤ Pr[φ] + δ)
      T_Q^ε = T_Q^ε ∪ φ;
   compute the success of prediction and the relative
   between predicted and actual paths;
forever
```

Fig. 6. Algorithm for Computing Typical Routes

D. Comfort Management at Minimum Cost

Although mobility prediction based on the Lempel-Ziv class of compressions techniques has been used for resource reservations in cellular networks [23], the novelty of our approach lies in the fact that we are not only predicting the inhabitant's locations/zones, but also the *typical* routes leading to those zones. This is more efficient in developing the comfort management and resource optimization scheme in the indoor environments. Predicting typical routes can be useful for robot assistants and "follow-me" multimedia applications around the house. More precisely, successful prediction of inhabitant's location and routes aids in creation of an amicable indoor environment without his/her explicit awareness, a prime objective of context-aware computing paradigm.

In order to get an estimate of the overall energy consumption in this environment, we have considered three different energy plans: (1) The static-energy scheme with centralized temperature controlling system, where an average number of devices are assumed to remain on during the inhabitant's stay in the house; (2) the optimal, manual energy scheme with distributed temperature control, where every device is switched on and off manually as the inhabitant enters and leaves a particular zone of the house; and (3) the predictive energy scheme, where the automated devices are pro-actively operated along the inhabitant's future routes.

Static Energy Plan: Let, $\mathcal{P}_i$ denote the power of i^{th} device (light, fan, etc.), M denote the maximum number of devices which remained turned on in the entire house, t denote the time that the device remains turned on, and let $p(t)$ denote the probability density function of uniform time distribution. Then the expected average energy consumed ($\mathcal{E}_1$) due to lights and devices will be:

$$\mathcal{E}_1 = \sum_{i=1}^{M} \mathcal{P}_i \int_a^b t\,p(t)\,dt = \sum_{i=1}^{M} \mathcal{P}_i \int_a^b \frac{t}{b-a}\,dt = \frac{b-a}{2} \sum_{i=1}^{M} \mathcal{P}_i. \tag{3}$$

where a and b are the maximum and the minimum time the devices remained turned on and $p(t) = \frac{1}{b-a}$. Similarly, let $\mathcal{P}_a$ denote the power required by the temperature control device to change one cubic feet space by 1^o $Farenheit$, $\gamma(T_o - T_c)$ denote the rate of change of temperature in unit time, ν_H denote the volume of the entire house. Assuming uniform distribution of the time that the device remains on, the energy consumed ($\mathcal{E}_2$) by the temperature control device can be estimated as:

$$\begin{aligned} \mathcal{E}_2 &= \mathcal{P}_a\,\nu_H\,|\gamma(T_c - T_o)|\,\sigma \int_a^b t\,p(t)\,dt \qquad (4)\\ &= \frac{b-a}{2}|\gamma(T_c - T_o)|\,\mathcal{P}_a\,\sigma\nu_H. \end{aligned}$$

where the thermostat factor σ is computed as the fractional time the temperature control system remains on during the inhabitant's stay at the house. Thus, the total estimated energy cost in the static plan will be: $\mathcal{E}_{stat} = \mathcal{E}_l + \mathcal{E}_2$.

Optimal Energy Plan by Manual Operations: Let, $\mathcal{P}_{ij}$ denote the power of the i^{th} device in the j^{th} zone (room, passageway, etc.), η denote the maximum number of devices which remained turned on in the particular zone, R denote the number of zones, t denote the time that device remains turned on, and let $p(t)$ denote the probability density function of uniform time distribution. Then the expected average energy consumed ($\mathcal{E}_3$) due to lights and devices will be:

$$\mathcal{E}_3 = \sum_{j=1}^{R}\sum_{i=1}^{\eta} \mathcal{P}_{ij} \int_p^q t\,p(t)\,dt = \frac{q-p}{2} \sum_{j=1}^{R}\sum_{i=1}^{\eta} \mathcal{P}_{ij}. \tag{5}$$

where q and p are the maximum and the minimum time the devices remained turned on in a particular zone. Proceeding in a similar way, if ν_j denote the volume of a particular zone j, then the energy consumed by the optimal temperature control plan will be:

$$\begin{aligned} \mathcal{E}_4 &= \sum_{j=1}^{R} \nu_j\,\mathcal{P}_a\,|\gamma(T_c - T_o)|\,\sigma \int_a^b t\,p(t)\,dt \qquad (6)\\ &= \frac{q-p}{2}|\gamma(T_c - T_o)|\,\mathcal{P}_a\,\sigma \sum_{j=1}^{R} \nu_j. \end{aligned}$$

Hence, an estimate of the total optimal energy consumption will be: $\mathcal{E}_{opt} = \mathcal{E}_3 + \mathcal{E}_4$.

Predictive Energy Plan: The predictive plan will attempt to reach the optimal energy plan when the prediction-success approaches 100%. However, a wrong prediction incurs more energy consumption, which is assumed to be bounded by twice the optimal energy-plan scheme. Moreover, in the predictive energy plan, all the devices are turned on in advance, before the inhabitant actually reaches the zone. Hence, there always exists a time lag (Δ_t) in this scheme. Thus, if the success rate of prediction is denoted by s, then an estimation of the energy consumptions will be:

$$\mathcal{E}_5 = \frac{q-p+\Delta_t}{2} \sum_{j=1}^{R} \sum_{i=1}^{\eta} \mathcal{P}_{ij} \times (2-s) \quad (7)$$

$$\mathcal{E}_6 = \frac{q-p+\Delta_t}{2} |\gamma(T_c - T_o)| \times \mathcal{P}_a \times \sigma \sum_{j=1}^{R} \nu_j \times (2-s),$$

where p and q are as defined earlier. Hence, total estimated energy consumption in our predictive environment will be: $\mathcal{E}_{pred} = \mathcal{E}_5 + \mathcal{E}_6$. For a good prediction mechanism s will be close to 1, and $\mathcal{E}_{pred} \rightarrow \mathcal{E}_{opt}$, i.e. the predictive energy-plan will approach towards the optimal energy plan.

Although the optimal plan provides the minimum energy consumption scheme, it lies in the opposite pole of automation and inhabitant's comfort. The inhabitant needs to manually operate every switch during his/her entrance or departure from every zone. In the predictive environment, the inhabitant needs to manually operate the switch only when the prediction fails. In such cases, there will be an extra cost overhead bounded by twice the manual cost. Thus, if λ denote the number of switches handled by the inhabitant (manual operations) in the zone, the maximum number of switching operations ($\hat{\lambda}$) in the predictive plan will be: $\hat{\lambda} = 2\,\lambda(1-s)$. If $\bar{\tau}$ denote the average time spend behind the manual operations of all devices, then the amount of time spent in our predictive environment will be $\bar{\tau_p} = 2\,\bar{\tau}(1-s)$. The intelligent prediction scheme will result in high values of s thereby, reducing the values of $\hat{\lambda}$, $\bar{\tau_p}$ and attempting to provide the necessary comfort.

IV. Simulation Study

With this theoretical foundation we will now look into the quantitative performance of our predictive platform. In this section, we first describe the design of our predictive framework for simulating the inhabitant's mobility and subsequent comfort management process. We then describe a series of experiments to demonstrate the performance of our proposed framework.

A. Simulation Environment

We have developed an object-oriented discrete-event simulation environment for supporting inhabitant's movements, associated prediction of likely paths and comfort management scheme. In order to obtain the inhabitant data for testing, the appliances in the MavHome are equipped with $X10$ ActiveHome kit and HomeSeer [10], thus allowing the inhabitant to automatically control the appliances. The time spent by the inhabitant in different locations is obtained from the motion sensors placed along the walls. Figure III shows a sample of the data used. The simulation environment consists of different entities like inhabitant, events, stations, lifetime in every station, paths and typical paths.

The different zones/locations of the house, where the inhabitant performs specific tasks are termed as *stations*. The lifetime in every station represents the inhabitant's expected stay at that station. The different events are inhabitant's actions (behaviors), which result in the probabilistic movement from one station to another depending on his/her lifestyle. All such events are time-stamped and the simulation progresses in strictly increasing order of time stamps. Whenever the inhabitant leaves

TABLE III

Sample of Data Collected from $X10$ Devices

Time	Device Usage	Location	Time Spent
7 : 20 AM	RestRoom Light On	Restroom	5 mins 20 secs
7 : 25 AM	RestRoom Light Off		
7 : 30 AM	Kitchen Light On	Kitchen	15 mins 32 secs
7 : 31 AM	Kitchen Coffeepot On		
7 : 40 AM	Kitchen Coffeepot Off		
7 : 45 AM	Kitchen Light Off		
7 : 47 AM	Garage Locks Open	Garage	2 mins 19 secs
7 : 49 AM	Garage Locks Closed		

the house, an *idle event* is spawned which again generates new events during his/her return. An event queue is used for holding and scheduling these dynamic events. During the movements the set of sensor-ids are collected to form the inhabitant's paths. There can be multiple paths from one station to another. The inhabitant probabilistically uses one of such paths. Finally, the typical-set of paths consists of only those path segments which reflects the inhabitant's most likely path segments at the current context. The schematic diagram of our simulation environment is shown in Figure 7. Provisions have been kept to

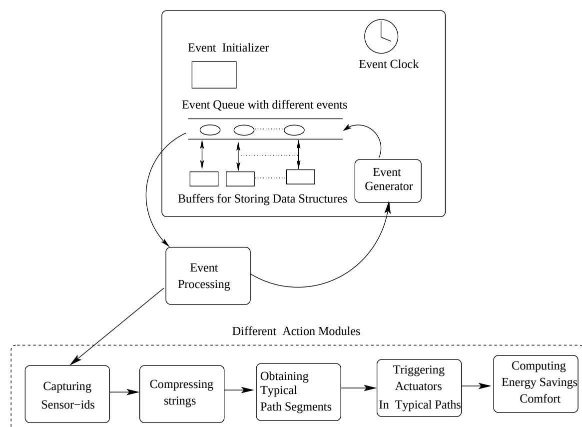


Fig. 7. Schematic diagram of the simulation environment

reflect different activities in the same location at different times. The inhabitant is also assumed to follow a different lifestyle in the weekends and holidays, with more household activities than during the weekdays. The major action modules responsible for data compression, probability and typical-set computation, and comfort management system executes in the profile-server in MavHome network depicted in Figure 2.

B. Assumptions

Before presenting the details of the experimental results, let us enumerate a set of common assumptions used in our simulation: (i) The delay between sensor data acquisition, processing and trigerring the actuators is assumed to be negligible. The typical-set computation and calculation of cost, comfort and prediction success is performed as the inhabitant leaves every station for his/her next station; (ii) The time spent at each destination is assumed to be uniformly distributed between the maximum and minimum stay at that particular destination. (iii) The simulation environment is tested with four different granularity of predictions. In the first case, at a coarse granularity only the inhabitant's next destination station (zone) is predicted. In the second case, we have predicted not only the next destination but also the path followed by the inhabitant towards that particular destination. The third case deals with a more naive and brute-force approach is kept which predicts every next sensor from a particular sensor. Finally, in a finer granularity, we have tested the prediction mechanism on every device-specific data to predict the next device to be used from the current device.

C. Performance Results

The entire results are presented by sampling every sensor at a time and observing the simulation environment for a period of 11 weeks. Success rate is the key factor for evaluation of any prediction scheme. Incorrect predictions results in erroneous system behavior, thereby incurring huge cost and performance overhead. Figures 8 provides a comparative picture of success

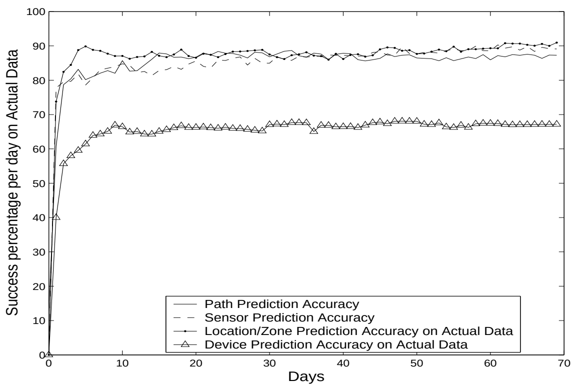


Fig. 8. Comparative View of Prediction Success

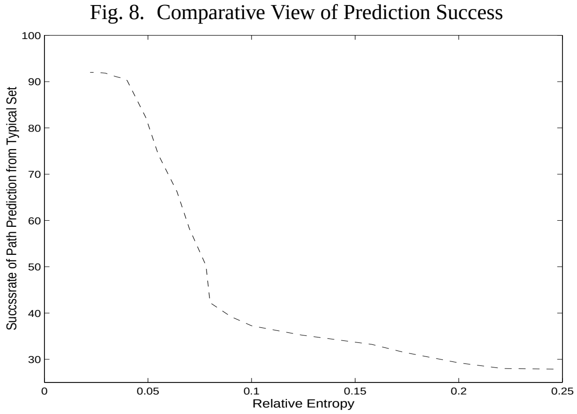


Fig. 9. Variation of Success Rates with Relative entropy (ϵ)

rates for all prediction schemes. Initially, the success rate is low as the system goes through the *learning phase*. Once the system becomes cognizant of the inhabitant's contexts the success rate for location-prediction saturates to around 89%. The success rates for predicting the typical path segments along with the final locations remain slightly lower (around 85%) than the location prediction. However, the success rate (62% – 69%) of the device-by-device prediction scheme is substantially lower than the other success rates. The very high granularity, coupled by the noisy nature of the data collected from X10 devices, is responsible for this low success rates of device prediction. The small peaks and valleys in the plots reflect the subtle changes in the inhabitant's patterns in his/her daily routine. Two major factors influencing the success rates are *relative entropy* and *dictionary size*. The success rate increases with the reduction in

TABLE IV

Comparison with Existing Prediction Scheme

Algorithm	Window-size	Prediction Success
SHIP (Top 3 Predictions)	50	50.30%–59.2%
	All History	57.66%–63.3%
Our Prediction Scheme	Sampling at every Device Specific Location	62.4%–69.1%

the bounds of relative entropy between the predicted path segments (calculated from the typical set of paths) and the actual paths taken by the inhabitant. Figure 9 depicts the asymptotic increase of success rate with decreasing values of relative entropy and thus demonstrates the power of typical-set in influencing the success rate. One important aspect to note is that this accuracy of route-prediction is obtained using only a modest dictionary-size (order of 2 kbytes). Figure 10 corroborates this relationship between predictive accuracy and dictionary size over the entire simulation period. A comparison in terms of device prediction success, of our predictive framework with the existing SHIP algorithm [15] is shown in Table IV. The contribution of higher-order models together with the computation of *typical set* of phrases results in the higher success rate of our algorithm.

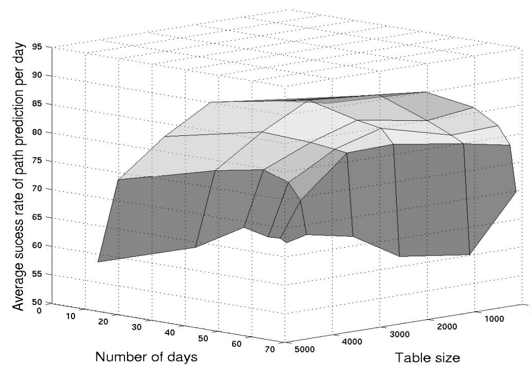


Fig. 10. Variation of success rate of path prediction with dictionary size

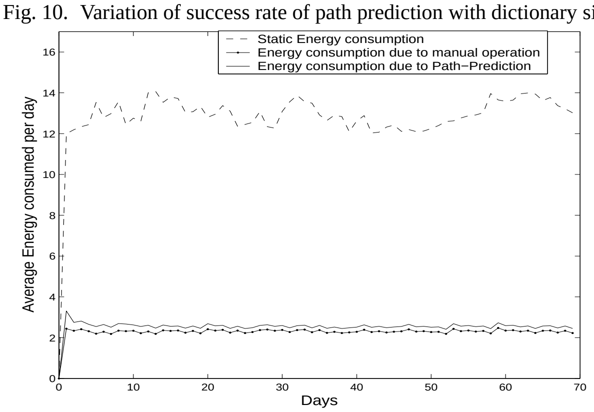


Fig. 11. Avg. Daily Energy Savings for Predictive Location-Awareness

Energy Savings and Inhabitant-Comfort: The main objective of this predictive framework at the context of Smart Home is to provide the inhabitant with necessary comfort at minimum possible cost. We argue that efficient prediction is a key factor to meet the minimum energy consumption in the house. While moving from a particular zone to another, correct prediction of *typical routes* and next destination helps in triggering the actuators *only* along those routes, thereby attempting to optimize the energy consumption. In Figure 11 we have compared this amount of energy consumption scheme resulting from our *predictive location-awareness* with the static and optimal energy plans and observed that our scheme closely follows the optimal energy consumption process. The minor deviation of this scheme from the optimal energy consumption process is a direct consequence of high prediction success rate. In order to get a good picture of the inhabitant-comfort provided by our predictive scheme, we have chosen two parameters as our performance metrics: (i) the average number of manual operations performed, and (ii) the amount of time the inhabitant can save. Intuitively, it is clear that successful prediction can lead to fully automated activation of lights and devices without any explicit intervention by inhabitants. Wrong predictions, however small it might be, incur inhabitant intervention to switch on and off the correct and incorrect devices, thus consuming his/her time and effort. Figure 12 depicts a clear view of this reduction in switching operations. Intelligent control of automated devices helps the inhabitant save his/her invaluable time. Figure 13 gives a view of this reduction of daily average time spent by using our predictive framework.

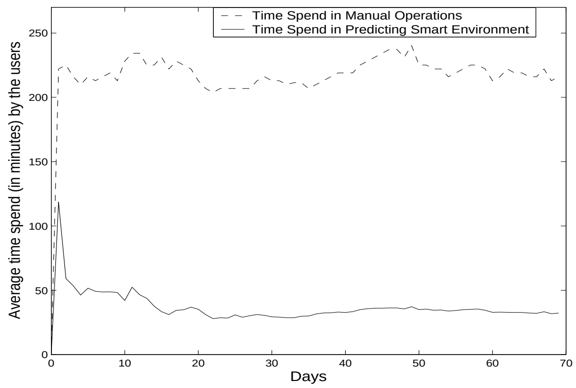


Fig. 12. Reduction in Switching Operations in Predictive Environment

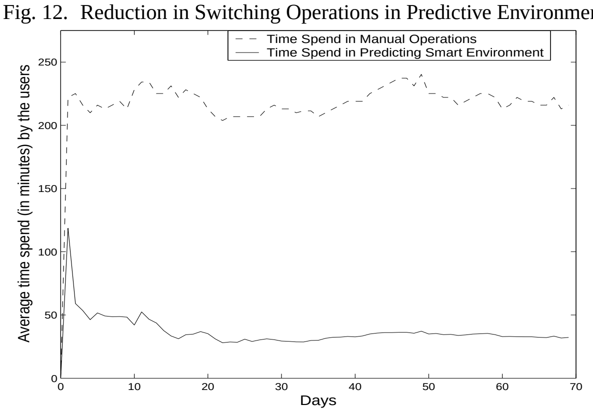


Fig. 13. Reduction in Time Spent by the Inhabitants

V. Conclusion

In this paper, we have studied the location-aware resource management in a smart home environment. The location management is formulated as a dynamic optimization problem, where the inhabitant's movement data is characterized as piecewise stationary, ergodic, stochastic process. In order to minimize the uncertainty created by the inhabitant's mobility, we have adopted the Lempel-Ziv compression as the underlying technology for sensory data acquisition. The concept of typical set and asymptotic equipartition property helps in selecting the inhabitant's most likely paths from the current context, which aids in minimizing the relative entropy between the system's predicted paths and the inhabitant's actual paths. Thus reservation of resources and automated activation of devices along those typical paths assists in providing inhabitant's necessary comfort at near optimal cost. Our future interest lies in extending the work to incorporate the multi-inhabitant home scenario, with possible exchange of mutual information in a dynamic environment. We hope that the findings in this paper will be helpful in for design and implementation of new *intelligent location-aware* environments.

References

[1] G. D. Abowd, C. G. Atkeson, J. Hong, S. Long, R. Kooper and M. Pinkerton, "Cyberguide: A mobile context-aware tour guide," *ACM/Baltzer Wireless Networks*, vol. 3, no. 5, October 1997, pp. 421-433.

[2] "Technical Description of DC Magnetic Trackers," *Ascension Technology Corp.*, Burlington, VT, 2001.

[3] P. Bahl and V. Padmanabhan, "RADAR: An In-Building RF-based User Location and Tracking System," *Proc. IEEE Infocom*, IEEE CS Press, Los Alamitos, CA, 2000, pp. 775-784.

[4] A. Bhattacharya and S. K. Das, "LeZi-update: An information-theoretic approach to track mobile users in PCS networks," *Proc. Ann. Int'l Conference on Mobile Computing and Networking*, August 1999, pp. 1-12.

[5] A. Bhattacharya and S. K. Das, "LeZi-update: An information-theoretic approach for personal mobility tracking in PCS networks," *ACM-Kluwer Wireless Networks* (WINET), vol. 8, no.2, pp.121-137, 2002.

[6] T. M. Cover and J. A. Thomas, *Elements of Information Theory*, John Wiley, 1991.

[7] S. K. Das, D. J. Cook, A. Bhattacharya, E. Hierman, T. Y. Lin, "The Role of Prediction Algorithms in the MavHome Smart Home Architecture", *IEEE Personal Communications, Special Issue Smart Homes*, Dec. 2002 (To Appear).

[8] A. Harter and A. Hopper, "A distributed location system for the active office," *IEEE Network*, vol. 8, no. 1 January/February 1994, pp. 62-70.

[9] A. Harter, A. Hopper, P. Steggles, A. Ward and P. Webster, "The anatomy of a context-aware application," *Proc. 5th Annual Int'l Conference on Mobile Computing and Networking*, August 1999, pp. 59-68.

[10] Homeseer and X10 web resources available at `http://www.homeseer.com` and `http://www.x10.com`.

[11] A. Hopper, "Sentient computing," *The Royal Society Clifford Patterson Lecture, 1999*.

[12] "House_n Living Laboratory Introduction", web resource available at `http://architecture.mit.edu/house_n/web/publications`.

[13] J. Krumm, S. Harris, B. Meyers, B. Brumitt, M. Hale, S. Shafer "Multi-Camera Multi-Person Tracking for Easy Living," *Proceedings of 3rd IEEE International Workshop on Visual Surveillance*, IEEE Press, Piscataway, NJ, 2000, pp. 3-10.

[14] Lesser et al. , "The Intelligent Home Testbed", *Proc. of Autonomy Control Software Workshop*, Jan 1999.

[15] T. Y. Lin , "Action Prediction Using History Pattern Matching in Automated Homes", *Masters Thesis, Dept. of Computer Sc. and Engg., UT Arlington*, May 2002.

[16] M. C. Mozer, "The Neural Network House: An Environment that Adapts to its Inhavitants", *Proc. of the American Association for Artificial Intelligence Spring Symposium on Intelligent Environments*, pp. 110-114, 1998.

[17] R. J. Orr and G. D. Abowd, "The Smart Floor: A Mechanism for Natural User Identification and Tracking," *Proceedings of 2000 Conference on Human Factors in Computing Systems* (CHI 2000), ACM Press, NY, 2000.

[18] N. Priyantha, A. Chakraborty and H. Balakrishnan, "The Cricket location support system," *Proc. 6th Ann. Int'l Conference on Mobile Computing and Networking*, August 2000, pp. 32-43.

[19] S. Shekhar and D. Liu, "Genesis and Advanced Traveler Information Systems (ATIS): Killer applications for mobile computing?" *Proc. NSF MOBIDATA Workshop on Mobile and Wireless Information Systems*, November 1994.

[20] M. Weiser, "The computer for the 21st century," *Scientific American*, vol. 265, no. 3, pp. 94-104, September 1991.

[21] O. Wolfson, P. Sistla, B. Xu, J. Zhou and S. Chamberlain, "DOMINO: Databases for moving objects tracking," *Proc. ACM Int'l Conference on Management of Data*, May-June 1999, pp. 547-549.

[22] A. Wyner and Z. Ziv, "Some Asymptotic Properties of the Entropy of a Stationary Ergodic Data Source with Applications to Data Compression", *IEEE Transactions on Information Theory*, vol. 35, no. 6, pp. 1250-1258, Nov. 1989.

[23] F. Yu and V. Leung, "Mobility-based Predictive Call Admission Control and Bandwidth Reservation in Wireless Cellular Networks", *Computer Networks*, vol. 38, pp. 577-589.

[24] J. Ziv and A. Lempel, "Compression of individual sequences via variable-rate coding," *IEEE Transactions on Information Theory*, vol. 24, no. 5, September 1978, pp. 530-536.