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In personal communications systems, it is an emerging necessity to adapt services prior to delivery according to up-to-date customer profiles and mobility behaviors. Therefore, it is important to determine distinct mobility descriptors that would successfully model the entire sample space of different mobility characteristics. The aim of this paper is to define unique descriptors that are to be extracted from mobility patterns of a single mobile user and to investigate the level of distinctness of each defined descriptor. We finally show how the studied descriptors can be used in service adaptation.

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# Mobility Characteristics for Multimedia Service Adaptation

Zafer Sahinoglu, **zafer@merl.com**
Anthony Vetro, **avetro@merl.com**
Tel: (908) 363 0504 Fax: (908) 363 0550
Mitsubishi Electric Research Labs Inc.,
Murray Hill, NJ 07974

**Abstract**

***In personal communications systems, it is an emerging necessity to adapt services prior to delivery according to up-to-date customer profiles and mobility behaviors. Therefore, it is important to determine distinct mobility descriptors that would successfully model the entire sample space of different mobility characteristics. The aim of this paper is to define unique descriptors that are to be extracted from mobility patterns of a single mobile user and to investigate the level of distinctness of each defined descriptor. We finally show how the studied descriptors can be used in service adaptation.***

## I. Introduction

In the literature, the movement patterns of users have been extensively studied for performance analysis and resource management in wireless networks [1-18]. For instance, signaling traffic generated due to handovers and location management is a function of the movement patterns [4,6]. Also, how mobile terminals move impinge on channel holding times in circuit switched services, and on call dropping and blocking probabilities [6,7,14,15,16,18]. From a different point of view, mobility characteristics carry key information for both application and network service providers for delivery of differentiated, personalized and adapted services to their customers. Assume a communication triplet consisting of a mobile terminal (MT), a main server located within the network, and an application service provider (ASP). In such a triplet, the main server monitors the MT's movement and collects location information and then extracts mobility related information; upon request, the main server provides the ASP with corresponding mobility profile data. Therefore, it is important to analyze mobility patterns, and investigate distinct descriptors that would successfully span and model the entire space of different mobility characteristics.

As illustrated in Fig.1, we define a hierarchical structure of four virtual levels consisting of the mobility level, the description level, the processing level and the application level respectively. At the mobility level, mobility types are classified into two as group mobility and individual terminal mobility. Group mobility represents movements of a group of MTs. It can be characterized by a flux density (a change in the number of MTs in a monitored region) and diffusivity (defines how subgroup *m*'s motion in one direction affects subgroup *n*'s motion in another direction). Since the scope of this paper is classification of individual mobility characteristics, we do not elaborate on group mobility and descriptors of group mobility.

Mobility types are identified by both unique and common descriptors at the description level. List of such descriptors for a single terminal mobility consists of the `Speed` *(s*peed of an MT), `Direction` (direction of the movement), `Directivity` (an angular change in the direction of a movement with reference to its previous direction), `UpdateInterval` (the time interval between two consecutive location updates of the MT), and `Erraticity` (a measure of how erratic the movement of a MT is within a corresponding location update interval). Two MTs traveling at the same speed may have quite different mobility characteristics. The `Speed` can be derived from `UpdateInterval` and the `Erraticity` as we show later in Section V. The network service provider (NSP) extracts the `Direction` from periodic location information of the MT. The NSP can further compute the `Directivity` from the `Direction`*,* and may provide the ASP with the `Directivity`. In this paper, we study only the mobility descriptors that the ASP would be provided with to classify mobility characteristics as shown in Fig.2: the `Directivity`, `UpdateInterval`, and `Erraticity`.

The description level provides the processing level with values and ranges of values of the measured descriptors. At the processing level, the mobility descriptors can be exploited for two main purposes:

- Classification of terminal types: in one potential classification scheme, MTs may be classified as pedestrian, highway vehicular, and urban vehicular etc. according to their mobility characteristics. In fact, how to classify the terminal types and how to exploit mobility descriptors are left to the ASP. It is important to note that restricting classifications to only two or three semantic labels would limit the flexibility in adapting services and tailoring content for wider range of mobility classes. In such a case, if a profile did not fall under any defined set of semantic labels after analysis of the descriptors, what would be the criteria in service delivery? As a result, mobility classes such as trains, subway cars, boats and airplanes could not be identified.
- Data mining: extracting spatial and temporal information that is correlated with repetitive mobility patterns or behaviors.

The output of the processing level leads to adaptation of services and their content at the application level. The service adaptation is a higher layer process than that of the content. A service is composed of multiple contents. For example, video streaming is a service, and video streams A and B may form two different contents available for the streaming service. On the other hand, which stream to deliver according to what mobility descriptors is typically a subject of service adaptation. How to deliver a video stream, at what bit rate or frame rate, or at what resolution are example decisions for content adaptation. The motivational factors behind description-based content and service adaptation are that data rates available to wireless users in wireless cellular networks are greatly dependent on their mobility characteristics; and that battery power constraints may vary from a user to another. The first one is due to the nature of wireless channel impairments, in particular multi-path fading, and to the time delay and signaling overhead due to hand-offs. The effect of fading becomes more severe in highly mobile environments [19]. It requires increased coding protection and more retransmissions, resulting in reduced data rate. Descriptor based content adaptation is a preemptive solution to adjust bit/frame rates and resolution of the content to transmit at lower data rates, but on the other hand to allow more space for protective coding against adverse fading effects. Also, the hand-off rate would increase with high mobility having low directivity. Intuitively, each hand-off generates signaling overhead and associated delay, thus affecting the quality of the service being offered to the users. The second factor results from the fact that some MTs (e.g., pedestrians) will have more stringent battery power constraints than others (e.g., vehicular). Therefore, to extend battery lifetime of a MT the delivery rate of content may be reduced based on mobility profiles.

With regards to multimedia adaptation, Part 7 of MPEG-21, referred to as Digital Item Adaptation (DIA), is defining a set of descriptors and tools to enable transparent and augmented use of multimedia resources across a wide range of networks and devices [20]. In the context of MPEG-21, a Digital Item is defined as a structured digital object with a standard representation, identification and description. This entity is also the fundamental unit of distribution and transaction within the MPEG-21 framework [21]. The description tools described in this paper were first proposed to MPEG in May 2002 [22] and have been adopted into the current draft of the standard [20].

The remainder of this paper is structured as follows: In Section II, we give a brief summary of random mobility models in the literature and introduce our own model, which is based on the fractional Brownian motion. The focus of this study is to investigate and define unique descriptors that are to be extracted from mobility patterns. Therefore, in Section III, we elaborate on these descriptors and their extraction methods. In Section IV, we present an analysis of these descriptors to (1) prove the level of distinctness, and (2) indicate their dependency on certain system variables. In Section V, we discuss how the studied descriptors can be used to adapt services with relation to mobility profiles. Finally, we summarize the main contributions of this paper and areas for future work in Section VI.

## II. Mobility Models

In mobile wireless networks, modeling of user mobility is an essential building block in simulation-based and analytical system studies. Mobility models are needed to develop strategies for low-cost location updating and paging, network planning and dimensioning. For example, in [23], the effect of user mobility parameters on the quality of service parameters of new call blocking probability and handoff call blocking probability is studied. The choice of a mobility model has direct impact on the obtained results. The models basically vary in modeling of speed, direction, and sojourn times of MTs. Each mobility parameter can be modeled either deterministically or probabilistically. In section II.1, we explain some of the random speed and direction based mobility models used in the literature. In our simulations, we implemented a model based-on the Fractional Brownian motion (FBM). It is explained in section II.2 in detail.

### *II.1 Brownian Motion*

Brownian motion originally refers to the random motion observed under microscope of pollen immersed in water. Einstein pointed out that this motion is caused by random bombardment of (heat excited) water molecules on the pollen. In approximation of the 2-D Brownian motion, each step (in both x- and y- directions) is an independent normal random variable.

Assume that $X_t$ is a position of the particle at time *t*. Its position at time $t+\Delta t$ can be given by $X_{t+\Delta t}=(X_t \pm \delta)$, with equal probabilities of being $+\delta$ or $-\delta$ where $\delta$ is a small distance. In general, for any $t \geq 0$ and $\Delta t > 0$, the increment $X_{t+\Delta t} - X_t$ is normally distributed with zero mean and variance $\Delta t$. Brownian motion is used in the literature to model terminal mobility in Personal Communications Services (PCS) systems. For instance, in [1], they use the FBM for modeling movements of mobile subscribers; in [2,3,4], standard Brownian motion with drift process is used for individual mobility modeling; in [4], an approach to simplify the two-dimensional random walk models capturing the movement of mobile users in PCS networks is proposed; in [5], a simplified two dimensional random walk model is used for performance analysis of PCS networks; in [24], a random walk based mobility model in which the distribution of aggregate distance and direction covered by an MT over a specific time interval is characterized to determine the conditional probability that the nodes will be within range of each other at time. The model requires three parameters: the epoch lengths, (identically and independently distributed with exponential mean), the direction (during each epoch uniformly distributed over [0, 2π]), and the speed (normal distribution with a mean and variance), all of which are uncorrelated. In reality, a MT moving in a certain direction at a certain speed would be likely to go in the same direction without a major change in its speed. The random walk based mobility models cannot consider this fact, because the increments of the process are independent. We can achieve correlated increments using FBM. The FBM is a long memory process, because the covariance between far apart increments decreases to zero as a power law.

II.2 *Fractional Brownian Motion*

FBM with Hurst parameter $H \in (0,1)$ is a real centered Gaussian process $X_t^H, t \geq 0$ of covariance $E(X_t^H X_s^H) = \frac{c(H)}{2}(s^{2H} + t^{2H} - |t-s|^{2H})$ where $s,t \geq 0$ [25]. It is easy to prove that $E[(X_t^H - X_s^H)^2] = c(H)|t-s|^{2H}$. Hence, the increments are independent only if $H=0.5$. In that case, it becomes a standard Brownian motion. The increments are negatively correlated if $H<0.5$, and positively correlated if $H>0.5$. In general, the process $X_t^H$ can be generated from (1).

$$X_t^H = \frac{1}{\Gamma(\alpha)} \int_{-\infty}^{t} ((t-s)^{\alpha-1} - (-s)_+^{\alpha-1}) dB_s \tag{1}$$

where $B_S$, $t \geq 0$ is a standard Brownian motion and $\alpha = H + 0.5$. We approximate the long memory part $Y(t) = \int_0^t h(t-s)dB_S$ as explained in [25]. First, assume a small step size $|\Delta_n| = 1/n$ for the partitions to use. For $t = r/n$ where r is an integer, *Y(t)* is approximated as

$$Y(t) \cong \frac{1}{\sqrt{n}}(h(\frac{1}{n})\xi_r + h(\frac{2}{n})\xi_{r-1} + ...) \tag{2}$$

where $\xi_i = \sqrt{n}(B_s(i+1) - B_s(i))$ are i.i.d. normal distributed random variables and $h(u) = \frac{1}{\Gamma(\alpha)}u^{\alpha-1}, u > 0$ *. Accordingly, at time instant $t + \Delta_n$, $Y(t+\Delta_n)$ would be approximated as $Y(t+\Delta_n) \cong \frac{1}{\sqrt{n}}(h(\frac{1}{n})\xi_{r+1} + h(\frac{2}{n})\xi_r + ...)$.

To create 2D trajectories, we generate $B_S$ as a vector of complex numbers *(x+iy)* with length *n*. The realization of each coordinate *x* and *y* are created from two Gaussian distributed variables with means *Vx, Vy* and variances *Dx* and *Dy* that is $p(dx = x) = \frac{1}{\sqrt{2\pi D_x}} e^{-(x-V_x)/2D_x}$ and $p(dy = y) = \frac{1}{\sqrt{2\pi D_y}} e^{-(y-V_y)/2D_y}$. Variables *Vx, Vy* determine the mean velocities of the MTs in *x* and *y* directions; and *Dx* and *Dy* the diffusivity (in units of $m^2/s$) in each direction. The angle of the long-run drift in the model is determined by $\tan^{-1}\frac{V_x}{V_y}$.

**III. Mobility Characteristics**

This paper studies unique mobility descriptors of a single mobile user. These descriptors are the `Directivity`, `UpdateInterval`, which is the descriptor of location update intervals, and

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* The Gamma function $\Gamma(z)$ is defined as a definite integral for $\Re[z] > 0$ such that $\Gamma(z) = \int_0^\infty t^{z-1}e^{-t}dt$.

the Erraticity. To the best of our knowledge, Directivity and Erraticity have not been investigated before. On the other hand, the topic of location updates has been subject to many research studies. For example, in [26] the authors scrutinize the communication complexity of different location update schemes from periodic to distance based. A link is established between the probability distribution function of location update intervals and corresponding mobility classes such as pedestrian, vehicular and highway vehicular in [2, 3]. Furthermore, in [28] the authors present a general architecture and functional entities of a reconfiguration control and service provision platform (RCSSP) for reconfigurable networks. The internal functional entity of the RCSPP is responsible for retrieving, managing and exploiting information related to mobility and location of MTs; and it performs mobility aware QoS management directed by the location manager. With this service the QoS provided to MTs follows the location updates induced by their mobility, which would include adaptation of multimedia services and content (e.g., voice-to-text, video-to-voice etc.) based on user location and associated user preferences. However, in the literature there is a gap to link service adaptation with mobility characteristics.

In this paper, we aim to provide means for exploiting the aforementioned descriptors for service and content adaptation. Figure 3 shows the syntax of these mobility descriptors under MobilityCharacteristicsType, which is a tool defined in the DIA part of MPEG-21 [20] for describing the mobility characteristics of a User, that is the MT. The following sub-sections explain each descriptor in detail together with methods of their extraction and use.

### *III.1* Directivity

Directivity is defined to be the amount of angular change in the direction of the movement of a mobile terminal (MT) compared to a previous measurement. One possible scenario to measure directivity is that, assuming each MT is capable of computing its location, the network pages MTs periodically to get their location information, and then extracts directivity values. We name the period of the retrievals “the time scale” of the directivity measurements, and denote it as *T*.

Intuitively, pedestrians compared to vehicular MTs present large directional changes. Furthermore, directivity of a pedestrian taking a walk in a park would be also quite different from that of shopping in a mall. The `Directivity` can be used as an efficient descriptor to distinguish mobility behaviors at time scales in orders of seconds.

In order to have a single directivity measurement, three coordinates and a specified time scale is required as shown in Fig.4. The first two coordinates $(x_{n,} y_n)$ and $(x_{n+1,} y_{n+1})$ determine the direction of a movement within *(t, t+T)* such that $\theta_n = \arctan \frac{y_{n+1} - y_n}{x_{n+1} - x_n} = \arctan \frac{dy_{n,n+1}}{dx_{n,n+1}}$; and similarly the last two determine $\theta_{n+1} = \arctan \frac{dy_{n+1,n+2}}{dx_{n+1,n+2}}$ within time interval *(t+T, t+2T)*. Hence, a directivity element is equal to $\beta_n = \theta_{n+1} - \theta_n$ at time scale *T*. Computation of $\theta_i$ depends on which quadrant of the Cartesian coordinate system the location coordinates fall, and the movement is directed. The vector $\underline{\beta}(T,N) = [...\beta_n \beta_{n+1} \beta_{n+2}...]$ is called the "directivity vector", which includes the last *N* directivity measurements. $\underline{\beta}(T,N)$ is stored in, and updated by the NSP. Knowing $\underline{\beta}(T,N)$, the standard deviation and other statistical values of directivity can be obtained. It is important to note that directivity values would vary from one time scale to another.

A description of the `Directivity` is needed to efficiently store, process and communicate the directivity information. The description should be compact and should accurately represent the entire set of data samples during a given time period, and at a given time scale. We assert that the `Mean` and `Variance` of the samples contained in the directivity vector be specified for that purpose, and defined as fields of the `Directivity`. More specifically, the `Mean` describes the mean of the directivity elements measured at T-second intervals. The range of the `Mean` is [0-180] degrees. On the other hand, the `Variance` describes the variance of the directivity elements measured at T-second intervals. The range of the `Variance` is also [0-180] degrees. The histogram of the directivity elements carried in $\underline{\beta}(T,N)$ also helps to distinguish mobility patterns in a concise way by capturing information related to the degree and frequency of directional changes. We denote the field of the `Directivity` that carries histogram data as the `Values`. The `Values` contains the frequency of directivity elements that are measured at T-second intervals; and they are presented after being normalized by the number of elements in $\underline{\beta}(T,N)$. Fig.5 illustrates the syntax of the `DirectivityType` in [20] embodying the introduced fields of the `Directivity` descriptor. Alternative or other candidate fields for the `Directivity` descriptor have not been seen in the literature according to our survey.

The histogram contains $M$ bins. The $i^{th}$ bin covers a range from $i*\pi/M$ to $(i+1)*\pi/M$ radians, where $i$ takes values from $0$ to $M-1$. Assume that a MT moves on the x-axis and that after a while it deviates either $5\pi/3$ ($-\pi/3$) or $\pi/3$ degrees from the x-axis towards –y or +y axis respectively. The relative directional change in either case would only appear as $\pi/3$ to the network. In general, the directional change would never be greater than $\pi$. Therefore, the range of the histogram is set from 0 to $\pi$, but not 2 $\pi$. For a given interval of time during which the MT travels and a given time scale, the histogram specifies the frequency of angular changes corresponding to the range of each bin. Smaller values of $M$ provide a more concise representation of the directivity vector. However, if the value of $M$ is too small, the histogram descriptor is less accurate. To perform mobility classification based on the histogram, we suggest $M$ to be 16. In a uniformly distributed 16-bin histogram, each bin would cover 11.25 degrees. Based on the analysis of generated trajectories, 11.25 degrees separation is adequate to distinguish different mobility characteristics represented by the most recent 64 directivity values. Increasing the number of elements in $\underline{\beta}(T,N)$ makes the histogram represent directivity characteristic of the MT within a longer time frame.

*III.1.1 Example*

The following example shows an instance of the `Directivity`. The `Mean` and the `Variance` gives the mean and the variance of the directivity elements in degrees. The `Values` show the normalized frequency of directivity elements within the range of each bin in the histogram.

```
<Directivity>
	<Mean>35</Mean>
	<Variance>27</Variance>
	<Values>
		0.1 0.2 0.5 0.2 0.0 0.0 0.0 0.0
		0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
	</Values>
</Directivity>
```

*III.2* `UpdateInterval`

The location update interval (LUI) is the time interval between two consecutive location updates of a particular mobile terminal. Location updates can be done centrally in a way that the network requires an MT to update its location. On the other hand, there are suggestions in the literature [26] that, to alleviate the signaling load on the network due to periodic updates, the MT updates its location whenever it crosses a boundary of a pre-determined area (e.g., circular, elliptic, etc.) centered at the coordinate of its last location update as illustrated in Fig.6. Due to a need to update directivity measures periodically, we already assume that the network pages the MTs every *T* seconds to retrieve location information, from which the directivity is derived. It is the NSP's responsibility to track whether an MT crossed the location area boundary or not, after each paging. If so, the NSP computes the location update interval and updates its location database.

In Fig. 7, the syntax of the `UpdateIntervalType` as adopted into MPEG-21 DIA Part 7 [20] is given. It embodies the fields of the `UpdateInterval` descriptor. These fields are `xRadius`, `yRadius`, `LastUpdatePoint`, `LastUpdateBinIndex`, `LastUpdateTime`, `Lmax` and `Values`.

To explain the use of location update intervals, we first need to define the area that the mobile terminal is contained. The network can specify the shape and parameters (e.g., radius etc.)

of a location update area. Consistent with the specification of the Location Interoperability Forum [27], it is assumed that the location area is either circular or elliptic. When the location update is not circular but elliptic, the radius has to be specified in both x and y directions. Therefore, for generalization we specify `xRadius` and `yRadius`. The `xRadius` describes the radius of the location update area on its x-axis (major axis) in units of meters, while the `yRadius` is the radius on its y-axis (minor axis). The x-axis is defined to be the axis that the movement of the mobile terminal is directed onto, at the time of the last location update. The y-axis is set perpendicular to the x-axis. Besides depending on the mobility characteristics of the MT, the frequency of location updates is a function of the radius of the location update area, because the location of a MT is updated whenever it crosses the boundary of the area. For a given pair of `xRadius` and `yRadius`, slow moving MTs such as pedestrians or bicycle riders update their location less often than fast moving MTs such as vehicular.

The field `LastUpdatePoint` describes the `latitude` and `longitude` at the coordinate of the last location update. The `longitude` gives how far east the coordinate on the equator from the null-meridian is. The `latitude` shows how far north to move from the equator. Negative values map onto the opposite direction. The histogram of the location update intervals forms another field of the `UpdateInterval`. When there is low mobility or no mobility at all, the histogram is quite rarely updated. Therefore, it is rather useful for long-term mobility characteristics, and it provides a coarse classification when there is mobility. On the other hand, it is helpful on learning mobility patterns, event detection, event sequencing, and modeling transitions between different mobility types. For example, assume that the MT transitions from one mobility characteristic type to another (e.g., pedestrian->highway or highway->pedestrian etc.) within the number of location updates included in the histogram. The resulting histogram would reveal two separate regions proving the existence of such a transition (see Fig.8), although the histogram itself does not give the direction of the transition. In order to clarify the direction of the transition, two fields are defined: `Lmax` and `LastUpdateBinIndex`. The `Lmax` describes the maximum location update interval that has been observed, while the `LastUpdateBinIndex` is the bin index corresponding to the last LUI. The number of bins can greatly affect the appearance of the histogram. According to the way we define the paging of the Users by the NSP to be periodic with period *T* (see Section III.1), checking of location updates occur only at time instants *nT*, where *n* is an integer. Hence, the lower bound for LUIs is *T*. However, `Lmax` may vary from order of seconds to hours, and it determines the range of the histogram. We suggest that the histogram of the LUIs is built from 128 latest LUI values. Intuitively, having a larger set may be preferred to decrease the probability that `Lmax` would take a new value, but it would be at the cost of longer acquisition time of those many LUIs. Based on our experiments, we suggest using a 32-bin histogram, because less number bins make tracking of state-to-state transitions (which are illustrated in Fig. 8) difficult. Accordingly, the `LastUpdateBinIndex` has a range of [1,32]. The `Values` describes the histogram containing the frequency of location update intervals. Each bin corresponds to a range of time intervals, where a single time interval is defined as the time difference between two consecutive location updates. The range of each bin is `Lmax`/32. The values represent the frequency of occurrence for a given range of time intervals, which are normalized by the total number of location updates. To prevent the ambiguity of how old the histogram is, the time stamp corresponding to the last location update time, `LastUpdateTime`, is also needed as another field in the descriptor. `LastUpdateBinIndex` and `LastUpdatePoint` are considered as descriptor fields for short-term analysis. On the other hand, `Lmax` and `Values` (histogram) are for analysis of long-term observations and history of the MT's mobility.

*III.2.1 Example*

The following example shows an instance of the `UpdateInterval`. The `xRadius` and `yRadius` define a circular location update boundary with radius of 250 meters. The `LastUpdatePoint` gives the `longitude` and `latitude` of the MT at the time of last update respectively. The example shows the use of `LastUpdateTime` in defining an instant on September 20, 2002, at 15:22, in a time zone that is 1 hour different from UTC (Coordinated Universal Time). The UTC is an international time standard, which was commonly referred to as Greenwich Meridian Time. The range of each bin is dynamically adjusted according to `Lmax`. The bins are uniformly distributed such that they are equally spaced between *[0,* `Lmax`*]*. The `Values` gives the bin values in the histogram with a vector of length 32.

```
<UpdateInterval>
	<xRadius> 250 </xRadius>
	<yRadius> 250 </yRadius>
	<LastUpdatePoint latitude="43.3" longitude="101.6"/>
	<LastUpdateBinIndex>8</LastUpdateBinIndex>
	<LastUpdateTime>
		<mpeg7:TimePoint>2002-09-20T15: 22+01:00 </mpeg7:TimePoint>
	</LastUpdateTime>
	<Lmax>138</Lmax>
	<Values>
		0.1 0.2 0.1 0.0 0.1 0.1 0.0 0.3
		0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
		0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
		0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.1
	</Values>
</UpdateInterval>
```

*III.3* `Erraticity`

Assume that a circle of radius *r* defines the region for the location updates as illustrated in Fig.9. When the MT traverses a distance $d$ from the time of a location update ($t_O$) at position O to the next one ($t_A$) at position A, we denote the corresponding erraticity within time frame $[t_O, t_A]$ as $\mathrm{E}(t_O, t_A)$, and express it analytically as in (3).

$$E(t_O, t_A) = (1 - \frac{r}{d}) \quad (3)$$

If the shape of the location update area is circular, the `xRadius` and `yRadius` is the same. In that case, we can express the `Erraticity` as a function of the ratio of the `xRadius` to the distance the MT traverses between two consecutive location updates. If the shape is elliptic, we formulate the erraticity as in (4).

$$Erraticity = \max\left(0, 1 - \left(\frac{xRadius + yRadius}{2}\right)\left(1 + \frac{3h}{10 + \sqrt{4 - 3h}}\right) / d\right) \quad (4)$$

where $h = \left(\frac{xRadius - yRadius}{xRadius + yRadius}\right)^2$. The numerator expression in (4) that replaces $r$ in (3) is the approximate perimeter of the ellipse normalized by $2\pi$. Please note that when `xRadius=yRadius`, the numerator becomes equal to the `xRadius`. The `Erraticity` reveals how erratic the MT moves from one location-update-location to the next, and it distinguishes two different mobility characteristics at times they have the same location update intervals. The comparison of the erraticity levels is made within each corresponding location update interval. Therefore, we suggest use of the `Erraticity` in conjunction with the `UpdateInterval`. The syntax of the `ErraticityType` as adopted into MPEG-21 DIA Part 7 [20] is given in Fig.10. The syntax consists of a `single` field characterizing the `Erraticity` descriptor, which is the `Values`. `The Values` describe the raw erraticity values in a vector of length 128, because of the fact that the `UpdateInterval` uses the most recent 128 LUIs to create the histogram of location updates, and each erraticity value corresponds with a LUI.

*III.3.1 Example*

The following example shows an instance of the `Erraticity`. Erraticity has no units, and takes values from [0,1] where 1 indicates the highest level of randomness (e.g., a Brownian motion without drift), and 0 the lowest level (e.g., movement with no directional change between two consecutive location updates). It is possible to send only the latest erraticity value. Then, it would correspond to the latest location update interval. The `Values` give the most recent 128 erraticity values.


```
<Erraticity>
      <Values>
            0.33 0.21 0.35 0.11 0.05 0.15 0.20 0.16
            0.17 0.20 0.32 0.43 0.26 0.13 0.23 0.20
            ……………………………………………
            ……………………………………………
            0.10 0.11 0.18 0.15 0.20 0.23 0.18 0.21
      </Values>
</Erraticity>
```


**IV. Analysis of the Descriptors and Key Issues**

The introduced descriptors are not completely orthogonal to one another. In other words, while some information extracted from one descriptor may be implied by other descriptors, even though they would not be identical, each descriptor may carry unique information independent from other descriptors. This section explains the inter-descriptor differences and similarities, presents results regarding dependencies of descriptors on certain variables, addresses open issues arisen from the analysis and exemplifies how the descriptors can be used in classification of different mobility patterns.

We first generate mobility trajectories using the FBM based mobility model given in II.2. This model allows us to create wide range of trajectories in 2-D space by only controlling four parameters: mean speed (m/s) and variance ($m^2$ /s) in each direction. From the generated trajectories, we extract the introduced descriptors and study how successful they are to distinguish each trajectory from the others. In Fig.11a-b, two generated sample trajectories are shown. Rather than semantic labeling based classification, we focus on the possibility to specify numeric measures only. The ASPs, e.g., can then exploit those measures to perform their own classifications. We feel that this would offer a more useful and flexible classification of user profiles.

*IV.1 Directivity*

Directivity measurements are assumed to be collected at periodic time intervals, and they vary from one time scale to another. Figure 12 shows how a simulated trajectory sampled at 1s, 3s and 10s result in quite different mobility patterns. Accordingly, a change in the mobility pattern directly impinges on the directivity values. Assume that T=10s, and the length of the directivity vector $\underline{\beta}(T,N)$ is 64. The $\underline{\beta}(T,N)$ and the corresponding `Values` would reflect the mobility information of the past 640s. To monitor the mobility characteristics of the movement pattern during the last 640s continuously, after each time a new directivity element is obtained by the NSP, $\underline{\beta}(T,N)$ must be updated. The update is performed by dropping the oldest directivity value in the vector, and by appending the new one. The `Mean` and `Variance` now would also describe the statistical properties of the updated vector.

*IV.1.1 Conversion of Directivity from a Time Scale to Another*

Assume that $\underline{\beta}(T,N)$ is computed at time scale $T_1$. It is not possible to derive a vector of directivity elements for coarser time scales than $T_1$ by only using $\underline{\beta}(T,N)$. Such a conversion would require a-priori location information corresponding to each element in $\underline{\beta}(T,N)$. Only in the existence of the vector of original location coordinates $L_1$, the new directivity vector at time scale $kT_1$, $\underline{\beta}(T_1 k, N/k)$, can be easily computed after down sampling $L_1$ by an integer $k$ where *k*>1. Therefore, for time-scale-to-time-scale conversions, the network must keep the raw location information of the MT. If an ASP requires certain directivity descriptors extracted at a time scale different from the original time scale, the network has to exploit the stored location information for conversion.

*IV.1.2 Orthogonality of the Fields of the "*`Directivity`*"*

In Fig.13, histograms of the directivity measurements of five mobility trajectories each with a different set of parameter values are shown. The simulations are run at time scale of 10s. The velocities *Vx* and *Vy* are both 0 in case (I) and (II). It is clear, in this example, that if one to choose the speed as a mobility descriptor, it would be misleading to distinguish trajectories. It can be deduced from the histograms that the first may belong to the profile of a pedestrian shopping in a mall, and the second that of a pedestrian walking on a relatively straight street structure. A pedestrian walking in a shopping mall is more likely to change his direction within a given time frame than that walking on a straight street. Therefore, we would expect the directivities to be higher in (I) than that in (II) as shown in Table I. Furthermore, directivity data sets (II) and (III) have the same `Mean` and similar histogram patterns. However, in their comparison, $\sqrt{\texttt{Variance}}$ is distinguishing. These observations prove that each directivity field contributes to classifying different mobility patterns, and they are complementary to one another. The histogram of (IV) is more spread than that of (V). For (V), the mobility parameters are *Vx*=64m/s, *Vy*=11m/s; and for (IV), *Vx*=30m/s, *Vy*=11m/s. Moreover, these results support the intuition that fast moving MTs would have smaller directivities.

Table I `Mean` and $\sqrt{\texttt{Variance}}$ of the histograms of the `Directivity` which are shown in Fig.13.

| `Directivity` | I | II | III | IV | V |
|---|---|---|---|---|---|
| `Mean` *(degrees)* | 87 | 66 | 66 | 28 | 6.3 |
| $\sqrt{\texttt{Variance}}$ *(degrees)* | 53 | 50 | 65 | 32 | 18 |

*IV.2 UpdateInterval*

One of the fields defined for this descriptor is the `Values` (histogram). The next section shows how the histogram of LUIs differs with relation to certain parameters such as speed and radius.

*IV.2.1 Histogram of Location Update Intervals*

Figure 14 gives histograms of location updates for three different trajectories. In (a) and (b), the trajectories consist of 1000 samples each, while trajectory (c) includes 3000 samples. Samples define the coordinates of the movements at 1s intervals. The length of trajectory (c) is chosen to be longer to be able to generate a sufficient number of location updates. The location update area is a circle with radius of 80m. Average velocity is the highest (4m/s) in (a), while it is the lowest (0.2m/s) in (c). The histogram in (b) is more spread than that in (a), and it has longer update intervals. The MTs with low average speed and speed variances would have longer update intervals compared to the MTs with higher average speed and speed variances. This is clearer in (c) in which the maximum LUI goes up to 250s.

Figure 15 illustrates the impact of the radius of the location update region on histograms of the LUIs. Mobility model parameters $Vx = 4m/s$, $Vy = 0m/s$, $Dx = 18m^2/s$, $Dy = 8m^2/s$ are kept the same, and the `xRadius` is set to 1400m, 800m and 500m respectively in (a), (b) and (c). The key observation is that the `Lmax` increases with the radius. The distribution in the histogram shifts to the left, as the radius gets shorter. Intuitively, the MT starts updating its location more often and in shorter time intervals, when the radius is decreased.

*IV.3 Erraticity*

The significance of the `Erraticity` is in that it helps to distinguish movements having similar LUIs. Consider Fig.9 again in which two different movements with the same location update intervals are illustrated. Assume that for both movements, the first updates occur at coordinate O at the same time, and also that the second updates occur at coordinates A and B again at the same time. From O to A, the distance traversed is ($d_{a1}$+$d_{a2}$+$d_{a3}$), while from O to B, it is ($d_{b1}$+$d_{b2}$). It is clearly illustrated in Fig.9 that the distances traversed in each case are not the same, and this leads to different erraticity levels. It would be possible to distinguish these two movements within that specific location update time frame by exploiting the `Erraticity`. Fig.16 shows the erraticity measurements of the two trajectories that generated the histogram of update intervals in Fig.14a and 14.b. It is clear that in (a) erraticity values vary in a wider range than those in (b), even though the `Values` of the `UpdateInterval` look similar in both cases.

At some instances, a link may be established between the erraticity and the directivity. Mobility patterns with very low erraticity are less likely to make large directional changes. Hence, it results in low directivity. For example, if the last LUI is equal to $kT$, where $k \geq 2$ and $T$ is the period of directivity measurements, and the corresponding erraticity is zero, it can be analytically easily shown that the last $(k-1)$ directivity measurements will return zero too. However, it is not always possible to quantify such a relation.

## V. Multimedia Service Adaptation

In the previous sections, the descriptors and their extraction methods are explained, and analysis results are given. This section emphasizes the use of mobility characteristics in service and content adaptation in an illustrated example. There are two essential components to perform mobility-characteristics-based service adaptation: the network service provider (NSP) and the application service providers (ASP). The NSP is responsible for keeping track of the locations of MTs. Based on the location data received; the mobility characteristics descriptions are formed and continually updated. These descriptions are then delivered to the ASPs. After receiving the descriptions, the ASPs can first determine the MTs mobility profiles, and then perform service and content adaptation. In what follows, we give an example way of exploiting mobility descriptions for detecting correct mobility profile, and using that information in service and content adaptation.

Each ASP may have unique way of classifying mobility profiles according to values and ranges of the subject descriptions. Figure 17 illustrates a simple, yet effective method for mobility profile detection exploiting the fields of the `Directivity`. In this example, assume that the ASP defines three mobility profiles that are highway vehicular, urban vehicular and pedestrian; and divides the histogram into three regions such that the region of bin index [1-3] corresponds to the highway vehicular profile, [4-8] to the urban vehicular, and [9-16] to the pedestrian as shown in Fig.17. This separation is suggested based on the conclusion given in Section IV.I.2 that fast moving Users will have mostly smaller directivities. It is expected that each profile will generate some directivity values that may also fall in other regions, but the density of the directivities of a profile still will be the highest in its designated region. Therefore, the ASP may first want to compare the average energy within each mobility profile region, and consider the one with the highest energy as the most likely mobility profile. The average energy $E$ within a histogram region can be computed as $E = \frac{1}{(n-m+1)}\sum_{i=m}^{n} H^2(i)$, where $m$ and $n$ are the first and the last bin index defining each region and $H(i)$ is the value of $i^{th}$ bin. The output decision may be confirmed, if $\texttt{Mean} \pm \sqrt{\texttt{Variance}}$ also falls into the selected region. This verification would prevent any false profile detection. The following pseudo-code algorithm illustrates the approach explained here, after computing average energies in the profile regions. The algorithm clearly indicates how $\texttt{Mean} \pm \sqrt{\texttt{Variance}}$ may be exploited to perform profile verification.

```
//After computing energies within each profile region in the histogram
// A= Average energy within the highway-vehicular region
// B= Average energy within the urban-vehicular region
```

```
// C= Average energy within the pedestrian region
// Mean and Variance are the fields of the Directivity
// 11.25 is the range of each bin in the histogram of Directivity

If ((Mean + √Variance)<(11.25*3)) && (A>B))
     return HIGHWAY;
Else if ((Mean − √Variance)>11.25*3) && (B>A && B>C)
&&((Mean + √Variance)<11.25*8)
     return URBAN;
Else if ((Mean − √Variance)>11.25*8) && (C>B && C>A)
     return PEDESTRIAN;
Else
     return NONE;
End
```

If the above algorithm returns NONE, the `UpdateInterval` and `Erraticity` fields may be exploited for profile detection. This is exemplified with a simple algorithm below such that the average speed of the User within the last location update interval is inferred from the descriptor fields, and the resulting speed is compared to a set of speed ranges achievable by each mobility profile. Accordingly, the profile decision is made. The distance traversed within the last LUI can be derived from the last erraticity value, which is `Values`[127], and `xRadius`. On the other hand, the last LUI is inferred from `Lmax` and `LastUpdateBinIndex`. Hence, the average velocity is the ratio of the distance traversed to the last LUI. The final step is the comparison of the resulting average speed to a set of thresholds preset by the ASP. This procedure is given as a pseudo-code algorithm below.

```
// The descriptor fields are italic
// Values is the field of the Erraticity
// Compute the distance traversed within the last location update interval
DistanceTraversed = xRadius / (1 – Values [127]);

 //Compute the last update interval from the LastUpdateBinIndex value
LastUpdateInterval = (Lmax/32) * LastUpdateBinIndex;

//Compute the average estimate of the velocity within the last update region
AverageVelocity = DistanceTraversed / LastUpdateInterval;

//Perform supportive classification based on average velocity value
// Alpha: maximum achievable speed by a pedestrian
// Gamma: maximum achievable speed by an urban vehicular
If (AverageVelocity<Alpha)
```

```
          return PEDESTRIAN;
Else If  ((Alpha<=AverageVelocity)&&(AverageVelocity<Gamma))
          return URBAN;
Else
          return HIGHWAY;
End
```

As for service and content adaptation, the content that a pedestrian may be interested (e.g., clearance items and their prices in a shopping mall, etc.) would be quite different from the content that a user driving a car may be interested (e.g., gas prices, promotions on car maintenance services, etc.). After profile detection, mobility-based service adaptation might be performed as follows:

```
If (HIGHWAY)
Initiate Service-I;
Else If (PEDESTRIAN)
Initiate Service-II
End
```

Service-I might be related to nearby service station info, while Service-II to sales events in nearby shopping centers. It is important to note that actual content associated with multimedia services may be available in collection of different formats such as jpeg image, and mp3 etc. Therefore, further content adaptation is also possible based on terminal, network capabilities and user preferences, besides mobility characteristics. This section illustrates ways of how to use mobility descriptions for detection of mobility profiles and for service adaptation in a simple example. The ASPs may perform more complex routines exploiting the introduced descriptors to achieve accurate profile detections.

## VI. Conclusion

This study is aimed to investigate distinct descriptors of single terminal's mobility characteristics for the purpose of exploiting them in service adaptation and customization of the service contents. The descriptors studied in depth are the `Directivity`, `UpdateInterval` and `Erraticity`. We show dependency of the descriptors on certain system parameters, and explain how they can be used for service adaptation. Our future study would look into whether non-uniform distributed bins would improve the efficiency of mobility characterization, and also would target investigating descriptors for characterizing group of terminals' mobility.

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## FIGURE CAPTIONS

**Figure 1** Hierarchical levels for use of group and single terminal mobility information in applications.

**Figure 2** Illustration of the extraction and conversion process of descriptors from periodic location information of the MTs for use in service adaptation.

**Figure 3** Syntax of mobility descriptors under `MobilityCharacteristicsType`, which is a tool defined in the DIA part of MPEG-21 [20] for describing the mobility characteristics of a User.

**Figure 4** Illustration of a single directivity measurement $\beta_{n,n+1}$.

**Figure 5** Illustration of the syntax of the `DirectivityType` [20], which is a tool describing the relative angular changes in the direction of a User's movement.

**Figure 6** Illustration of the circular and elliptic location update areas.

**Figure 7** Syntax of `UpdateIntervalType`, which is a tool defined in the DIA part of MPEG-21 [20] for describing information related to a User's location updates.

**Figure 8** Illustration of state-to-state transitions inferable from the histogram of location update intervals.

**Figure 9** Illustration of two movements with the same location update intervals, but different erraticity. For the first one, updates occur at coordinates O and A, for the latter at O and B.

**Figure 10** Illustration of the syntax of the descriptor `Erraticity`.

**Figure 11** Sample mobility trajectories generated by the FBM model (a) $Vx = 5$, $Vy = 0$, $Dx = 7.1$ and $Dy = 10$, (b) $Vx = 0$, $Vy = 0$, $Dx = 7.1$ and $Dy = 4.6$.

**Figure 12** Illustration of the impact of time scale on directivity measurements as the change in the pattern of a sample trajectory.

**Figure 13** Directivity histograms of different mobility characteristics with mobility model parameters of (I) $Vx$=0 m/s, $Vy$=0m/s, (II) $Vx$=0m/s, $Vy$=0 m/s, (III) $Vx$=3.0 m/s, $Vy$=2.6m/s, (IV) $Vx$=30m/s, $Vy$=11m/s (V) $Vx$=64m/s, $Vy$=11m/s. Note: Histograms are 16-bins as specified.

**Figure 14** Histograms of LUIs for various mobility characteristics under a circular location update region with radius r=80m (a) $Vx = 4m/s$, $Vy = 0m/s$, $Dx = 18m^2/s$, $Dy = 8m^2/s$, (b) $Vx = 2$, $Vy = 0$, $Dx = 14$, $Dy = 8$, (c) $Vx = 0.2$, $Vy = 0$, $Dx = 3$, $Dy = 2$ Note: Trajectory (a) and (b) consists of 1000 samples each, and (c) of 3000 samples.

**Figure 15** Illustration of the impact of the radius of location update area on the histograms of LUIs. In the shown simulation result $Vx = 30m/s$, $Vy = 0m/s$, $Dx = 1m^2/s$, $Dy = 5m^2/s$ for radius (a) `xRadius`=*1400m,* (b) *800m,* (c) *500m.*

**Figure 16** Corresponding erraticity values of the two trajectories given in Fig.14 (a) $Vx = 4m/s$, $Vy = 0m/s$, $Dx = 18m^2/s$, $Dy = 8m^2/s$, (b) $Vx = 2$, $Vy = 0$, $Dx = 14$, $Dy = 8$.

**Figure 17** Illustration of the histogram of `Directivity` with 16-bin representation, but with non-uniform separation of mobility profile regions. Note: The bin index [1-3] corresponds to the highway profile, [4-8] to the urban vehicular, and [9-16] to the pedestrian. Note: The `Mean` and `Variance` are the fields of the `Directivity`.

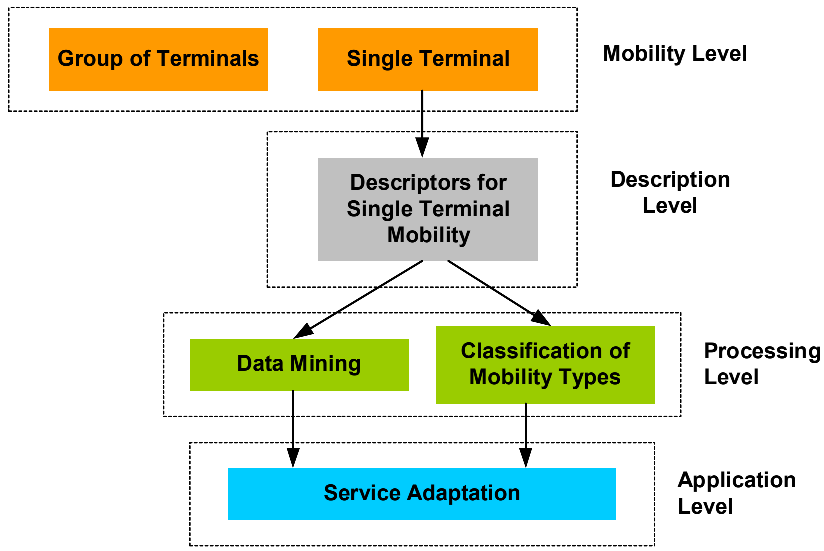


**FIGURE 1** Hierarchical levels for use of group and single terminal mobility information in applications.

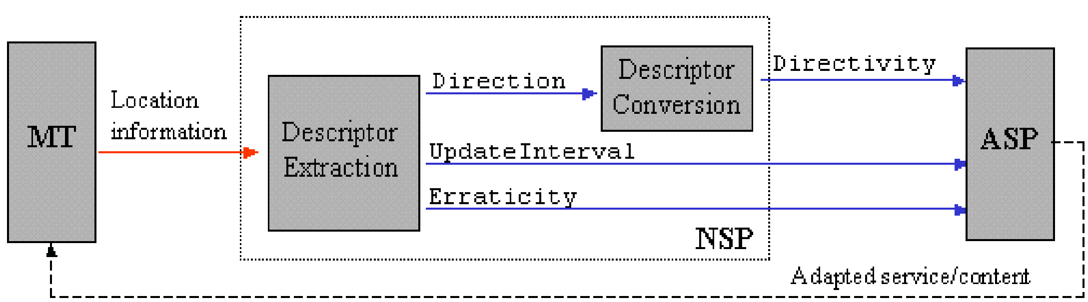


**FIGURE 2** Illustration of the extraction and conversion process of descriptors from periodic location information of the MTs for use in service adaptation.

```
<complexType name="MobilityCharacteristicsType">
    <complexContent>
         <extension base="dia:DIABaseType">
            <sequence>
               <element name=„Directivity" type="dia:DirectivityType"
                        minOccurs="0" maxOccurs="1"/>
               <element name=„UpdateInterval" type="dia:UpdateIntervalType"
                        minOccurs="0" maxOccurs="1"/>
               <element name="Erraticity" type="dia:ErraticityType"
                        minOccurs="0" maxOccurs="1"/>
            </sequence>
         </extension>
     </complexContent>
</complexType>
```

**FIGURE 3** Syntax of mobility descriptors under `MobilityCharacteristicsType`, which is a tool defined in the DIA part of MPEG-21 [20] for describing the mobility characteristics of a User.

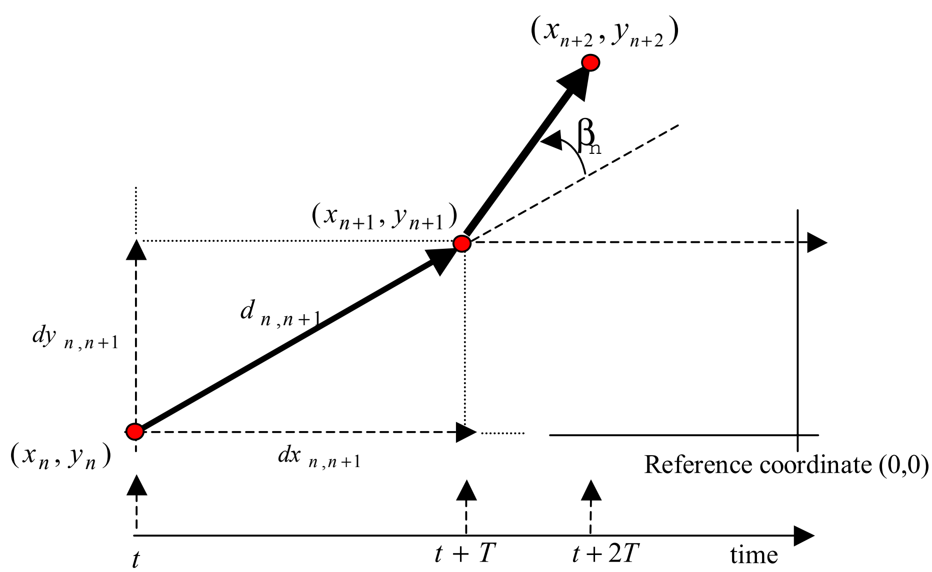


**FIGURE 4** Illustration of a single directivity measurement $\beta_n$

```
<complexType name="DirectivityType">
    <complexContent>
      <extension base="dia:DIABaseType">
          <sequence>
             <element name="Mean" type="float" minOccurs="0"/>
             <element name="Variance" type="float" minOccurs="0"/>
             <element name="Values" minOccurs="0">
                 <simpleType>
                    <restriction base="mpeg7:probabilityVector">
                           <minLength value="16"/>
                           <maxLength value="16"/>
                    </restriction>
                 </simpleType>
             </element>
          </sequence>
      </extension>
    </complexContent>
</complexType>
```

**FIGURE 5** Illustration of the syntax of the `DirectivityType` [20], which is a tool describing the relative angular changes in the direction of a User's movement.

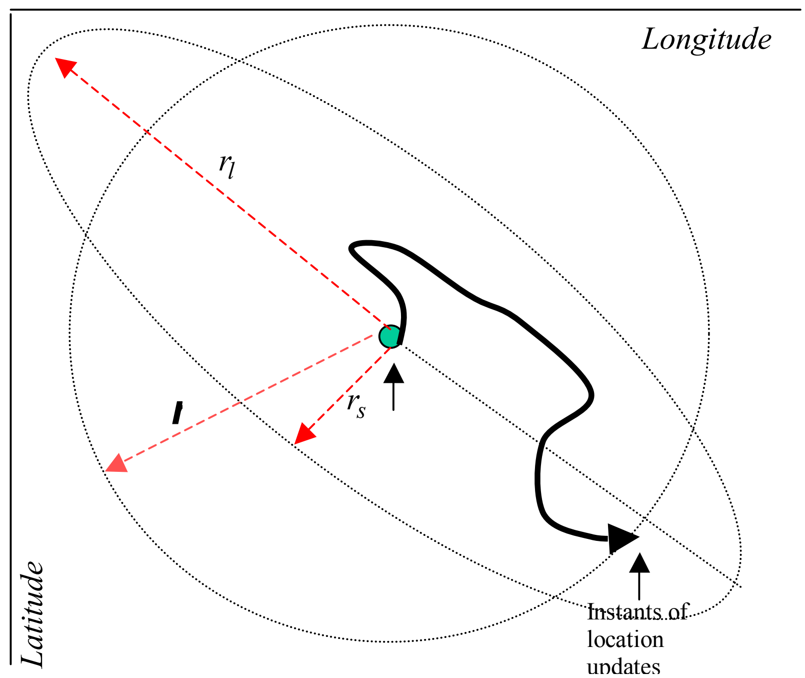


**FIGURE 6** Illustration of circular and elliptic location update areas.

```
<complexType name="UpdateIntervalType">
    <complexContent>
        <extension base="dia:DIABaseType">
            <attribute name="xRadius" type="integer" use="optional"/>
            <attribute name="yRadius" type="integer" use="optional"/>
            <sequence>
                <element name="LastUpdatePoint" type="mpeg7:GeographicPointType"
                    minOccurs="0"/>
                <element name="LastUpdateBinIndex" type="integer" minOccurs="0"/>
                <element name="LastUpdateTime" type="dia:TimeType" minOccurs="0"/>
                <element name="Lmax" type="integer" minOccurs="0"/>
                <element name="Values" minOccurs="0">
                    <simpleType>
                        <restriction base="mpeg7:probabilityVector">
                            <minLength value="32"/>
                            <maxLength value="32"/>
                        </restriction>
                    </simpleType>
                </element>
            </sequence>
        </extension>
    </complexContent>
</complexType>
```

**FIGURE 7** Syntax of `UpdateIntervalType`, which is a tool defined in the DIA part of MPEG-21 [20] for describing information related to a User's location updates.

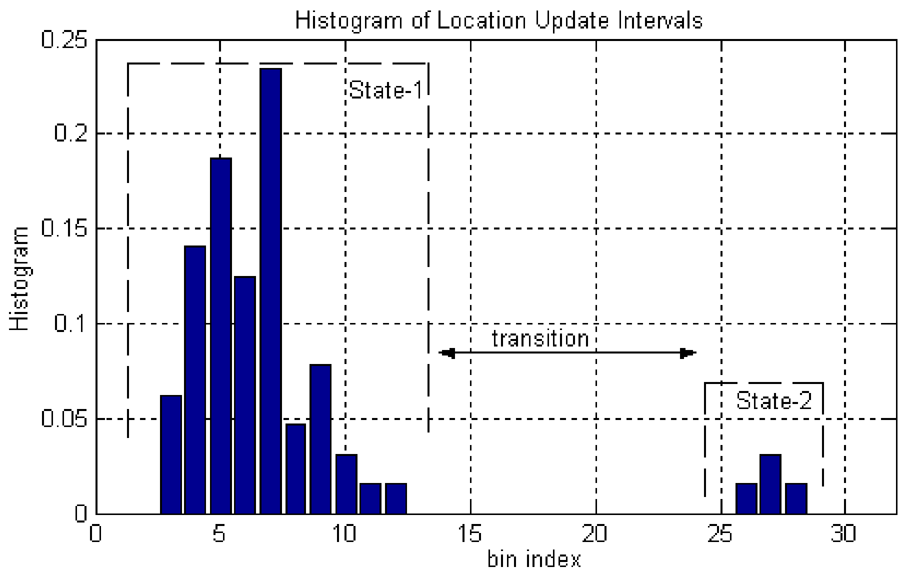


**FIGURE 8** Illustration of state-to-state transitions inferable from the histogram of location update intervals.

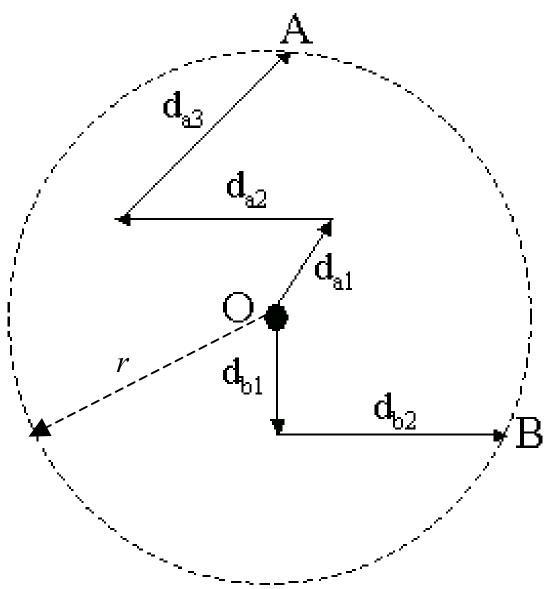


**FIGURE 9** Illustration of two movements with the same location update intervals, but different erraticity. For the first one, updates occur at coordinates O and A, for the latter at O and B.

```
<complexType name="ErraticityType">
    <complexContent>
        <extension base="dia:DIABaseType">
            <sequence>
                <element name="Values" minOccurs="0">
                    <simpleType>
                        <restriction base="mpeg7:probabilityVector">
                            <minLength value="1"/>
                            <maxLength value="128"/>
                        </restriction>
                    </simpleType>
                </element>
            </sequence>
        </extension>
    </complexContent>
</complexType>
```

**FIGURE 10** Syntax of `ErraticityType`, which is a tool defined in the DIA part of MPEG-21 [20] for describing erraticity levels of a User's movements.

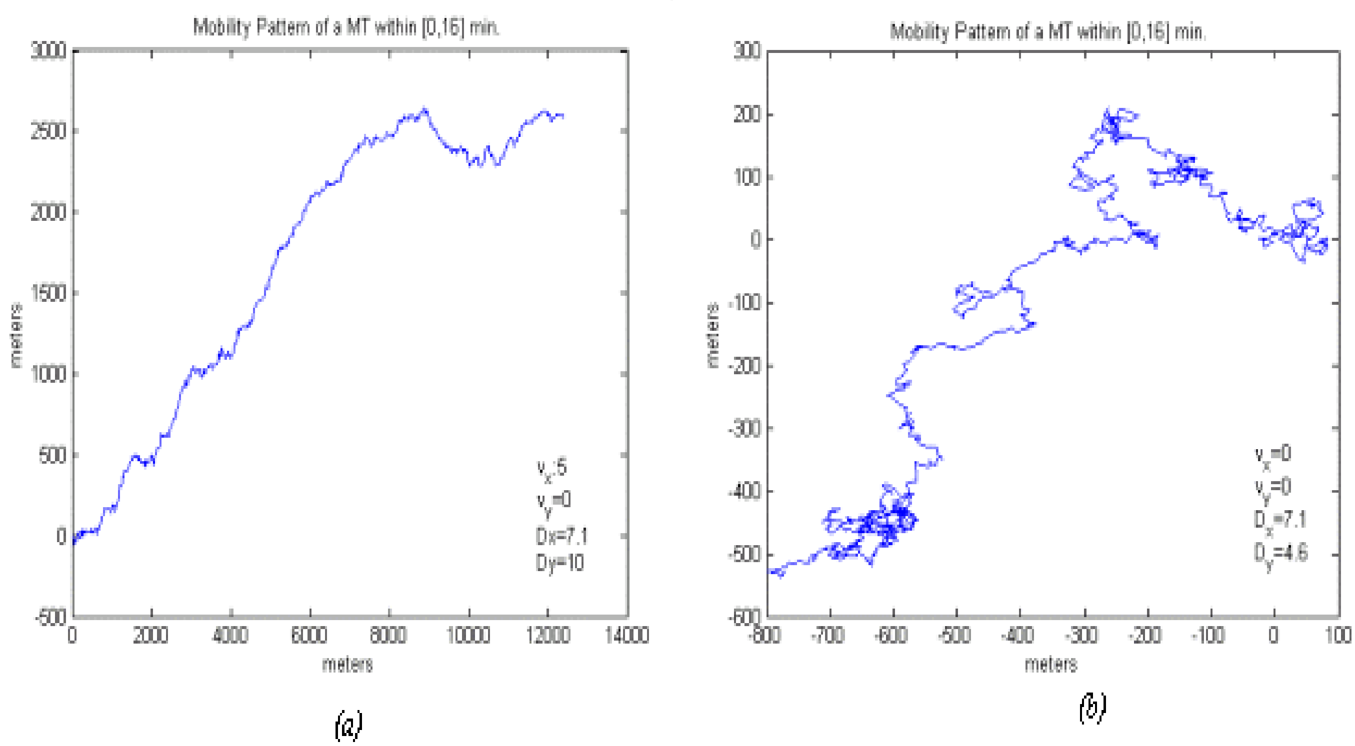


**FIGURE 11** Sample mobility trajectories generated by the FBM model (a) $Vx = 5$, $Vy = 0$, $Dx = 7.1$ and $Dy = 10$, (b) $Vx = 0$, $Vy = 0$, $Dx = 7.1$ and $Dy = 4.6$.

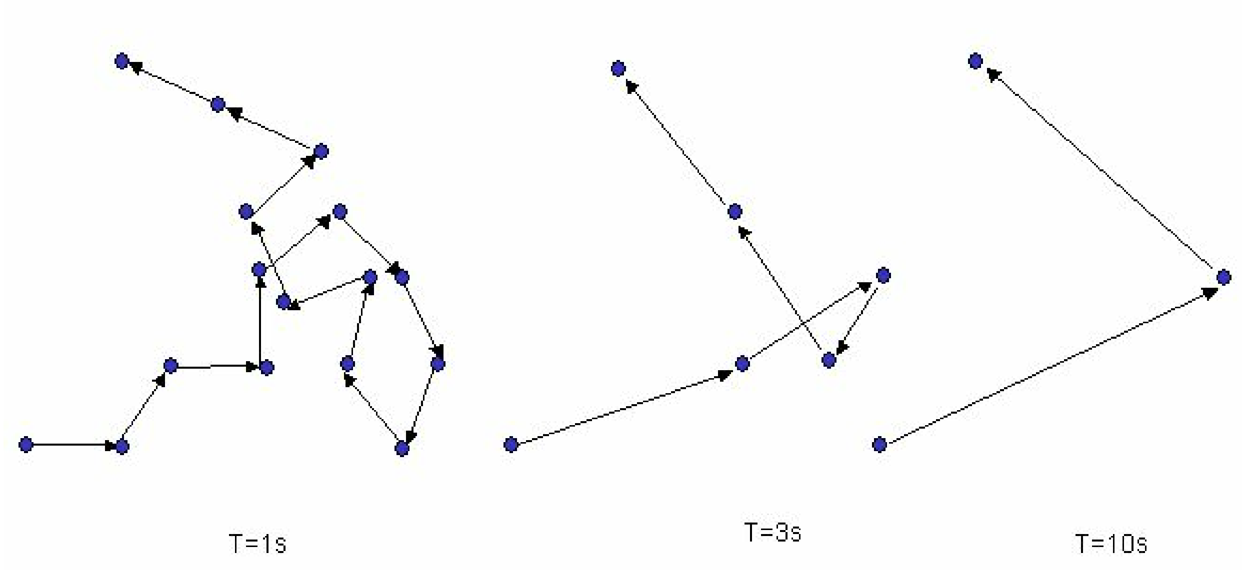


**FIGURE 12** Illustration of the impact of time scale on directivity measurements as the change in the pattern of a sample trajectory.

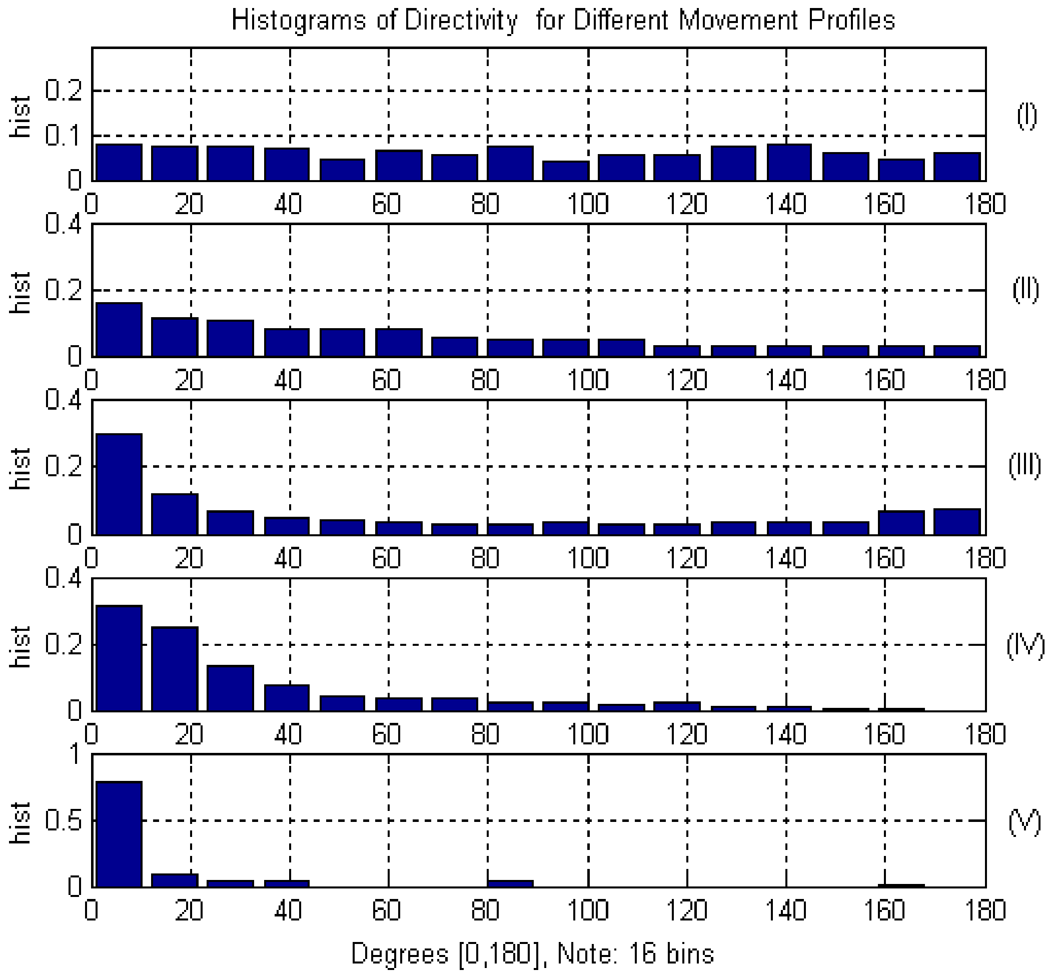


**FIGURE 13** Directivity histograms of different mobility characteristics with mobility model parameters of (I) *Vx*=0 m/s, *Vy*=0m/s, (II) *Vx*=0m/s, *Vy*=0 m/s, (III) *Vx*=3.0 m/s, *Vy*=2.6m/s, (IV) *Vx*=30m/s, *Vy*=11m/s (V) *Vx*=64m/s, *Vy*=11m/s. Note: Histograms are 16-bins as specified.

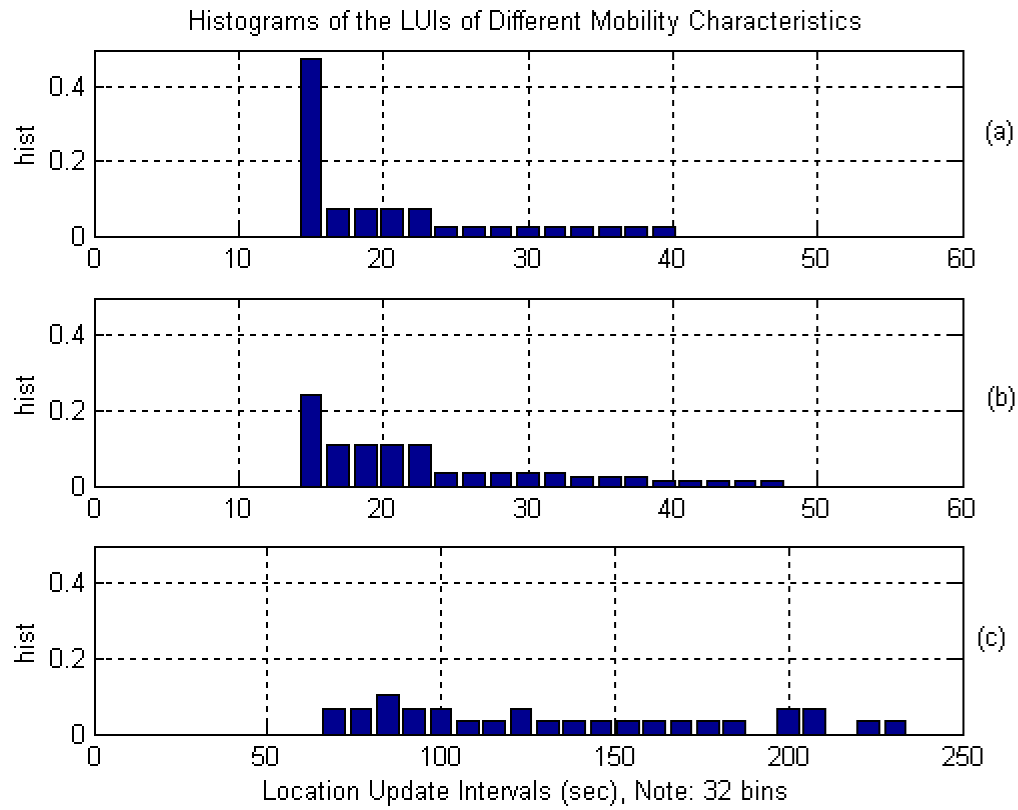


**FIGURE 14** Histograms of LUIs for various mobility characteristics under a circular location update region with radius r=80m (a) $Vx = 4m/s$, $Vy = 0m/s$, $Dx = 18m^2/s$, $Dy = 8m^2/s$, (b) $Vx = 2$, $Vy = 0$, $Dx = 14$, $Dy = 8$, (c) $Vx = 0.2$, $Vy = 0$, $Dx = 3$, $Dy = 2$ Note: Trajectory (a) and (b) consists of 1000 samples each, and (c) of 3000 samples.

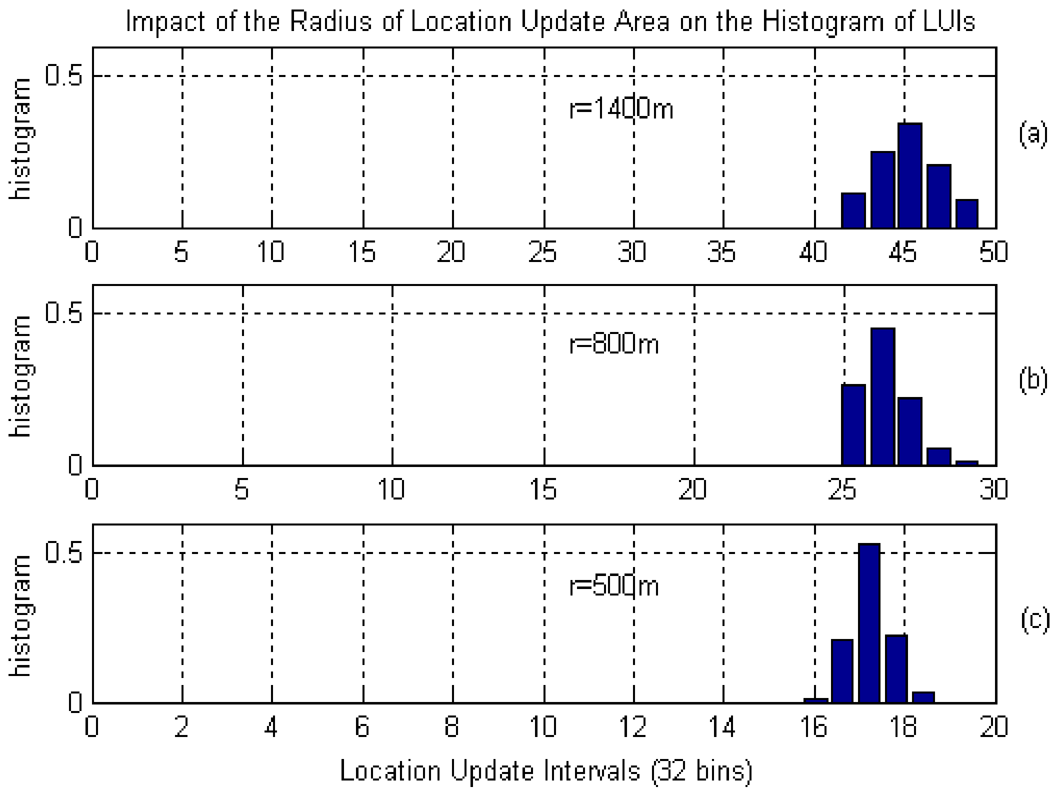


**FIGURE 15** Illustration of the impact of the radius of location update area on the histograms of LUIs. In the shown simulation result $Vx = 30m/s$ , $Vy = 0m/s$ , $Dx = 1m^2/s$ , $Dy = 5m^2/s$ for radius (a) *r=1400m,* (b) *800m,* (c) *500m.*

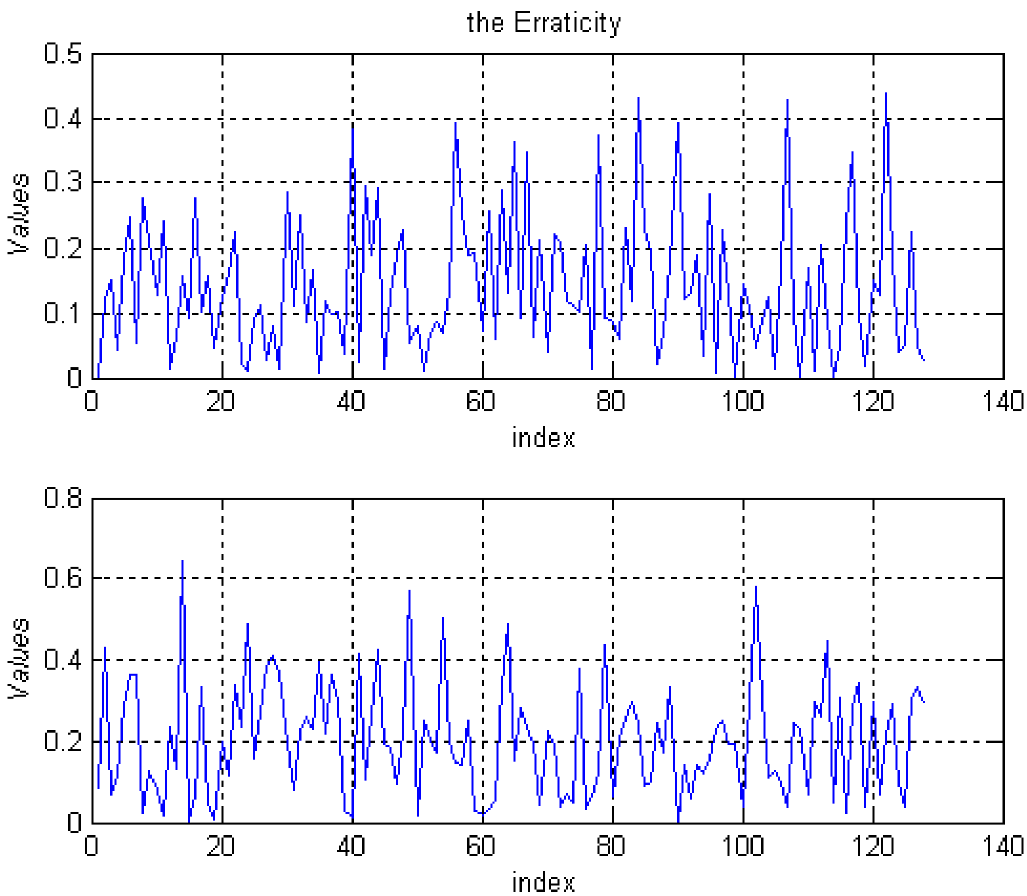


**FIGURE 16** Corresponding erraticity values of the two trajectories given in Fig.14 (a) $Vx = 4m/s$ ,$Vy = 0m/s$ , $Dx = 18m^2/s$ , $Dy = 8m^2/s$ , (b) $Vx = 2$ ,$Vy = 0$ , $Dx = 14$ , $Dy = 8$ .

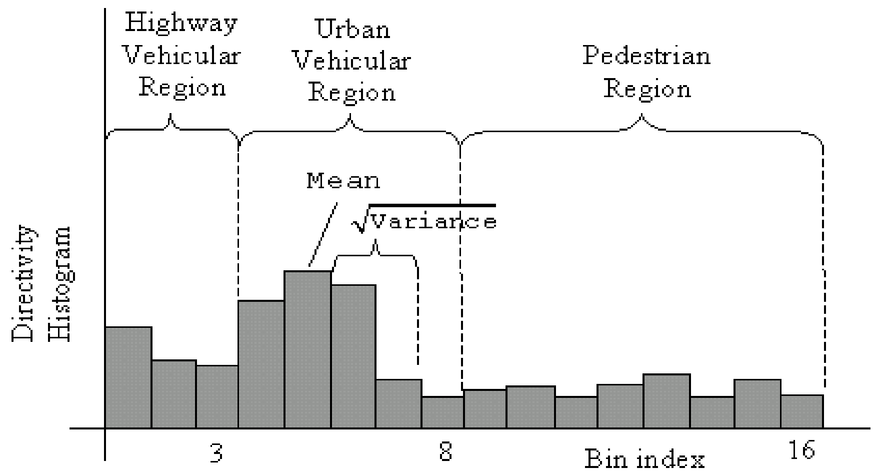


**FIGURE 17** Illustration of the histogram of `Directivity` with 16-bin representation, but with non-uniform separation of mobility profile regions. Note: The bin index [1-3] corresponds to the highway profile, [4-8] to the urban vehicular, and [9-16] to the pedestrian. Note: The `Mean` and `Variance` are the fields of the `Directivity`.