A Handoff Algorithm for Wireless Systems Using Pattern Recognition

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ABSTRACT

A new handoff algorithm based on recognition of patterns in received signal power is presented. The handoff algorithm uses the constancy of the large scale signal variation with respect to a base station to improve handoff performance in comparison with the conventional hysteresis rule. A probabilistic neural network (PNN) is used for a pattern classifier. For a given environment, a training run is performed. A set of training patterns consists of averaged signal power samples (in dB) from nearby base stations within adjacent spatial windows. A probability of failure based on signal strength is defined and determines the possible serving base station(s) for each training class. A handoff is performed if a nearby class in the sequence of classes requires a handoff. Performance comparison of this handoff algorithm and the hysteresis rule is made for environments with four and five base stations. Simulation results indicate that for a fixed probability of failure, the pattern recognition-based handoff algorithm results in considerably fewer handoffs in comparison to the hysteresis rule. This reduction of unnecessary handoffs decreases signalling load.

I. INTRODUCTION

One significant characteristic of wireless systems is the signal variation caused by the movement of the mobile stations. The existing radio link between a base station and the mobile station may deteriorate while the radio link between the mobile station and another base station may improve as time passes. It is necessary to switch, or handoff, the communication link from one base station to another for two main reasons: to maintain the signal quality and to minimize interference caused to other radio links.

In many environments, a direct path is not present between the base station and the mobile station. The received signal consists of a sum of waves which have been reflected by mountains, trees, buildings, etc. The sum of many waves at the receiver gives rise to small scale spatial variation (on the order of a wavelength) of the received signal. For distances on the order of building sizes, the mean of the small scale variation changes considerably, resulting in a nonstationary signal. This large scale variation of the mean is known as shadow fading. Since shadow fading is constant for a given path, pattern recognition techniques can be applied to handoff algorithms.

In current wireless systems, the decision to execute a handoff to a nearby base station is made according to the following hysteresis rule: a handoff is executed if the signal from a nearby base station exceeds that of the base station providing the link by a hysteresis level. In order to mitigate the effect of small scale variation, the signal samples spanning a few wavelengths in space are averaged before applying the hysteresis rule. However, the averaged signal still exhibits fluctuations from the shadow fading. This fluctuation causes unnecessary handoffs when the hysteresis rule is applied. These unnecessary handoffs can be avoided by pattern recognition techniques, thereby reducing the signalling load on the network.

A method to reduce unnecessary handoffs is to utilize the fact that the shadow fading is constant between a base station and a given location. Thus, the averaged signals of mobile stations which travel along the same path will be similar, and the averaged signal, as well as information regarding handoff decisions, can be stored in nearby base stations. The signal from a mobile station which travels along the same path can then be compared with the stored signal to determine if handoff is necessary. In this paper, a new technique is presented to recognize patterns in the signal from a mobile station using probabilistic neural networks [1]. In Section II, a propagation model is presented. Section III describes probabilistic neural networks for use in pattern recognition. In Section IV, a handoff algorithm based on pattern recognition is presented. For purposes of comparison, performance results are given in Section V for handoff algorithms based on pattern recognition and the hysteresis rule. In Section VI, some conclusions are drawn and future work is outlined.

II. WIRELESS PROPAGATION MODEL

The small scale variation considered here is assumed to be caused by the sum of several waves with random phases and amplitudes with no direct path between the base station and the mobile station. Under these conditions, the envelope r_k of the received signal at a distance d_k from the base station to the mobile station can be modeled as a Rayleigh distributed random variable with probability density function given by

$$f(r_k) = \frac{r_k}{p_k} \exp\left(-\frac{r_k^2}{2p_k}\right), r_k \geq 0, \tag{1}$$

where p_k is a parameter of the density function. The mean of the Rayleigh distribution is $E[r_k] = \sqrt{\pi p_k/2}$. The small scale variation which can be modeled by Equation (1) is called "Rayleigh

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fading". The variation of received signal power with distance is modeled as $1/d_k^n$, with n ranging from 2 to 6.

The shadow fading is modeled as a correlated lognormal random process as described in [2, 3]. Let $R_L(d)$ denote the autocorrelation function of the shadow fading random process $L(d)$, where d is a position variable and $L(d)$, measured in decibels (dB), is a normally distributed random process. The autocorrelation, $R_L(d)$, is given by:

$$R_L(d) = \sigma_L^2 \exp\left(-\frac{|d|}{d_0}\right), \quad (2)$$

where σ_L^2 and d_0 are the variance and correlation length of $L(d)$, respectively. From Equation (2), the power spectrum $S_L(\nu)$ of $L(d)$ is given by:

$$S_L(\nu) = \frac{2d_0\sigma_L^2}{1+(2\pi\nu d_0)^2}, \quad (3)$$

where ν is spatial frequency. For a total distance travelled, D, the shadow fading process can be shown to be:

$$L(d) = \sum_{j=-J}^{J} \sqrt{\frac{2}{BD} S_L\left(\frac{j}{D}\right)} \cos\left(\frac{2\pi j d}{D} + \phi_j\right), \quad (4)$$

where

$$B = \frac{1}{\sigma_L^2 D} \sum_{j=-J}^{J} S_L\left(\frac{j}{D}\right), \quad (5)$$

$$J = D\nu_m, \quad (6)$$

ν_m is the maximum spatial frequency taken into account, and ϕ_j is an independent, identically distributed uniform random process in $[0, 2\pi)$. The process $L(d)$ is sampled at $d = d_k$ to obtain L_k.

In the absence of Rayleigh fading, the signal is expressed in dB by

$$m_k = C_0 - 10n\log_{10} d_k + L_k, \quad (7)$$

where C_0 is a constant which includes the power transmitted, antenna parameters, and carrier frequency. Thus, the received signal, including Rayleigh fading (in dB), is given by:

$$s_k = 20\log_{10} r_k, \quad (8)$$

where r_k is a Rayleigh distributed random variable with parameter $p_k = (1/2)10^{(m_k/10)}$. The mean and variance of s_k are given by:

$$\begin{aligned}\bar{s}_k &= 10\log_{10}(2p_k) - \frac{10\gamma}{\ln 10} \\ &= m_k - \frac{10\gamma}{\ln 10}, \end{aligned} \quad (9)$$

$$\sigma_{s_k}^2 = \frac{50\pi^2}{3\ln^2 10}, \quad (10)$$

where $\gamma \approx 0.577216$ is Euler's Gamma. The signal is nonstationary since $\bar{s}_k$ is not constant and varies according to Equation (9). The model presented here is used in Section V for performance evaluation of the hysteresis rule and the pattern recognition handoff algorithm developed in Section IV.

III. PATTERN RECOGNITION USING PROBABILISTIC NEURAL NETWORKS (PNN'S)

A probabilistic neural network (PNN) is used in developing the handoff algorithm of Section IV. The following notations will be used to describe the PNN. Let $X = [x_1, x_2, \ldots, x_N]^T$ denote a test vector to be classified, $X_p = [x_{p,1}, x_{p,2}, \ldots, x_{p,N}]^T$ represent the p-th training vector, c_p be the class associated with X_p, and $W_p = [w_{p,1}, w_{p,2}, \ldots, w_{p,N}]^T$ be the weight vector of the p-th neuron in the PNN. The output y_p of the p-th neuron is given by:

$$y_p = \exp\left[-\frac{\|X - W_p\|^2}{\sigma_N^2}\right], \quad (11)$$

where σ_N^2 is a "smoothing parameter" of the PNN. Let P be the number of training vectors or neurons ($p = 1, 2, \ldots, P$) and C be the number of classes ($c_p = 1, 2, \ldots, C$). Figure 1 illustrates the structure of the PNN. The weights of the neurons are set equal to

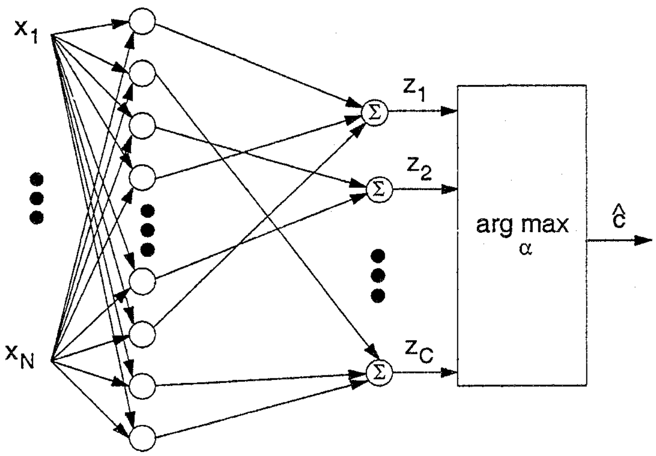

Figure 1: Diagram of Probabilistic Neural Network for Pattern Recognition.

the training vectors,

$$W_p = X_p, \quad p = 1, 2, \ldots, P. \quad (12)$$

Let

$$Y_\alpha = \{y_p : c_p = \alpha\}, \quad p = 1, 2, \ldots, P, \quad (13)$$

$$z_\alpha = \sum_{y_p \in Y_\alpha} y_p, \quad \alpha = 1, 2, \ldots, C. \quad (14)$$

The set of outputs of all neurons whose training patterns X_p belong to class α is Y_α, and the sum of the elements of Y_α is z_α. The test vector X is associated with class $\hat{c}$ according to the following rule:

$$\hat{c} = \arg\max_{\alpha} z_\alpha. \quad (15)$$

The above classification rule assumes that the ratio of the number of training patterns for class α to the *a priori* probability of occurrence of class α is equal for all classes $\alpha = 1, 2, \ldots, C$. In the next section, a handoff algorithm based on pattern recognition using PNN is described.

IV. HANDOFF ALGORITHM BASED ON RECOGNITION OF PATTERNS IN SIGNAL POWER

A new handoff algorithm is presented using the following performance criterion: a handoff is executed to ensure that the probability of link failure, P_F, is less than or equal to a specified value $P_{F,\max}$. For this analysis, failure occurs if the received signal s_k falls below the receiver threshold S_T. The design requirement is then:

$$P_F \equiv \Pr\{s_k < S_T\} \quad \leq \quad P_{F,\max}. \tag{16}$$

From Equations (1) and (8), we have:

$$\begin{aligned} P_F &= \Pr\left\{r_k < 10^{S_T/20}\right\} \\ &= 1 - \exp\left\{-\frac{10^{S_T/10}}{2p_k}\right\}. \end{aligned} \tag{17}$$

An inequality for $\overline{s}_k$ can be derived using Equations (9) and (16), with the result

$$\overline{s}_k \geq S_T - 10\log_{10}\left[\ln\left(\frac{1}{1-P_{F,\max}}\right)\right] - \frac{10\gamma}{\ln 10}. \tag{18}$$

Figure 2 plots the minimum value of $\overline{s}_k - S_T$ as a function of $P_{F,\max}$. For $P_{F,\max} \ll 1$, the following approximation to Equation (18) can be used:

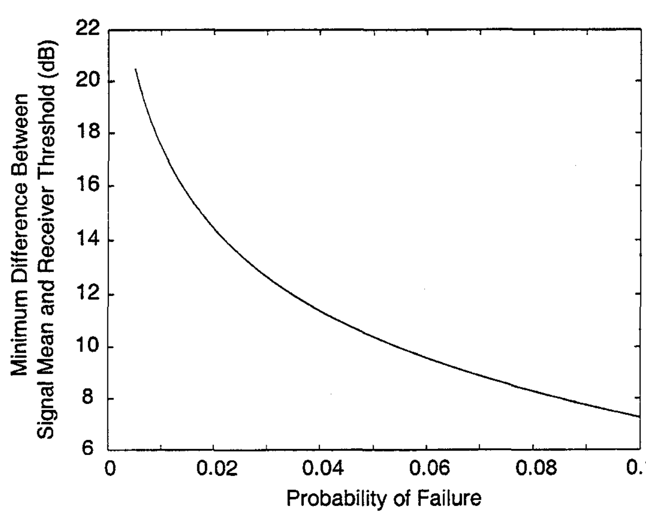

Figure 2: Minimum Difference Between Signal Mean and Receiver Threshold as a Function of Probability of Failure.

$$\overline{s}_k \geq S_T - 10\log_{10}(P_{F,\max}) + \frac{5P_{F,\max} - 10\gamma}{\ln 10}. \tag{19}$$

In practice, $\overline{s}_k$ is not easily measurable. An estimate of $\overline{s}_k$ is obtained by averaging the past M samples of s_k:

$$\xi_k = \frac{1}{M}\sum_{m=0}^{M-1} s_{k-m}. \tag{20}$$

It is assumed that the s_k are obtained by sampling at equal spatial intervals. This assumption is equivalent to constant velocity of the mobile station and temporal sampling at regular intervals, or variable velocity and temporal sampling at correspondingly irregular intervals. Furthermore, it is assumed that the distance spanned by the samples $s_{k-(M-1)}, \ldots, s_k$ is much less than the correlation length d_0 of the shadow fading process and the distance between adjacent samples is sufficiently large such that adjacent samples are approximately independent. Under these conditions, ξ_k is the sum of independent, identically distributed random variables. For sufficiently large M, the Central Limit Theorem states that ξ_k approaches a Gaussian distributed random variable with mean $\overline{\xi}_k = \overline{s}_k$ and variance $\sigma^2_{\xi_k} = \sigma^2_{s_k}/M$. For $\overline{s}_k$ to satisfy Equation (18) with 99% confidence, we require

$$\xi_k \geq S_T - 10\log_{10}\left[\ln\left(\frac{1}{1-P_{F,\max}}\right)\right] - \frac{10\gamma}{\ln 10} + 3\sigma_{\xi_k} + \xi_{\text{margin}}, \tag{21}$$

where ξ_{margin} is a margin of safety.

Using Relation (21) on the averaged signal, a handoff algorithm based on pattern recognition is outlined below. A pattern vector consists of a set of signal samples from nearby base stations B_i $(i = 1, \ldots, i_{\max})$ within a spatial window. Let N_w denote the length (in number of samples per base station) of the spatial window. A training run is made along a particular path to initialize the PNN for pattern recognition. The averaged signal samples from the nearby base stations are recorded. Let $\xi^i = [\xi^i_0, \xi^i_1, \ldots, \xi^i_{N_{\max}-1}]^T$ and $\xi^j = [\xi^j_0, \xi^j_1, \ldots, \xi^j_{N_{\max}-1}]^T$ denote the averaged samples from base B_i and base B_j, respectively. The total number of samples recorded from each base station is $N_{\max}$. The number of classes is therefore

$$C = \left\lfloor \frac{N_{\max}}{N_w} \right\rfloor. \tag{22}$$

For each distinct training class $\alpha_t, t = 0, 1, \ldots, C-1$, a training vector X^{FWD}_t is formed from the samples of all $i_{\max}$ base stations within the spatial window. The class label α_t denotes the midpoint of the spatial window. The ordering of the samples correspond to travel in the same direction as the training run. The second training vector X^{REV}_t for class α_t is formed by reversing the order of the samples of X^{FWD}_t to account for travel in the opposite direction of the training run. Most pattern recognition applications require more than one training vector per class. However, in this handoff algorithm, one independent training vector per class has given good results since the use of averaged signals together with class sequencing contributes to fewer misclassifications by the PNN.

Once the training vectors from the training run are stored, the patterns which correspond to handoff locations are determined as follows. The minimum sample, $\xi^i_{t,\min}$, corresponding to base B_i is determined for each class α_t:

$$\xi^i_{t,\min} = \min(\xi^i_{tN_w}, \xi^i_{tN_w+1}, \ldots, \xi^i_{(t+1)N_w-1}), i = 1, 2, \ldots, i_{\max}. \tag{23}$$

Base B_i is an acceptable serving base station for class α_t if $\xi^i_{t,\min}$ satisfies Relation (21).

The method of determining handoff for a test run is described below. As a test mobile station travels along the path, a vector of the averaged received signal samples within a spatial window is fed as input to the PNN. The direction of travel by the mobile station can be deduced by observing the progression of the outputs of the PNN. To account for misclassifications, a tolerance T_M can be set for the difference between PNN outputs corresponding to adjacent pattern windows. Let $\hat{c_k}$ denote the class output for the k^{th} pattern window, β_k denote the corresponding set of allowable serving base stations (determined during training), and $B_k \in \beta_k$ denote the serving base station. Also, let $\Delta\alpha$ be the distance between adjacent training class labels. Conditions (24)–(27) are computed for the determination of handoff:

$$\|\hat{c}_k - \hat{c}_{k-1}\| \leq (\Delta\alpha)T_M \tag{24}$$

$$\{B_k\} \bigcap \beta_{k+j} = \emptyset, \text{ for some } j \in \{1, 2, \ldots, T_M\} \tag{25}$$

$$\bigcap_{i=1}^{l+1} \beta_{k+i} = \emptyset, \text{ for } l > 0 \tag{26}$$

$$\bigcap_{i=1}^{l} \beta_{k+i} \neq \emptyset. \tag{27}$$

Condition (24) verifies that the recognized classes for adjacent windows are "close" with a tolerance T_M. Condition (25) determines whether a handoff is needed in the near future. Conditions (26) and (27) determine the base station to which handoff is to be performed. If Conditions (24)–(27) are satisfied, a handoff is made to an element of $\bigcap_{i=1}^{l} \beta_{k+i}$. Simulation results of the above handoff algorithm are given in Section V.

V. SIMULATION RESULTS

The performance of the handoff algorithm of Section IV is compared by simulation to the performance of a system that uses a handoff algorithm based on the hysteresis rule. Simulations were performed for the cases of four and five nearby base stations. A mobile station is assumed to move in a straight line at constant velocity. In this case, sampling at equal time intervals corresponds to sampling at equal spatial intervals.

Let s^i_k and s^j_k denote the signals received at the mobile from Bases B_i and B_j. Assuming the mobile station is communicating with base B_i, the hysteresis rule is as follows: a handoff from Base B_i to Base B_j is performed if $\max_{l=1,\ldots,i_{\max}} s^l_k = s^j_k$, and $s^j_k - s^i_k > H$. The hysteresis level H is specified in dB. Simulations are performed for several environments. Figure 3 illustrates the geometry of the base stations and two paths of the mobile station for the case of four nearby base stations. The propagation model of Section II is used with independent lognormal shadow

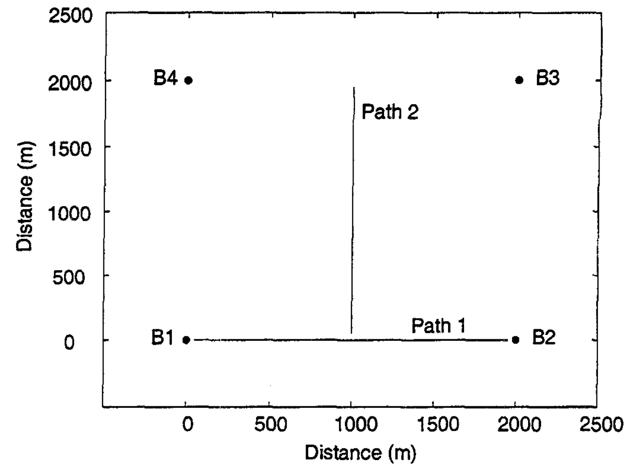

Figure 3: Geometry of Four Nearby Base Stations and Paths of Mobile.

fading for a given environment, path, and base station. Table 1 indicates the parameters used in the simulations.

Table 1: Parameters for Simulation.

Carrier Wavelength (λ)	1/3 m
Minimum Base Station Separation	2000 m
Length of Pattern Window	100 m
Exponent of Distance Dependence (n)	4
Standard Deviation of Shadow Fading (σ_L)	8 dB
Correlation Length of Shadow Fading (d_0)	20 m
Number of terms in (4) for Shadow Fading	401
Sampling Distance	λ
Target Probability of Failure ($P_{F,\max}$)	0.02
Number of Samples (M) to Estimate $\overline{s}_k$	10
Smoothing Parameter for PNN (σ_N^2)	1000
Margin of Safety (ξ_{margin})	$3\sigma_{\xi_k}$
Misclassification Tolerance (T_M)	2

Simulations were performed for 50 different environments for four paths of the mobile station for each base station geometry. Only one training run was used for each environment and path. In reality, the test runs might start and end at different locations with respect to the training runs. This aspect is accounted for by aligning the test patterns with the training patterns to minimize misclassifications. For each environment, four paths of the mobile station and five test runs per path were considered. Thus, the total number of test runs is 1000 for each case of four and five base stations.

Figures 4 and 5 plot the difference between the minimum output signal for the test runs and the required signal level (obtained from Relation (21)) versus the number of handoffs for Paths 1 and 2. Each figure corresponds to a particular path for the case of four base stations. Performance results for various other paths of the

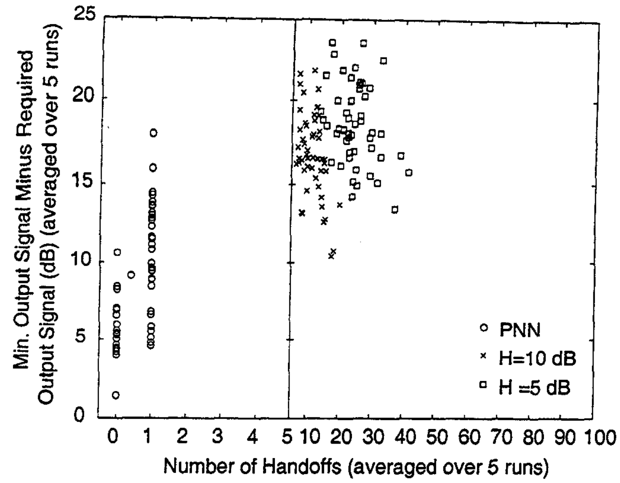

Figure 4: Minimum Signal Level versus Number of Handoffs for Four Base Stations, Path 1 (Note: change of scale in x-axis).

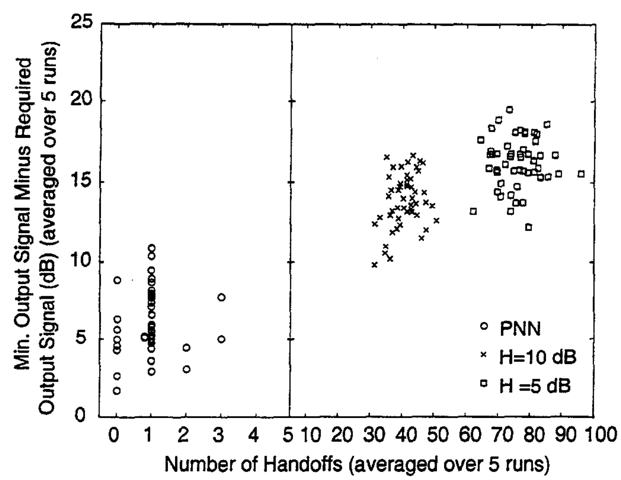

Figure 5: Minimum Signal Level versus Number of Handoffs for Four Base Stations, Path 2.

mobile station and for the case of five nearby base stations are qualitatively similar to the results presented here. Each data point represents an average over five runs for a given environment. For clarity, the region from 0 to 5 handoffs has been magnified. The plots compare the handoff algorithm using a probabilistic neural network with the conventional hysteresis rule using hysteresis levels of $H = 5$ dB and $H = 10$ dB. The hysteresis level H cannot be increased indefinitely to yield lower number of handoffs without resulting in an increased failure rate and possible handoffs to incorrect base stations. Out of a total of 2000 test runs, use of the PNN resulted in 99% of the runs having minimum signal levels above the required signal level for 2% probability of failure. Furthermore, around 97% of the runs resulted in accurate classification by the PNN. It is important to note that only one training run was used for each environment and path. The misclassification rate can be reduced if more training runs are used. For a given probability of failure, the pattern recognition based handoff algorithm performs fewer handoffs while the hysteresis rule executes several unnecessary handoffs. In some instances, the pattern recognition based handoff algorithm executes no handoffs because the signal is sufficiently strong to satisfy Relation (21). In reality, one would expect a handoff as the mobile approaches another base station with a stronger signal. This performance can be achieved by modifying Relation (21) to include interference from other mobiles. Since fewer handoffs result in a smaller signalling load on the network, the pattern recognition based handoff algorithm presented here performs better than the hysteresis rule.

VI. CONCLUSIONS

A new handoff algorithm based on pattern recognition for wireless communication systems is presented. A criterion for system performance is proposed and utilized in determining the necessity for handoff. A window of signal samples from nearby base stations constitutes a pattern vector which is classified using a probabilistic neural network. The use of averaged signals and the sequencing of classes allow for a small number of training vectors for the pattern classifier. The results presented here required only one training vector per class. Simulation results indicate that, for a given probability of failure, the pattern recognition based handoff algorithm yields fewer handoffs than the hysteresis rule.

The handoff algorithm based on pattern recognition can be extended to other possible performance criteria. The algorithm is being extended to consider mobile stations changing paths at intersections with variable speeds. Various feature extractors, pattern classifiers, and neural network architectures [4] will be incorporated. Finally, unsupervised learning methods can be applied to eliminate the necessity of training runs.

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