Handoff Optimization Using Hidden Markov Model

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Abstract—This letter establishes the similarity between the sensor scheduling problem and the handoff (i.e., base station assignment) problem in cellular networks. A mobile user behavior is then modelled by a Hidden Markov Model (HMM). The handoff problem is formulated as an optimization problem of base station scheduling that minimizes a cost function that involves the HMM state estimation error and base station measurement costs. The optimization problem can be solved using algorithms known as partially observed Markov decision processes.

Index Terms—Cellular networks, handoff, hidden Markov models, sensor scheduling.

I. INTRODUCTION

Handoff is the process of transferring an ongoing voice or data call from one cell to another as user moves through a coverage area of a cellular system. Processing handoff is key for telecommunication providers to meet required quality of service for users and to reduce cost. This is especially important in a congested inner city environment with small cell sizes where efficiency can greatly be improved by avoiding many unnecessary handoffs due to frequent back-and-forth switching between base stations (known as the ping-pong effect). Handoff is often modeled by a Markov process that defines the probability of the next state for each state and action. The Markov assumption, that the next state is solely determined by the current state (and current action), is valid for the handoff decision making if we can neglect the ping-pong effect. We show that the most probable base station sequence can be estimated if the user movement is modeled by HMM. The sensor scheduling problem [1]–[4] (often solved using HMM) is equivalent to the handoff optimization (also called the base station scheduling) problem in cellular networks. This has inspired this study to take a similar approach in solving the handoff optimization problem. Our contribution here is to show that Hidden Markov Model (HMM) can be effectively used to reduce unnecessary handoffs. This will reduce total cost associated with handoff to the service provider.

II. PRELIMINARIES

The base station assignment at each sample point has certain similarity to the sensor selection in the sensor scheduling problem. In the handoff problem, we consider three modes of observation analogous to the selection of sensors in the sensor scheduling. We observe the signal strengths from various base stations at any sample point to make a decision on the base station to be assigned (base station mode). If the handset is satellite enabled then an available satellite can be an alternative handoff option (satellite mode). We can also predict the next assigned base station without observing any base stations or satellites (predictive mode). In current practice, mobile service providers consider only the base station mode. However, measuring base station signal strengths at any sample point may not be necessary in the following scenarios: i) when the base station assigned to the previous sample point is still a suitable candidate in the new sample point and no handoff is required, or ii) when the signal strength at the new sample point may not be sufficient to observe the signal strengths at the new sample point. Therefore, the base station selection based on prediction instead of observation may be useful in such cases, hence, the prediction mode has the potential to improve performance.

The base station and satellite observation modes are identical to the HMM optimal filtering problem and the predictive mode is identical to the prediction problem known in HMM. The cost function for both modes can be formulated including the state estimation error and mode selection cost. The stochastic backward dynamic programming recursion can be used for estimating the optimal HMM mode scheduling policy. The dynamic programming recursion should be transferred to practical solutions using various heuristic algorithms reported, for example, in [1], [5]. There are various linear programming based algorithms for solving partially-observable Markov decision processes (POMDPs) described in [5]. Most optimal scheduling solutions are based on cost functions that are linear. However, an approximation of nonlinear cost functions by piecewise linear functions is used in [1]. In this letter, we derive new methods for finding the optimal schedule that minimizes a set of cost functions.

III. FRAMEWORK FOR HANDOFF OPTIMIZATION

We consider a cellular mobile network with $M$ base stations designated $B_1, B_2, \ldots, B_M$. Let a sample path be an arbitrary path in which a mobile user is traveling. Sample points are points on the sample path for which the signal strength values...
received from base stations are measured. Let \( i = 1, 2, \ldots, T \) denote discrete sample points. Let \( S_{Bi} \) be the signal strength at sample point \( i \) received from base station \( B_j \). Let \( S_{\text{min}} \) be the minimum signal strength below which the signal quality is unacceptable for the user, thus a successful handoff must fulfill \( S_{Bi} \geq S_{\text{min}} \), where \( B_j, 1 \leq j \leq M \) is base station assigned to the \( i \)th sample point. Denote the base station \( (B_j) \) assigned for the user at a sample point \( i \) by \( B_{ij} \) or \( B_{ij}^H \), \( j \in \{1, 2, \ldots, M\} \), depending on whether there was a handoff at that sample point.

In a hidden Markov model, the state transitions are not directly known but are estimated through feature vectors that have a probability distribution within each state. Assume \( X_t \) is an \( S \)-state HMM with state space \( \{s_1, s_2, \ldots, s_S\} \), where \( s_k \) denotes the \( S \)-dimensional unit vector with \( 1 \) in the \( k \)th position and zeros elsewhere. Consider an \( S \) state HMM with a discrete set of possible observation symbols \( \{O_j(\theta_m), \ldots, O_{N_m}(\theta_m)\} \), for observation mode \( \theta_m \) and \( m \in \{1, 2, \ldots, G\} \). Therefore, the total number of discrete possible observation symbols \( N_0 \) is given by \( N_0 = \sum_{m=1}^{G} N_m \). The initial probability vector, \( \pi_0 = [\pi_0(0)|s_1, \pi_0(s_2)|s_1, \ldots, \pi_0(s_S)|s_1] \), is defined as the probability of being in state \( s_k \) at the beginning of the state sequence, where \( X_0 \) is an initial state. The state transition probability matrix is \( A = [a_{kl}]_{S \times S} \), where \( a_{kl} = P(X_{t+1} = s_l|X_t = s_k) \), \( k, l \in \{1, 2, \ldots, S\} \) and \( \sum_{l=1}^{S} a_{kl} = 1 \). Let \( y_{ki}(u_{ki}) = O_{el}(\theta_m) X_{t-1} = e_k \), \( k = 1, 2, \ldots, S; \) \( r = 1, 2, \ldots, M; \) \( m = 1, 2, \ldots, G \). A joint probability that \( y_{ki}(u_{ki}) \) is an observation symbol at the sample point \( i \) using an \( u_m \) observation mode given that the HMM is in state \( e_k \) at the previous sample point (i.e., \( X_{t-1} = e_k \)). Here \( u_m \) is the mode of observation at sample point \( i \) selected as \( \theta_m \in \{\theta_1, \theta_2\} \) (as in Fig. 1), recall that \( G \) is the total number of available observation modes and \( 1 \leq m \leq G \). We consider that \( Y_t = \{y_{1i}(u_{1i}), y_{2i}(u_{2i}), \ldots, y_{pi}(u_{pi})\} \) represents the information available at the sample point \( i \), and the selection of the observation mode at the sample point \( i + 1 \) is based on \( Y_t \). Similar to sensor scheduling, we can proceed with the following stages: i) Scheduling: generate \( u_{i+1} = f_{i+1}(Y_t) \), where \( f_{i+1} \) denotes the policy to determine the next observation mode, ii) Observation: observe the symbols \( y_{i+1}(u_{i+1}) \), iii) Estimation: find the optimal state estimate \( \pi_{i+1} \) (which is a column vector of dimension \( S \)) of the Markov model \( X_{i+1} \) using the forward algorithm \( [1] \): \( \pi_{i+1} = E\{X_{i+1}|Y_i\} \). Since we consider that \( X_t \) is a unit vector, \( \pi_i(j) = P(X_t = e_k Y_t) \), where \( k \in \{1, 2, \ldots, S\} \). We represent the state of a mobile user at sample point \( i \) by \( e_j \), assuming mobile user continues with the previously allocated base station \( j \in \{1, 2, \ldots, M\} \) or by \( e_{i+M}(B_{ij}^H) \) if there is a handoff to base station \( B_{ij} \) \( (i \in \{1, 2, \ldots, M\} \). For example, if a user is allocated the base station sequence of \( B_j, B_j, B_j, B_j, B_j, B_j, B_j, B_j, B_j \) along the sample points \( i, i + 1, i + 2, i + 3, i + 4, i + 5, i + 6 \) the state transition sequence will be \( e_j, e_j, e_j, e_{i+M}, e_j, e_{i+M}, e_{i+M} \). Hence, user movements through the sample points can be modeled as an HMM with \( S = 2M \).

We consider the cost functions \( c(X_t = e_k, u_{i+1} = \theta_m) \) in selecting appropriate base station at sample point \( i \) in mode \( \theta_m \). The observation mode selection is associated with two types of costs: i) State estimation cost: state estimation error can be computed as the weighted distance \( E^m_{i+1} = \alpha_i(\theta_m)(|X_t - \pi_i|_D) \), where \( \alpha_i(\theta_m) \) are known positive weights for all observation modes, and the distance function \( |X_t - \pi_i|_D \) is assumed to be a convex function. For example, \( D \) can represent the \( L_2 \) norm then \( |X_t - \pi_i|_D \) refers the Euclidean distance among \( X_t \) and \( \pi_i \), its estimate \( \pi_i \). ii) Mode usage costs: The cost \( c(P_{i+1} \theta_m) \) is the cost of using the mode \( u_{i+1} = \theta_m \), when the state of Markov chain is \( X_t \). In our application, if \( X_t \in \{e_M+1, \ldots, e_{2M}\} \), there will be handoff related costs associated with the mode selected for the subsequent sample point. Further, a cost that is inversely proportional to the signal strength of the assigned base station will be added, in addition to the constant cost associated with each mode. We can represent the cost function as the summation of the above two components: \( c(X_t = e_k, u_{i+1} = \theta_m) = c_i(X_t, \pi_i)|X_t - \pi_i|_D + c_i(X_t, \pi_i) = E^m_t + c_i(X_t, \pi_i) \).

We consider the following four cost functions as in Fig. 2:

\[
\begin{align*}
\theta_1 & = \pi_v(X_t = \pi_v, u_{i+1} = \theta_1) = \rho^s + \frac{r^s}{S_{B_1}} + E^1_t \\
\theta_2 & = \pi_v(X_t = \pi_v, u_{i+1} = \theta_2) = \rho^p + \frac{r^p + r^h}{S_{B_1}} + E^2_t
\end{align*}
\]

\[
\begin{align*}
\theta_1 & = \pi_v(X_t = \pi_v, u_{i+1} = \theta_1) = \rho^s + \frac{r^s}{S_{B_1}} + E^1_t \\
\theta_2 & = \pi_v(X_t = \pi_v, u_{i+1} = \theta_2) = \rho^p + \frac{r^p + r^h}{S_{B_1}} + E^2_t
\end{align*}
\]

where \( k \in \{1, 2, \ldots, S\} \), \( \rho^s \) and \( \rho^p \) denote the direct cost of using \( \theta_1 \) and \( \theta_2 \) respectively, \( r^s \) is the cost associated with receiving lower signal strengths, and \( r^h \) and \( r^h \) are the handoff costs associated when using the modes \( \theta_1 \) and \( \theta_2 \). We can assume that \( \rho^s > \rho^p \), meaning that the use of received signal strengths is more costly than using the prediction. The cost is inversely proportional to the received signal strength with the constant \( \alpha^s \) in both modes, as we wish to maximize the received signal strength. We may select the handoff costs \( r^h \) to encourage the use of prediction immediately after a handoff. The state estimation error costs can be defined using \( L_2 \) norm cost (\( D = 2 \)):

\[
\begin{align*}
\theta_1 & = \pi_v(X_t = \pi_v, u_{i+1} = \theta_1) = \alpha_v(1 - \pi_i) \alpha_i(X_t, \pi_i) = \alpha_v(1 - \pi_i) \alpha_i(X_t, \pi_i)
\end{align*}
\]

Now we can obtain the base station scheduling defined by the following single objective unconstrained optimization problem:

\[
\min \ c(X_t, \theta_m)
\]

that minimizes a cost function that involves the HMM state estimation error and the base station measurement costs. A flow chart of the HMM-based handoff optimization is given in Fig. 3. Dynamic programming is often used to find the most appropriate mode schedule along the sample points that minimizes the
cost, as used in [1]. However, this approach is not scalable so efficient heuristics are required. It has been shown that for linear or piecewise linear cost functions, such approximations yield good results [1]. Nonetheless, it is still an unresolved problem for cost functions that cannot be approximated by piecewise linear functions. When the best mode schedule is known, we can estimate the states at all sample points, and obtain the optimal base station schedule.

IV. RESULTS AND DISCUSSION

For an illustration purpose, let us assume \( M = 3 \) (i.e., \( S = 6 \)). Let the probability of handoff between two consecutive samples be \( p_1 \), and assume that both handoff options (for example from \( B_2 \) to \( B_H^M \) or \( B_2^H \)) are equiprobable. By the definition of the states all transition probabilities from \( B_j \) and \( B_j^H \) to \( B_j^H \) are zero, where \( j \in \{1, 2, 3\} \) as mobile user does not handoff to same base station. The matrix \( A \) is given as follows: (see also Fig. 4):

\[
A = \begin{bmatrix}
1 - p_1 & 0 & 0 & 0 & p_2 & p_2 \\
0 & 1 - p_1 & 0 & 0 & p_2 & 0 \\
0 & 0 & 1 - p_1 & 0 & 0 & p_2 \\
1 - p_1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 - p_1 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 - p_1 & 0 & 0 & 0
\end{bmatrix}
\]

A reasonable estimate for the initial state vector is \( \pi_0 = [1/3, 1/3, 1/3, 0, 0, 0]^T \). Assume that there are two possible \( (G = 2) \) observation modes \( \theta_m \in \{\theta_1, \theta_2\} \). In \( \theta_1 \), we observe the signal strengths received from three base stations. It is then possible to use an HMM state filter (also known as the forward algorithm) to estimate the state at the \( i + 1 \)th sample point [1]. In \( \theta_2 \) we use an HMM state predictor to estimate the next state, without using the signal strengths received from the base stations. When using \( \theta_1 \), the observation (signal strength) \( S_{i+1,j} \) measured from base station \( B_j \) at the \( i + 1 \)th sample point is discretized into \( y_{i+1}(B_j) \in \{1, 0\} \), with two corresponding ranges of signal strength: 1 if \( S_{i+1,j} \geq S_{\text{min}} \), 0 if \( S_{i+1,j} < S_{\text{min}} \). There are \( 2^3 + 1 \) possible observation symbols \( y_{i+1} \) with \( M = 3 \) in the case of mode \( \theta_1 \) we have \( 2^3 \) observations, and there is an additional observation symbol “nothing” when \( \theta_2 \) is selected. All possible observation symbols \( \{N_0 = \sum_{m=1}^3 N_m = 9\} \) are \( O_1(\theta_1) = 000, O_2(\theta_1) = 001, O_3(\theta_1) = 011, O_4(\theta_1) = 100, O_5(\theta_1) = 101, O_6(\theta_1) = 110, O_7(\theta_1) = 111, O_8(\theta_2) = 000, O_9(\theta_2) = \text{nothing} \).

Let us assume that the probability of receiving \( S_{i+1,j} \geq S_{\text{min}} \) is \( p_2 \), where \( S_{i+1,j} \) is the signal strength received from \( B^j \) (the base station assigned to the \( i \)th sample point) at the sample point \( i + 1 \). The prediction (in \( \theta_2 \)) obviously leads to the observation symbol “nothing” with the probability of 1. We can define 6 × 9 matrix of symbol probabilities \( Z(u_i, \theta_m) = [P\{y_{i+1}(u_i) \in O_m | X_i = e_k, u_i, \theta_m\}]_{6 \times 9} \) for each observation option:

\[
Z(u_i, \theta_1) = \\
\begin{bmatrix}
\alpha & \alpha & \alpha & \alpha & \beta & \beta & \beta & \beta & 0 \\
\alpha & \alpha & \alpha & \alpha & \beta & \beta & \beta & \beta & 0 \\
\alpha & \beta & \alpha & \beta & \alpha & \alpha & \beta & \beta & 0 \\
\alpha & \alpha & \alpha & \alpha & \beta & \beta & \beta & \beta & 0 \\
\alpha & \alpha & \beta & \alpha & \beta & \alpha & \beta & \beta & 0 \\
\alpha & \beta & \alpha & \beta & \alpha & \beta & \beta & \beta & 0
\end{bmatrix}
\]

where \( \alpha = (1 - p_2)^4 \) and \( \beta = p_2/4 \) and

\[
Z(u_i, \theta_2) = \\
\begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]

The cost functions versus the signal strength graphs (Figs. 5–8) vary with the \( r^* \), as expected. At very low signal strengths, the cost is very high. Selection of a low \( r^* \) reflects the ability to work with a low signal strength at a reasonable cost. Selection of a high \( r^* \) would mean that the cost is very high at low signal strengths. All graphs show the dominating relationship between the total cost and the penalty associated with lower signal strengths. The sharp fall of the total cost when the penalty for low signal strength is low (and the signal strength is dropping towards zero) in Fig. 7 is as expected for the prediction mode.
in which the signal strength is no longer used. Therefore, when the penalty for low signal strength is low, the prediction mode is generally the lower cost option, whereas when it is high, the difference in the cost is minimal.

V. CONCLUSION

We have investigated the application of sensor scheduling to the scheduling of observation modes in the handoff problem leading to the estimation of the assigned base station sequence. We have developed and described new methods of finding the optimal schedule that minimizes a set of cost functions. In contrast to previously presented methods of base station sequence estimation, e.g., [6], the proposed method considers observation mode options, and creates an optimal schedule of observation modes, which can then be used to estimate the hidden states of HMM identical to the base station sequence.

REFERENCES