CLASSIFICATION-BASED RELAY SELECTION FOR VIDEO STREAMING OVER WIRELESS MULTIHOP NETWORKS

Mei-Hsuan Lu, Yu-Hsiang Bosco Chiu and Tsuhan Chen

Department of Electrical and Computer Engineering
Carnegie Mellon University
{meihsual,ychiu,tsuhan}@andrew.cmu.edu

ABSTRACT

Real-time streaming of audiovisual content over wireless networks is emerging as an important technology in multimedia communication. In this paper, we present a classification-based method to select appropriate relays in support of our prior work on Time-aware Opportunistic Relay for video streaming over wireless mesh networks. The proposed scheme works as follows: each candidate relay runs a Support Vector Machine (SVM) to decide whether it should participate in forwarding packets for a source-destination pair or not. The SVM considers features that are sensitive to video quality and is trained with an aim to maximize user perceived quality. Our evaluation results show that the classification-based approach outperforms the baseline scheme.

***Index Terms*—** wireless video streaming, opportunistic relaying, support vector machine

1. INTRODUCTION

Real-time streaming of audiovisual content over wireless networks is emerging as an important technology in multimedia communication. The development of new equipment, techniques, standards, and services makes streaming video an excellent tool for communication in enterprise, campus, home, and other environments.

In our prior work [1], a framework of Time-aware Opportunistic Relay (TOR) is proposed as a novel solution for sending video over error-prone, time-varying wireless environments. TOR improves streaming quality along two axes: *time* and *space*. In the time dimension, temporal characteristics of video data are exploited to better allocate the scarce wireless resource. The transmitter (the original source or an intermediate relay) inspects the transmission deadline of a packet and only sends the packet out if the deadline has not expired. Outdated packets are discarded by the transmitter to save bandwidth. In the space dimension, an opportunistic relaying technique that utilizes some of the gains from cooperative diversity is employed to increase throughput efficiency. Specifically, if the source is unable to reach the destination directly, out of the participating relays that overheard the packet, the one closest to the destination is chosen to forward the packet. If the elected relay still fails to reach the destination directly, a new relay is chosen to forward the packet based on the same principle. The process proceeds until the final destination receives the packet. As opposed to static relaying that predetermines the path of a packet, opportunistic relaying gives each transmission multiple opportunities to make progress, which results in great agility and flexibility in combating channel dynamics.

To implement TOR, two design issues need to be addressed: supporting time awareness and managing relays. [1] focuses on the first problem and leaves the second problem open. It adopts a naive relaying strategy that simply allows all nodes to participate. Such a naive scheme is not desirable because 1) including poor relays may dilute the opportunistic gain and 2) using too many relays may result in limited gain but significant overhead (e.g. increased collisions and cost in agreeing on the best forwarder). This is especially true in a large mesh network that consists of hundreds or even thousands of nodes.

To manage relaying effectively and efficiently, this paper presents a classification-based method to select a proper set of participating relays in a distributed manner. The proposed scheme works as follows: each candidate relay runs a Support Vector Machine (SVM) to decide whether it should participate in forwarding packets for a source-destination pair. The SVM considers features that are sensitive to video quality and is trained with an aim to maximize user perceived quality. While the problem of relay selection in opportunistic routing has been studied in the literature [2, 3], to the best of our knowledge, there has been no work addressing the specifics of media streaming over wireless networks.

This paper is organized as follows. Section 2 formulates the problem. Section 3 elaborates our classification-based approach in relay selection. Section 4 presents evaluation results. Section 5 concludes the paper.

2. PROBLEM STATEMENT

The problem of relay selection can be formulated as follows. Let N denote the number of nodes in a network. We define a selection instance as:

$$\Theta = [\theta_1, \theta_2, \cdots, \theta_N]^T \tag{1}$$

where $\theta_i = \{0, 1\}$ is a binary variable with one represents relay i is a participating relay and zero otherwise. It is clear from Eq.(1) that there are 2^{N-2} possible choices for a particular source-destination pair in a topology (i.e. source and destination nodes are always in the selection). The solution of the relay selection problem is then represented by

$$\Theta^* = \arg\max_{\Theta} Q(\Theta|\mathbf{p}, s, d) \tag{2}$$

where $\mathbf{p}$ is a $N \times N$ matrix with (i, j) element representing the link delivery probability between node i and node j and s and d specify the source-destination pair involved in the video transmission. The use of the best selection instance Θ^* leads to the highest received video quality Q at the destination.

Finding the optimal solution to Eq.(2) is nontrivial because: 1) deriving analytical expressions for Q as a function of link delivery probabilities is very challenging. In [5], a discrete-time Markov chain is used to model opportunistic routing performance. However, this model uses a $(2^{N-2} + 1) \times (2^{N-2} + 1)$ transition matrix to compute the probabilities of packet delivery status given a set of relays, which is too complex; 2) wireless channel conditions and video content characteristics may change over time, requiring frequent update of Eq.(2). As such, exhaustive searching all the possible choices is impractical due to the associated complexity, in particular in a large-scaled network. These issues lead us to use a distributed, classification-based method to solve the problem: Each node determines if it is suitable to participate in the forwarding of a video packet based on local information, rather than optimizing all of them jointly.

3. CLASSIFICATION-BASED RELAY SELECTION

We formulate relay selection as a binary classification problem. Each candidate relay is considered as a data point and the classification result indicates whether the candidate relay should participate in forwarding a packet for a source-destination pair.

3.1. Support Vector Machine

The classifier adopted in our classification task is Support Vector Machine (SVM) [6] which has been widely used in a variety of different classification problems. Besides constructing a hyperplane ($\mathbf{w} \cdot \mathbf{x} + b = 0$) to separate positive and negative examples like most classifiers, given training examples $(\mathbf{x_i}, y_i)$, SVM tries to maximize the margin between hyperplane and training examples through maximizing $1/||w||$. Together with hinge loss $((\mathbf{w} \cdot \mathbf{x}_j + b)y_j \geq 1, \forall j)$, after training completed, only data points that are on the margin need to be retained (support vectors) so we can discard a significant proportion of the original training data. Additionally, through mapping data into high dimensions using kernel functions, we can separate data which are originally not linearly separatable. An example of the separating hyperplane created by SVM to classify data is shown in Figure 1. Given sufficiently large traninig set, the benefit of SVM can outweigh the gain from using other classifiers with online adaptation (e.g. Gaussian Mixual Model). In our experiment setting, those nodes which should be selected as relays are labeled as positive examples and nodes which should not be selected are labeled as negative examples.

In the run time, the amount of computation depends on how many boundary points (the support vectors) are retained after training (which is done off line). When Gaussian kernel is used, the amount of computation will be three multiplication plus one exponent for each support vector retained. Combining with the sparse property of SVM, the amount of computation will be small if the training set is compact and representative enough for the overall data set during selection. Note that the classification is performed only during node initialization or when network conditions change. Other than that, relays simply make decision according to the last classification result. This suggests the complexity of classification can be spread over a sequence of packets which should be sustainable in most wireless routers.

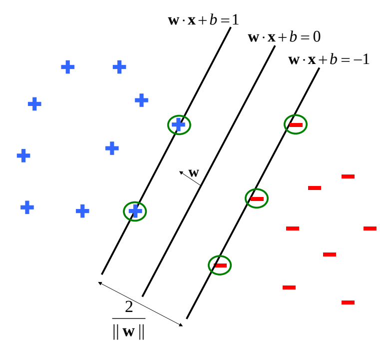

Fig. 1. Example for the maximum-margin hyperplane and margins for a SVM trained with samples from two classes. Support vectors are indicated by the circles.

3.2. Feature extraction

We adopt expected transmission count (ETX) [4] as the cost metric. The ETX of a link is the expected number of transmissions to deliver a packet over that link. The ETX of a path is the sum of the ETX of its composing links. It has been shown that ETX is an effective path metric for multi-hop wireless networks. Intuitively, if the path ETX from node X to node Y is large, X's transmission to Y involves long latency and high bandwidth consumption, both of which are harmful to video quality at the destination. Specifically, our features set includes the following:

3.2.1. Destination ETX

Destination ETX is the ETX of the lowest-ETX path from a node to the destination. Clearly, nodes that have a smaller destination ETX are more effective and should be favored.

3.2.2. Source ETX

Source ETX is the ETX of the lowest-ETX path from the source to a node. Given two candidate relays with identical destination ETX, the one that has a shorter source ETX is more effective than the other. Thus source ETX reveals important information so it is included in our feature set.

3.2.3. Source ETX and Destination ETX of neighboring nodes

The effectiveness of a node to function as a relay is relative to their neighbors. For example, the benefit of using a relay is insignificant if there exists a dominant neighbor that has a high likelihood to hear the source and a low cost to relay. The connectivity between a node and its neighbors also reveals the density of the network. There is a penalty to use too many relays as potential forwarders in a large dense network [2].

Based on the above rationale, by experiments, we consider the source ETX and destination ETX of the five nearest neighbors to be an important attribute and include them in our feature set. The definition of neighbors is based on a threshold of link delivery ratio. For nodes that have fewer than five neighbors, we fill in the remaining feature values with infinity.

The suitability of a node to function as as a relay is scenario dependent. A node with large source ETX or/and large destination ETX is not preferred when sources and destinations are close, but it may be an effective relay for distant sources and destinations. To account for differences across scenarios, we normalized the above features with the ETX of the lowest-ETX path between the source and the destination. By doing so, the features we extracted could be invariant across scenarios. The lowest-ETX path can be obtained by running Dijkstra's algorithm with link ETX as the edge cost.

3.3. Feature collection

The main benefit of using ETX as a cost metric is it is easy to obtain. In practice, nodes leverage the mechanism in [4] to collect features. Specifically, a node X periodically broadcasts a sequence-numbered probe packet. This allows each neighbor to calculate the link delivery ratio whenever it receives a probe from X. The ETX of a link is simply the reciprocal of the link delivery ratio. The ETX of a route is the sum of the ETX of its composing links, which is obtained via periodical link-state flooding.

4. EVALUATION RESULTS

4.1. Setup

To estimate performance of our classification-based scheme, we perform evaluations in a network with 100 stationary nodes randomly placed in a 1km-by-1km square, as illustrated in Figure 2. Link delivery ratios are computed assuming binary phase shift keying (BPSK) and log-distance path

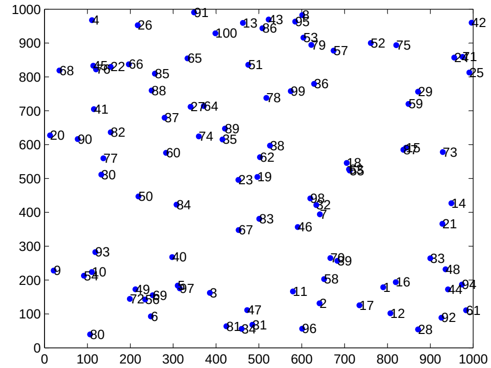

Fig. 2. Node topology used in the evaluation

loss in a free space [7]. Each attempt to transmit a packet is considered a Bernoulli trial with a probability of the link delivery ratio.

In our experiment, 55 pairs of nodes are randomly chosen as sources and destinations. The optimal selection (the ground truth data) corresponds to the set of relays with highest video quality at the destination. We ran a brute-force search on all possible sets of relays with a variety of video sequences, spanning from slow to high motions, to obtain the optimal set of relays for each source-destination pair. The video sequences are encoded with H.264/AVC software JM 14.2 [8] in QCIF and CIF format at a frame rate of 30 Hz. Each group of pictures (GoP) contains a leading I frame followed by 14 P frames. The initial delay is 500ms, which is equal to the interval of one GoP. The coded bitstream is packetized into 1024-byte MAC frames.

4.2. Training

During the offline training phase, 35 randomly selected source-destination pairs are used as the training set. Kernel SVM with Gaussian kernels are used to classify whether a node in a given scenario is selected as a relay. As a heuristic, nodes on the shortest path are always considered as relays. To obtain the weighting (C) of the hinge loss and the kernel bandwidth (γ) for Gaussian kernel SVM, a 7-fold cross

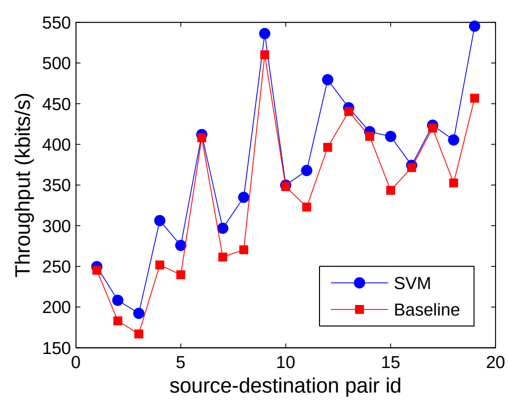

Fig. 3. Throughput result

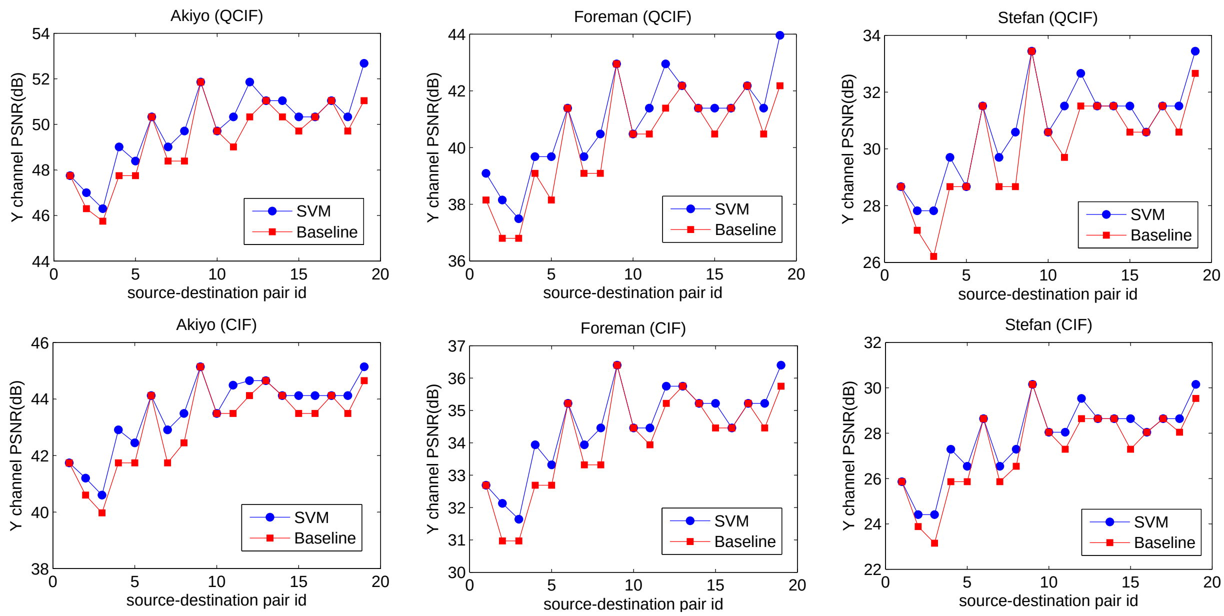

Fig. 4. Results of Y channel PSNR for Akiyo, Foreman, and Stefan in QCIF and CIF format

validation process is applied on the training data set. In the cross validation process, instead of using traditional averaged accuracy as our performance measure, we use a metric Δ which is defined in terms of video quality to select the best parameters for SVM training:

$$\Delta(\%) = (PSNR_{svm} - PSNR_{opt})/PSNR_{opt} * 100 \quad (3)$$

where $PSNR_{svm}$ is the PSNR value of the Y channel using the predicted best set of relays given a particular set of SVM parameters and $PSNR_{opt}$ is the PSNR value of the Y channel using the optimal selection of relays. The metric Δ represents the normalized distance to the optimum, in terms of video quality. We use Δ to train the SVM because the performance of interest is the user perceived video quality, rather than the classification accuracy over all nodes in a network. The metric is normalized by $PSNR_{opt}$ so that it is invariant across different scenarios.

4.3. Testing

The remaining 20 source-destination pairs are used in testing the SVM (with $C = 529$ and $\gamma = 8.8$ determined by cross validation as mentioned above). The baseline scheme uses relays on the shortest path between the source and the destination.

Figure 3 shows the throughput result. The source-destination pair id is ranked according to the physical distance between the source and the destination, from short to long. In general, our classification-based method outperforms the baseline scheme. For video quality, Figure 4 shows the PSNR of the Y channel. Again, we can see that our classification-based method outperforms the baseline approach across sequences with different motions and resolutions.

5. CONCLUSION AND FUTURE WORK

In this paper, we presented a distributed classification-based approach to select relays for opportunistic relaying in multi-hop wireless networks from video data's perspective. Each node runs a pre-trained Support Vector Machine (SVM) to decide whether it should participate in forwarding packets for a video source-destination pair. With an aim to maximize user perceived video quality by the SVM, our evaluation results show that the classification-based method outperforms the baseline scheme, both in throughput and PSNR. In the future, we plan to investigate more video coding features (e.g. intra or inter-coded frames, base or enhancement layers, or region-of-interest information) to improve the end-to-end quality.

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