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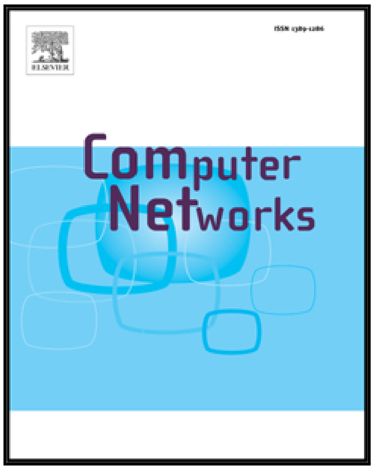

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Skipping-based Handover Algorithm for Video Distribution Over Ultra-Dense VANET

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Abstract

Next-generation networks will pave the way for video distribution over vehicular Networks (VANETs), which will be composed of ultra-dense heterogeneous radio networks by considering existing communication infrastructures to achieve higher spectral efficiency and spectrum reuse rates. However, the increased number of cells makes mobility management schemes a challenging task for 5G VANET, since vehicles frequently switch among different networks, leading to unnecessary handovers, higher overhead, and ping-pong effect. In this sense, an inefficient handover algorithm delivers videos with poor Quality of Experience (QoE), caused by frequent and ping-pong handover that leads to high packets/video frames losses. In this article, we introduce a multi-criteria skipping-based handover algorithm for video distribution over ultra-dense 5G VANET, called Skip-HoVe. It considers a skipping mechanism coupled with mobility prediction, Quality of Service (QoS)- and QoE-aware decision, meaning the handovers are made more reliable and less frequently. Simulation results show the efficiency of Skip-HoVe to deliver videos with Mean Opinion Score (MOS) 30% better compared to state-of-the-art algorithms while maintaining a ping-pong rate around 2%.

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1. Introduction

Next-generation communications will not only rely on new access technologies, such as Massive MIMO and Millimeter Wave, but they will also take advantage of existing communication infrastructures, such as WiFi and LTE, to provide ubiquitous and efficient communication [1]. In this sense, 5G networks will be composed of ultra-dense heterogeneous radio networks compared to 4G systems, increasing the data-rate at the network edge. For instance, densification consists of the massive deployment of macrocells, microcells, small cells, relays, and other communication solutions, achieving both higher spectral efficiency and higher spectrum reuse rates [2, 3, 4]. These cells can be used to offload traffic from macrocells to enable the communication of all kinds of devices in highly dense, ubiquitous, and heterogeneous environments, having an immense impact from business and social standpoints [5].

The next-generation wireless technology will pave the way for extensive use of high demanding applications such as video-based services for mobile users, anytime and anywhere [6], including real-time distribution of advertisement or entertainment videos over vehicular networks (VANETs). One of the critical issues for future and success of video distribution over VANETs will be the ability of heterogeneous networks to support efficient mobility and resource management schemes to increase the Quality of Experience (QoE), while optimizing the usage of high demanded wireless/radio resources [7]. However, the increased number of heterogeneous cells makes mobility management a challenging task for VANETs, since vehicles, especially in urban environments, frequently switch among different heterogeneous networks, *i.e.*vehicles travel leaving an area of a cell to enter another one very often [8]. Many handovers result in excessive signaling overhead, disconnection, and ping-pong effect, *i.e.*, a vehicle disconnects from a cell and afterward connects again to another one moments later [9]. These issues increase the packets/video frames losses, leading to a poor QoE for video applications in such a VANET scenario [10].

Skipping unnecessary handovers is beneficial to the network and also to the user's experience [2]. A skipping-based handover consists of avoiding consecutive handovers to maintain the QoE as high as possible, which means reducing the handover frequency by sacrificing some of the best cell connectivity associations [11]. Hence, this allows maintaining a longer service duration with the serving cell with at least a minimum service quality level, while reducing signaling overhead and zapping delay. For instance, a handover decision based on RSS skips some handovers even if they mean that the user is not receiving the best Signal-to-interference-plus-noise-ratio (SINR) at all times, mitigating ping-pong effect [2]. Skipping-based handover schemes are often associated with mobility prediction information to maximize the connection duration without compromising the network/application performance [12, 13]. This is achieved by giving priority to cells with the highest probability that the user remains connected for more time [14]. However, skipping-based handover schemes alone are not enough to deliver videos with QoE support. Hence, a handover decision based on a mobility prediction coupled with QoE and Quality of Service (QoS) parameters improve video delivery over VANETs by avoiding ping-pong handovers and by improving the usage of network resources [15].

In this article, we propose a multi-criteria skipping-based handover algorithm for video distribution over ultra-dense VANETs, called Skip-HoVe. It guarantees seamless handovers in an ultra-dense VANETs scenario to deliver videos with high QoE by taking into account mobility prediction, QoS, QoE, and radio parameters. Skip-HoVe supports an Analytic Hierarchy Process (AHP) to assign different degrees of importance for each criterion. Skip-HoVe considers proactive Ping-Pong avoidance for handover decision, by skipping handovers when QoE and QoS are acceptable and stable. The implementation of Skip-HoVe is available for downloading on Github[1].

We tested two mobility prediction technique with Skip-HoVe, namely AutoRegressive Integrated Moving Average (ARIMA) and Kalman Filter (KF). Based on a real-world vehicular dataset analysis, ARIMA provided a higher accuracy for mobility prediction compared with KF. Therefore, we chose ARIMA to be considered as a mobility prediction technique used by Skip-HoVe. Simulation results showed that the Skip-HoVe algorithm delivered videos with QoE 14% better compared to state-of-the-art algorithms in ultra-dense VANET scenarios. For instance, Mean Opinion Score (MOS) results showed a improvement of 30% in subjective evaluations, while ping-pong handover was kept at a low 2% rate. The main contributions of this work

[1]https://github.com/lsiddd/hove

are summarized as follows: (i) a skipping-based handover algorithm that maximizes connection time to a serving cell; (ii) a multi-criteria decision-making technique for handover decisions in an ultra-dense VANET scenario; and (iii) simulation results to show the performance of Skip-HoVe to deliver videos with QoE support in ultra-dense VANET scenarios compared to existing handover algorithms.

We organize the rest of the article as follows. Section 2 outlines the state-of-the-art about handover algorithms, their main drawbacks to provide video dissemination with QoE support. Section 3 describes the Skip-HoVe Algorithm. Section 4 discusses the simulation scenario and results. Finally, Section 5 presents the conclusion and possible extensions.

2. Related Work

Gong *et al.* [16] proposed a Fuzzy Analytical Hierarchical Process (FAHP) algorithm to reduce failure and ping-pong probability in Heterogeneous Ultra-dense by defining a Time-To-Trigger (TTT) during handover execution. Although it highlights the importance of a multi-parameter handover decision, the use of TTT can have undesired effects, such as link failures and delayed handovers [17]. Silva *et al.* [18] proposed an adaptive TTT handover based on Fuzzy logic and user speed. Such a handover algorithm collects mobility parameters to predict user location for content dissemination, and not for handover purposes, showing that offloading from macrocells to Small Cells can be essential in a heterogeneous environment. One of the main benefits of the proposed scheme is the reduced ping-pong rates in dense scenarios. However, it is not intended for multimedia traffic, and, thus, it does not consider QoE for decision making. Liu *et al.* [19] introduced an adaptive TTT to minimize the impact of frequent handovers in Ultra-Dense Networks. That work applies a Fuzzy TOPSIS decision to choose the best handover candidate to achieve proper QoS levels. However, it does not apply predictive metrics or any QoE monitoring, which can significantly enhance the quality of the decisions in a VANET scenario.

Arshad *et al.* [12] showed that handover introduces an overhead in the network and is, sometimes, redundant. Skipping some handovers can be beneficial for the network while maintaining a seamless QoS. However, that work offers small support for video transmission and may not be suitable for the strict requirements involved. Demarchou *et al.* [2] studied the challenge of reducing handover rates (*i.e.*, skipping) in ultra-dense networks. That work considers the trajectory prediction in the skipping decision, but only assumes a simple model based on position and velocity. Xu *et al.* [20] proposed a delay oriented cross-tier handover skipping to maximize the performance of low latency applications in ultra-dense networks. Their work derived an analytical expression for the adequate capacity of users during the handover execution and proposed a resource allocation scheme in Target Cells to reduce blocking probability. It does not employ predictive schemes, or mobility information into the decision, which may improve the decision quality and positively impact user QoE.

Medeiros *et al.* [21] showed the importance of performing a multi-criteria handover decision to balance metrics from different layers, namely, radio measurements, QoS, and QoE. That work uses AHP to balance the metrics according to predefined importance levels assigned to each, but the algorithm presents high handover rates, which is harmful to QoE in dense scenarios. Sargento *et al.* [22] proposed a connection manager for VANETs with heterogeneous technologies, VANET Connection Manager (VCM), which is based on an Analytical Hierarchic Process (AHP) that combines information from multiple sources (vehicle speed, GPS, heading, RSSI, and available technologies such as DSRC/WAVE, IEEE 802.11 and 4G Cellular), and decides what is the best connection available at all times, trying also to minimize the number of handovers. The AHP is optimized using interaction with a Genetic Algorithm (GA). This approach includes mobility prediction through the expected connectivity time but does not include QoE requirements. Zhang *et al.* [23] proposed a classification of applications sensitive and insensitive based on user experience. A handover decision switches to a more energy-efficient network during idle timer and a high-performance network when predicted. Chen *et al.* [24] proposed a QoE estimation to correlate QoS and QoE to improve user satisfaction, not focusing only on call blocking probability and handover dropping probability. However, video sharing requires more subjective metrics to describe QoE, such as MOS, which can be mimicked by machine learning algorithms and integrated into automated decisions.

Table 1 summarizes the main characteristics of analyzed handover algorithms in terms of QoE-awareness, mobility prediction-awareness, and skipping-based handover. Based on our analysis of the state-of-the-art, we conclude that video distribution over ultra-dense VANETs scenarios requires an efficient skipping-based handover algorithm to maintain a minimum number of disruptions and avoid occurrence of ping-pong. Such a scheme requires efficient mobility prediction technique to improve handover decisions. Furthermore, it is vital to consider a multi-criteria decision scheme to balance heterogeneous metrics that will directly or indirectly impact user experience on consuming video services. To the best of our knowledge, Skip-HoVe incorporates all of these critical features that have not been provided in a unified handover algorithm before.

Table 1: Summary of analyzed handover algorithms for ultra-dense VANET scenarios

	Features			
	Technique Used	QoE-Aware	Mobility Prediction	Handover Skipping
Gong et al. [16]	Adaptive TTT			
Silva et al. [18]	Adaptive TTT			
Liu et al. [19]	Fuzzy Logic			
Arshad et al. [25]	Handover Skipping			✓
Demarchou et al. [2]	Handover Skipping		Assumed present	✓
Xu et al. [20]	Delay-Oriented			
Handover Skipping			✓	
Medeiros et al. [21]	AHP	✓		
Sargento et al. [22]	AHP		Expected contact time	✓
Zhang et al. [23]	Q Learning	✓		
Chen et al. [24]	Q Learning	✓		
Skip-HoVe	ARIMA + AHP	✓	✓	✓

3. Skip-HoVe Algorithm

In this section, we introduce a multi-criteria skipping-based handover algorithm for video distribution over an ultra-dense VANET scenario, called Skip-HoVe. It aims to mitigate the adverse effects of frequent handovers while maintaining an acceptable QoE level of delivered videos. We employ a proactive skip avoidance condition during a handover decision, as well as the decision skips handovers when QoE and QoS are acceptable and stable, while always preferring cells that maximize the connected time.

3.1. Network and System Model

We consider a scenario composed of a set of n vehicles $V = \{v_1, v_2, ..., v_n\}$ with an individual identity ($i \in [1, n]$). Each vehicle v_i is assumed to have a radio transceiver to enable the communication between vehicles (V2V) and with an infrastructure (V2I). For V2I communication, we consider an ultra-dense cellular network as a K-tier cellular network, where each tier models the cell of a particular access network, such as macrocells, small cells, or picocells. In this sense, we consider a set of cells $B = \{b_1, b_2, ..., b_m\}$ with an individual identity ($j \in [1, m]$) and deployed in fixed known locations (x_j, y_j). The cells across tiers may differ in terms of the spatial density and transmit power P_j. We also assume a core network with high capacity fibers connected to avoid congestion on the backhaul links. We denote $N(b_j) \subset B$ as a subset of cells within the radio range (R_{max}) of a given vehicle v_i.

Regarding the video content, each compressed video is composed of three types of frames, *i.e.*, I-, P-, and B-frames [26]. These frames are arranged into sequences, called a group of pictures (GoP), which contains all the information required to decode a given video within a period. We denote a given Video Flow ($VF_i = g_1, g_2, ..., g_k$) as a set of k GoP g. Each frame in a given GoP g is divided into one or more video packets (p), depending on each frame size. Each packet p contains, in addition to the data payload, other encoder parameters, such as frame-type flag, Id, length, timestamp, and packet segmentation [26]. To obtain this information, a packet monitor at the client-side extracts the frame type and intra-frame dependency information for each packet p [27], since each VF starts with a sequence header followed by a GoP header, and then by one or more coded frames.

Each vehicle v_i can measure the received signal quality as a radio parameter from each available cell $N(b_j)$, which can be measured using the Reference Signal Received Quality (RSRQ). Each vehicle v_i is aware of its location $L(x_i, y_i, t)$ in a given timestamp t using a positioning system, such as GPS. Each vehicle v_i travels following a given trajectory $traj_i$ with a speed s_i ranging between a minimum (*e.g.*, s_{min}) and a maximum (*e.g.*, s_{max}) speed limit. Each vehicle v_i moves over different areas due to their fast movement, and, thus, it frequently has a different set of available cells $N(b_j)$.

The handover manager entity, such as LTE Mobility Management Entity (MME), performs all Skip-HoVe handover phases, namely: Measurement, Decision, and, if a handover is necessary, Execution. This entity must have a connection to each b_j, such as an S1 interface. Each vehicle v_i communicates with the handover manager logically through its current b_j to report the measurements, which can be requested by the mobility management if needed. Each vehicle v_i performs measurements, while the MME performs the handover decision and execution. At the measurement phase, the handover manager must obtain information from both v_i and $N(b_j)$. Afterward, the handover decision phase considers information collected in the previous phase to select the b_j that a given vehicle v_i must connect to. Finally, the handover execution phase is responsible for changing the connection between a given vehicle v_i from a serving cell to a target cell, chosen by a handover manager. In the following, we introduce more details about each phase.

3.2. Measurement Step

Skip-HoVe algorithm collects information from both vehicle v_i and available cells $N(b_j)$ at the measurement step. Specifically, Skip-HoVe gets from the vehicle v_i information about its estimated QoE, current location, QoS, and radio parameters. On the other hand, Skip-HoVe collects QoS and QoE information from the serving and candidates cells $N(b_j)$ to understand their performance to make a better decision. The handover manager assigns the maximum QoS and QoE values as soon as a given cell is idle to give preference to such cells, and, thus, providing load balancing. In the following, we introduce the description of the mobility prediction, QoE, and QoS monitoring modules.

3.2.1. Mobility Prediction

Vehicle mobility is approximately linear, increasing the accuracy of vehicular mobility prediction [28]. In this sense, a mobility prediction algorithm, such as ARIMA or KF [28], enables to estimate the position $L(x_i, y_i, t+1)$ of a given vehicle v_i in a future timestamp $t+1$ based on the vehicles speed and location using kinematics equations. Based on the mobility prediction, it is possible to avoid connections to a cell that might no longer be available in the future. It is useful to treat mobility as a time series, where each measurement constitutes an entry for the predictor to adjust the prediction model. The prediction granularity, in a spacial and temporal context, may be defined by a measurement frequency. For instance, Skip-HoVe performs a new prediction at every new measurement. We also evaluated the granularity of mobility prediction ranging from 0.1 to 2 seconds in steps of 0.2 seconds. Based on our evaluation, we adopted a granularity of 1 second, given the simplicity of the prediction module, which does not cause significant overhead. However, for other scenarios, this value can be adjusted in order to fit mobility and computing resources accordingly.

Based on the predicted vehicle location, Skip-HoVe computes the distance $d_{i,j}$ between the vehicle future position $L(x_i, y_i, t+1)$ and its available cells $N(b_j)$. Large distance means a cell from which the vehicle is distancing itself, which should be avoided. However, higher values correspond to a higher score for such b_j during a handover decision, and, thus, distances vector *Dists* are inverted, as shown in Eq. 1.

$$Dists = \begin{bmatrix} \frac{1}{d_{i,0}} & \frac{1}{d_{i,1}} & \frac{1}{d_{i,2}} & \cdots & \frac{1}{d_{i,3}} \end{bmatrix}. \quad (1)$$

Several values in the vector *Dists* could be near zero, due to distances being too high. In this sense, the vector *Dists* must be normalized by dividing every element by the absolute value of the vector *Dists*, which is computed based on Eq. 2.

$$|Dists| = \sqrt{(d_{i,0})^2 + (d_{i,1})^2 + \cdots + (d_{i,2})^2}. \quad (2)$$

These values can be fed to the algorithm when computing the score d to the individual cell b_j, which is computed based on Eq. 3.

$$d = \frac{d_{i,j}}{|Dists|}, \forall d_{i,j} \in Dists. \quad (3)$$

3.2.2. QoE-monitor

Skip-HoVe considers a low complexity hybrid QoE-monitor running on a given vehicle v_i to estimate the QoE of a given video flow VF_i, such as introduced by Medeiros *et al.* [21]. Hybrid QoE video quality assessment measures the video quality level in real-time based on information from IP and video codec packet headers [26]. In this sense, a machine learning technique, namely, a random forest, predicts the MOS value based on frame loss and video characteristics with low complexity.

At the client-side, a packet monitor examines the MPEG bitstream to verify which frame is lost in a GoP g to compute the frame loss ratio for each frame type. This is because the loss ratio of each frame and GoP size differently affect the QoE of transmitted videos [26]. We consider an entire machine learning process, *i.e.*, training, testing, and validation, to predict the MOS value for a given video flow VF. In this sense, the QoE-monitor considers a random forest as a low complexity machine learning technique to correlate the loss rate of I-, P-, and B-frames and GoP size with the assigned MOS values, achieving a final MOS score. Random forest works with the concept of forming smaller selections of a tree, informing different results in these smaller trees, and counting the most chosen solution (*i.e.*, majority tree) as the answer to a question: what is the estimated MOS value considering the GoP size and loss ratio of I-, P-, and B-frames?

3.2.3. QoS- and signal-monitor

Regarding QoS parameters, Skip-HoVe considers PDR to evaluate the connection between a given vehicle v_i and a cell b_j. Each vehicle v_i computes the PDR by using packet Ids to detect the lost packets, and associated with a cell b_j. From the radio perspective, Skip-HoVe algorithm considers the RSRQ value computed by a given vehicle v_i for each beacon message transmitted by a cell b_j (both serving and candidate cells). RSRQ measures the received signal quality in the LTE networks. All measurements are sent to the vehicle's serving cell and can be requested by the mobility management when they execute their decision step.

3.3. Decision Step

At this step, the handover Manager computes a score S_j to each available cell $N(b_j)$ based on Eq. 4, in order to find the best available cell b_j for a given vehicle v_i connect to. Skip-HoVe considers multiple metrics with different priorities for handover decisions, and, thus, it needs to assign a weight w_i for each input metric M_i, *i.e.*, QoE, QoS, and distance. For instance, weights can represent how many times QoE is more or less critical than QoS.

$$S_j = \sum_{i=1}^{n} w_i \times M_i. \tag{4}$$

We consider AHP [29] to compute the influence factor for each parameter since AHP provides a structured technique for decision-making of problems with multiple parameters involved. AHP decomposes a complex problem into a hierarchy of simpler sub-problems by combining qualitative and quantitative factors for the analysis, allowing the system to find an ideal solution when there are several criteria considered in the handover process. Specifically, AHP considers a pairwise comparison between the numerical values of each collected parameter and its relative degrees of importance, in order to adjust at runtime its weights. A numeric value represents this pairwise comparison, and pairs must not contradict each other, *e.g.*, if a metric i is two times more important than metric j, then j is 1/2 times as important as i. We define five importance levels to compare each pair of parameters, which indicate how vital one parameter is compared to others and the inverted comparison, as shown in Table 2.

Table 2: Pairwise context importance

$c_{i,j}$	Definition
4	i is much more important than j
2	i is more important than j
1	i is as important as j
1/2	i is less important than j
1/4	i is much less important than j

The handover Manager constructs for each vehicle v_i a comparison matrix $A = (C_{i,j})_{mxm}$, where lines and columns represent the metrics to represent all pair-wise comparisons, as shown in Eq. 5. We denote $c_{i,j}$ as how important the i-th element is compared with the j-th element, and m denotes the number of elements to be compared.

$$A = (C_{i,j})_{nxn} = \begin{pmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,n} \\ c_{2,1} & c_{2,2} & \cdots & c_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n,1} & c_{n,2} & \cdots & c_{n,n} \end{pmatrix}. \tag{5}$$

Matrix $C_{i,j}$ indicates which parameters have higher priority over others, as shown in Eq. 6. We denote d as the normalized distances computed by Eq. 2, QoE represents the predicted MOS score, and Signal represents the RSRQ intensity, and QoS means the PDR. For instance, in the first line, we observe that distance metric d is two times more important than QoE, and four times more critical than QoS and Signal. It is essential to highlight that if one criterion is considered to be two times more important than another one, then the other is 1/2 as relevant compared with the first, due to the inverted comparison. Note that the main diagonal of the Matrix must always contain the value 1, as the metric is compared with itself.

$$C_{i,j} = \begin{array}{c} d \\ QoE \\ QoS \\ Signal \end{array} \begin{array}{c} \begin{array}{cccc} d & QoE & QoS & Signal \end{array} \\ \begin{pmatrix} 1 & 2 & 4 & 4 \\ 1/2 & 1 & 2 & 2 \\ 1/4 & 1/2 & 1 & 1 \\ 1/4 & 1/2 & 1 & 1 \end{pmatrix} \end{array}. \tag{6}$$

We find the eigenvector of the matrix ($C_{i,j}$) by dividing each element by the sum of its column, obtaining the eigenvector $W = [0.5\ 0.25\ 0.125\ 0.125]$, meaning that that the normalized distances will have a weight of 0.5 for d, 0.25 for QoE, 0.125 for QoS and 0.125 for Signal as well. We analyzed the consistency ratio (CR) and the consistency index (CI) of the derived weight vector, *i.e.*. We analyzed if the derived weight vector is correct. In this sense, if CI = 0 and CR = CI/RI $\leq$ 0.1, then the inconsistency of the constructed comparison matrix is acceptable. Following the process of consistency checks, we can find out that the comparison matrix ($C_{i,j}$) in Eq. 6 has CI = 0 and CR = 0. Therefore, the inconsistency of the constructed pairwise comparison matrix is acceptable to meet the validation criteria defined for AHP [29].

The handover manager performs a product between the eigenvector and a vector that stores the measured values M_i, obtaining the score of S_i for all available cells $N(b_j)$. Hence, the handover manager selects the cell with the highest score S_i, which is the most suitable for the vehicle v_i to connect at the moment. In the decision/skipping step, the handover manager must decide if a handover is necessary based on a skipping-based handover decision since a handover execution is costly and should be avoided if not essential. Skip-HoVe considers a QoE threshold to trigger the handover, which is defined as 4 for the predicted QoE value [30]. As soon as the predicted QoE value computed by the QoE-monitor is above this threshold, a handover is considered unnecessary and skipped, since the video is already delivered to the vehicle v_i with an acceptable QoE. On the other hand, as soon as the handover is necessary, the decision step chooses the best available cells $N(b_j)$ for the vehicle v_i to connect, explained hereafter.

Skip-HoVe must also analyze if the decision constitutes a ping-pong handover (*i.e.*, when a vehicle leaves a cell and returns within up to 4 seconds [31]). If so, Skip-HoVe actively skips the execution of the handover, considered wasteful to network resources. On the other hand, the Skip-HoVe algorithm will consider such a cell for handover decisions after this time window has passed. Algorithm 1 introduces the primary operations performed by the

Skip-HoVe algorithm to deliver video content with QoE support over ultra-dense VANET. The handover manager executes all three phases, while the mobile node is connected to any cell.

Algorithm 1: Skip-HoVe algorithm

$\forall$ vehicles in the network $v_i \in V$
while *vehicle is connected* **do**
    Vehicle sends measurements to its serving cell *Handover Manager* to initiate the decision phase
    for *each available cell* $N(b_i) \in B$ **do**
        if *QoS is above a threshold and not decreasing* **then**
            Skip handover
        else
            Estimate the vehicle's next position
            Calculate the S_i score for the cell
    BestCellId $\leftarrow$ cell with the highest S_i
    if BestCellId $\neq$ ServingCellId **and** BestCellRSRQ $\geq$ Threshold **then**
        if *Handover is a Ping-Pong* **then**
            Skip handover
        else
            Initiate the handover execution phase

3.4. Mobility Prediction Scenario

We consider both ARIMA and KF as use cases for the mobility prediction technique considered by Skip-HoVe, but it can be any other position prediction scheme. Both ARIMA and KF can be used to predict the vehicle's future position $L(x_i, y_i, t+1)$ based on the current one $L(x_i, y_i, t)$. In this sense, Skip-HoVe iterates the mobility prediction algorithm every time a new measurement arrives, where the intervals between measurements define the granularity of the filter. In our tests, we adopted the granularity of 1 second.

3.4.1. ARIMA

ARIMA is a statistical model to analyze and forecast time series, which is one of the most general time series forecasting scheme. ARIMA works by taking values of series and making them stationary if necessary. A stationary time series has no trend, and the amplitude of its variations around the mean is constant. In the ARIMA model, future values of series are assumed to be a linear combination of past values and past moving averages.

ARIMA is described as a 3tuple (p, d, q), where p corresponds to the number of past measurements weighted in the estimation, d consists of the number of differencing series to make statistically stationary, and q corresponds to the number of past moving averages. The basic formulation of the model is given by Eq. 7. We denote past terms as y, past moving averages as ϵ, while θ and ϕ are individual weights for each term and will be trained by the model.

$$\begin{aligned} y_t = \theta_0 + \phi_1 y_{t-1} + \phi_2 y_{t-1} + \phi_3 y_{t-3} + \cdots + \phi_p y_{t-p} \\ \epsilon_0 + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-1} + \theta_3 \epsilon_{t-3} + \cdots + \theta_q \epsilon_{t-q}. \end{aligned} \tag{7}$$

The number of past value terms and past moving averages depends on the studied series, where some series are mostly dependant on weighted past values and do not need any moving average terms. The model can be represented by the notation $ARIMA(5, 1, 0)$, which means we use five past terms, perform one differentiation, and consider no past moving averages.

ARIMA is used to forecast a single-variable time series, and, thus, it has to be done a training step separately for the latitude and longitude measurements. The first step for the general ARIMA formulation is to define the differencing order, *i.e.*, the number of times each term is subtracted from the next one, given by the parameter d, as shown in Eq. 8). The ARIMA model can be used for the vehicle mobility prediction $L(x_i, y_i, t+1)$. In this sense, the model must be trained for each vehicle separately and for each coordinate (*i.e.*, latitude, and longitude).

$$y_t = \begin{cases} Y_t, & \text{if } d = 0 \\ (Y_t - Y_{t-1}), & \text{if } d = 1 \\ (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}), & \text{if } d = 2 \\ \text{and so on} \end{cases} \tag{8}$$

3.4.2. Kalman Filter

KF tries to estimate a state $x_t \in \mathbb{R}^n$ based on previous state x_{t-1}, *i.e.*, the filter only needs the value of the previous state to estimate the next one. The state x in a KF is a vector containing a pair of vehicle geographic coordinates g_t, namely latitude and longitude, at a given moment t (*i.e.*, $L(x_i, y_i, t)$). Explicitly, we model the process as in a stochastic difference equation shown in Eq. 9. We denote A as a $n \times n$ matrix that relates the previous state to the current one, and $w \in \mathbb{R}^n$ as noise estimation.

$$x_t = Ax_{t-1} + w_{t-1}. \tag{9}$$

The estimation considers a measurement given by Z_k, as shown in Eq. 10. It can be modeled in terms of the prediction with a correcting factor H and a noise v_k.

$$Z_k = Hxk + v_k. \tag{10}$$

We define $\hat{x}_k^-$ as previous state, x_k as predicted state, and $\hat{x}_k$ as following state, where $\hat{x}_k^-$ and $\hat{x}_k$ are real values of the process. We want to estimate x_k based on the measurement Z_k. The previous and following errors are defined by e_k^- and e_k, respectively, as shown in Eqs. 11 and 12.

$$e_k^- = x_k - \hat{x}_k^-. \tag{11}$$

$$e_k = x_k - \hat{x}_k. \tag{12}$$

Also, the previous state covariance can be defined based on Eq. 13, and the following state covariance by Eq. 14 as the expected value of the error, times the error matrix transpose. The goal of the filter is to minimize the error covariance P_k.

$$P_k^- = E\left[e_k^- e_k^{-T}\right]. \tag{13}$$

$$P_k = E\left[e_k e_k^T\right]. \tag{14}$$

We express the following state as a linear combination of the previous state, and a correction term proportional to the difference between measurement and state value, as shown in Eq. 15, the value of $\hat{x}_k$ corresponds to the vector of predicted coordinates in the next measurement g_{t+1}.

$$\hat{x}_k = \hat{x}_k^- + K\left(z_k - H\hat{x}_k^-\right). \tag{15}$$

The matrix K $n \times m$ is the gain, which should minimize the following error covariance. We can minimize the error by replacing Eq. 15 into Eq. 12 and, then, deriving the result. In this way, final formulas for computing the gain of the filter to be used in the estimation is given by Eqs. 16 and 17.

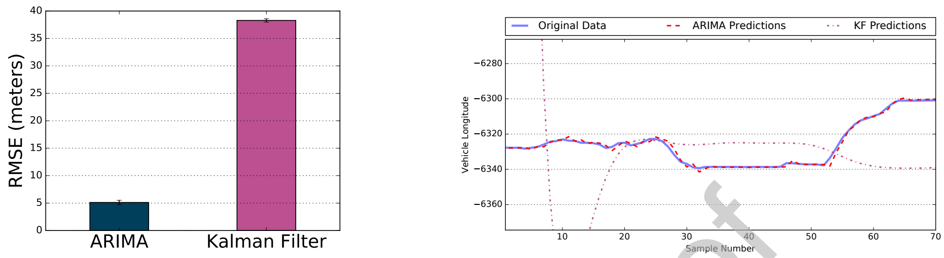
$$K_k = P_k^- H^T \left(H P_k^T H^T + R\right)^{-1}. \tag{16}$$

$$K_k = \frac{P_k^- H^T}{H P_k^- H^T + R}. \tag{17}$$

3.4.3. Mobility Prediction Accuracy

We tested the mobility prediction accuracy of KF and ARIMA in a real-world vehicular dataset to choose one of them to be part of the handover algorithm. In this sense, we considered a vehicular mobility trace collected from approximately 500 taxis from San Francisco [32]. The dataset consists of GPS measurements of 500+ cabs in the San Francisco bay area over a period of one month, generating more than 10 million samples. We consider ARIMA(2,2,1) in such a dataset, *i.e.*, it means that we consider two past values, the series is direffenced twice to make it stationary, and one moving average term. These parameters were found using a Grid Search estimator for better performance. We consider 60% of the data for training and the remaining 40% for tests.

Figure 1(a) shows the average Root-Mean-Square Deviation (RMSE) for the ARIMA and KF to predict each vehicle location in the dataset. By analyzing the results, we can observe that KF has an error 85.7% higher than the ARIMA. Vehicle movement may be irregular and non-linear for the most part, but KF is more accurate when the analyzed data has a linear nature due to its interactive nature. In this sense, KF needs time to adjust to mobility changes in parameters such as speed and direction, *i.e.*, KF makes adjustments online. On the other hand, ARIMA can predict the mobility pattern with high accuracy after being trained and is very robust even with non-linear data. RMSE results can be explained by means of Figure 1(b), which shows the vehicle's longitude over time for a given vehicle. By analyzing the results, we can conclude that ARIMA predictions are much closer to the original data points, while KF predictions, in some cases, are very distant from the original data points. For instance, at sample 30, the vehicle turned (left or right), and ARIMA can predict such vehicle mobility pattern, while the KF does not detect it.



(a) RMSE for ARIMA and the Kalman Filter Applied in the San Francisco Taxi Dataset

(b) Vehicle Longitude predictions for ARIMA and Kalman Filter applied for one vehicle of San Francisco Taxi Dataset

Figure 1: Mobility prediction results

4. Evaluation

This section describes the evaluation methodology, including scenario description, simulation parameters, and metrics used to evaluate the performance of different handover algorithms for video distribution in an ultra-dense VANET scenario.

4.1. Scenario description and methodology

We implemented the evaluated handover algorithms in the NS-3.29[2] simulator and the implementation is available for download on Github[1]. NS-3.29 implements the LTE protocol stack for V2I communication. We consider an ultra-dense VANET scenario such as described by Demarchou *et al.*[2] and 3GPP LTE release 13 [33], considering a 2 km × 2 km area with 7 macrocells covering the whole scenario to some degree, and 100 small cells distributed through the scenario. Macrocells have a transmission power of 46 dBm, while small cells have transmission power of 23 dBm. The simulation considers the Nakagami path loss model, which can be very suitable for urban scenarios [34]. We conducted 33 simulations with different randomly generated seeds

[2]http://www.nsnam.org/

fed to the simulator's pseudo-random number generator (MRG32k3a). Results show the values with a confidence interval of 95%. The main simulation parameters can be seen in Table 3.

Table 3: Simulation parameters

Parameter	Value
Number of vehicles	[50, 100, 150, 200]
Average Speed of Vehicles	43.81 km/h
Number of macrocells	7
Number of Small Cells	100
macrocell Transmission Power	46 dBm
Small Cell Transmission Power	23 dBm
Small Cell Height	10 meters
macrocell Height	45 meters
Propagation Loss Model	Nakagami
Scenario Size	2 km $\times$ 2 km
Video Sequence Tested	Highway [35]
Downlink Frequency	2120 (MHz)
Uplink Frequency	1930 (MHz)

We employed the San Francisco cabs mobility trace [32] for the simulation of traffic and vehicle mobility, as described in Section 3.4.3, varying the number of vehicles between 50, 100, 150, and 200 to evaluate the scalability. We consider the real scenario represented by the trace, *i.e.*, the San Francisco Bay area, due to its direct relation to the real world and human mobility patterns. Figure 2 depicts the distribution of macrocells and small cells. In this context, the coverage area of small cells tends to a Voronoi Tessellation [36], and we assume at least one macrocell is available at all points in the scenario, as expected in connected vehicles environments. A vehicle traveling with average speed of 43 km/h crossed the coverage area of 42.8 small cells during the simulations.

We consider a video with moderate complexity (*i.e.*, the Highway video sequence) levels in terms of motion and spatial complexity, which can be found in a well-known Video-trace repository [35]. The video has a duration of 66 seconds encoded with H.264, 30 fps and intermediate size (352 $\times$ 288 pixels), and a bitrate of 210 kbps. It should be noted that all evaluated videos are streamed in a loop. The decoder uses a Frame-Copy method as

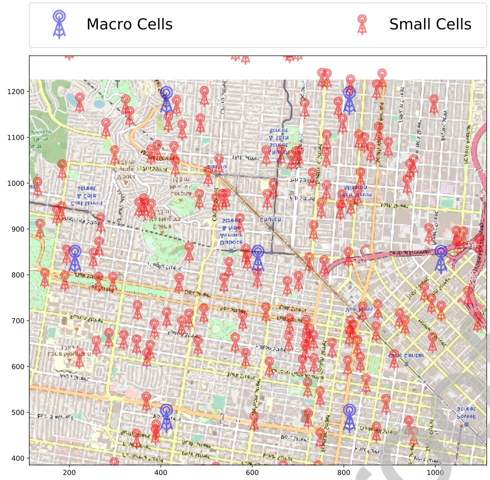


Figure 2: Sample of the simulation scenario with 7 macrocells and several small cells around each macrocell

error concealment, replacing each lost frame with the last received one to reduce the frame loss and to maintain the video quality.

We conducted simulations with five different handover algorithms as follows: (i) *SINR-based handover algorithm* is the most common and traditional. It considers only the signal strength for handover decision, where a handover occurs as soon as there is a radio cell with a higher signal strength value than the current one [37]; (ii) *PBGT handover algorithm*, also known as Strongest Cell Algorithm, performs a Power Budget based decision, in which the handover is executed if a neighbor cell has a received strength superior to the serving cell's plus a hysteresis value, and such difference is maintained throughout a previously set Time-To-Trigger [38]; (iii) *NC-Skipping handover algorithm*) takes into account the mobility for a Non-Cooperative Handover Skipping [2]; (iv) *SER handover algorithm* considers QoS and QoE information for handover decision [21]; and (v) *Skip-HoVe algorithm* considers multi-criteria for decision making, as well as an enhanced skipping-based handover algorithm to provide seamless mobility without ping-pong effects for video distribution, such as described in Section 3.

QoE metrics overcome the limitations of QoS metrics for video quality assessment since QoS metrics fail to capture subjective aspects of video content related to the human experience [15]. In this way, we measured the quality level of each transmitted video using well-known objective and subjective QoE metrics, namely Structural Similarity (SSIM) and MOS, respectively. Specifically, SSIM compares the variance between the original video and the original sequence concerning luminance, contrast, and structural similarity. SSIM values range from 0 to 1, where 0 is the worst case, and 1 means that the transmitted video has the same quality as the original video. We consider the video quality measurement tool (VQMT) to measure the SSIM values of each transmitted video.

Subjective evaluation captures all details that might affect the users experience. In this context, MOS is one of the most frequently used metric for subjective evaluation and requires human observers to rating the overall video quality. For MOS evaluation, we used the single stimulus method of ITU-R BT.500-11 recommendations, since it fits well to a large number of emerging multimedia applications [39]. The human observers watch only once the video and then give a score using ten-grade numerical quality scale, expressing the user experience in words, such as Best (Imperceptible), Good (Perceptible, but not annoying), Fair (Slightly annoying), Poor (Annoying), or Worse (Very annoying). In our subjective evaluation, 31 observers evaluated the videos, including undergraduate and postgraduate students, as well as university staff. They had normal vision, and their age ranged from 18 to 45 years. The distorted videos were played on a Samsung Galaxy Tab A 8.0 with a 8 inches display placed on the back seat of a car headrest, and evaluated by humans to define/score their MOS values during trips between 9 AM and 6 PM. The human behavior when they are evaluating videos, the distractions caused by the surrounding environment, and any other (subjective) psychological factors related to the human psychology are out of the scope of this article [40]. For instance, we will not discuss why observers are quick to criticize and slow to forgive or why they take less time to fall when distortions appear than to rise when distortions disappear.

We evaluated the handover effectiveness since every handover is a costly process for the infrastructure point-of-view. In this way, a handover should be carefully executed by the handover manager to avoid wasting limited resources. We considered two metrics to evaluate the unnecessary handover decision. The number of handovers is vital to provide details about the average times that a specific handover management algorithm supports a single mobile user to change its cell. Besides, ping-pong is an important metric to evaluate unnecessary handovers, since a ping-pong happens when the handover manager triggers the mobile device to perform a handover to a cell. However, a few moments later (4–6 seconds) the mobile device returns to the previously connected cell (performing a second handover).

4.2. Simulation results

Figure 3 shows the objective video quality assessment considering SSIM values for a video transmitted by different handover algorithms, *i.e.*, Skip-HoVe, NC-Skipping, SER, SINR-based, and PGBT. By analyzing the results, we can conclude that videos delivered by Skip-HoVe consistently have a near-one SSIM value regardless of the number of vehicles, which is not achieved by the state-of-the-art handover algorithms. For instance, Skip-HoVe delivered videos with SSIM 28%, 26%, 27%, and 30% higher compared to NC-Skipping, SER, SINR-based, and PGBT handover algorithms, respectively. This is because Skip-HoVe provided seamless and reliable handover decisions in an ultra-dense VANET scenario. To this end, Skip-HoVe considers a skipping mechanism coupled with mobility prediction, QoS- and QoE-aware decisions, meaning the handovers are made more reliable and less frequently. In this sense, Skip-HoVe reduced the I-frame loss rate and the number of handovers, especially the skip-handover, as discussed in the following. However, other handover algorithms lack at least one of these characteristics.

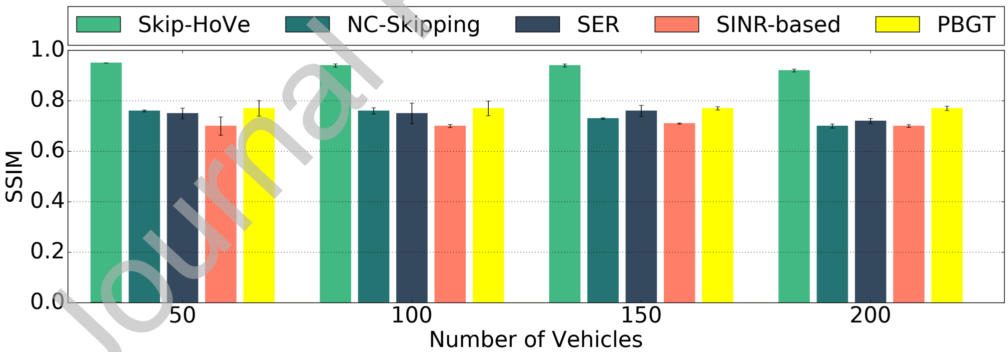


Figure 3: SSIM for videos delivered by different handover algorithms

Figure 4 shows the subjective video quality evaluation using the MOS metric for a video transmitted by different handover algorithms. The set of transmitted videos used for MOS evaluation is publicly available on YouTube[3].

[3]http://bit.ly/3aorpoG

By analyzing the MOS results, it is possible to conclude that Skip-HoVe delivered real-time videos over VANET scenario with frame losses ranging between imperceptible to perceptible, but not annoying (*i.e.*, MOS value of 8). At the same time, the other handover algorithms delivered videos with frame losses between annoying and very annoying (MOS value ranging between 1 (worse) and 3 (poor)). This is because ultra-dense scenarios lead to frequent handovers and ping-pong effect, increasing the packet losses, especially of more important video frames, leading to a poor MOS. In this context, Skip-HoVe selected a reliable candidate cell for a vehicle to connect to, and, thus, download the video content considering multiple metrics coupled with a skipping-based handover decision. On the other hand, NC-Skipping, SER, SINR-based, and PGBT do not consider efficiently skipping-based handover decisions coupled with QoE and QoS information. Hence, MOS results show significant improvements in the quality level of the delivered video using Skip-HoVe compared to other handover algorithms.

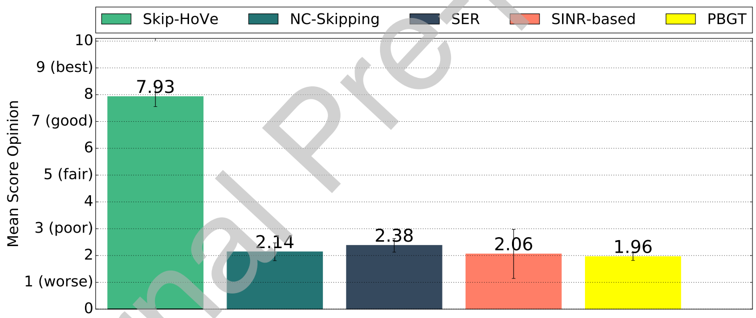


Figure 4: MOS for videos delivered by different handover algorithms

Figure 5 shows the I-frame loss ratio of videos delivered via Skip-HoVe, NC-Skipping, SER, SINR-based, and PGBT handover algorithms, which help to explain the QoE results. Real-time video dissemination requires low frame loss, especially of more important video frames, *i.e.*, I-frames, to support video dissemination with QoE support [15]. The loss of an I-frame causes severe video distortions based on the user perspective since the video quality only recovers when the decoder receives an unimpaired I-frame. Based on the simulation results, we concluded that Skip-HoVe reduced the losses of I-frames by approximately 94% compared to NC-Skipping, SER, SINR-based, and PGBT handover algorithms. Hence, Skip-HoVe transmitted priority frames with high deliver probability compared to other evaluated handover algorithms, increasing the video quality level. On the other hand, state-of-the-art handover algorithms delivered I-frames with loss ratio ranging from 60% to 80% regardless of the number of vehicles in the scenario, and, thus, the video takes longer to recover the QoE.

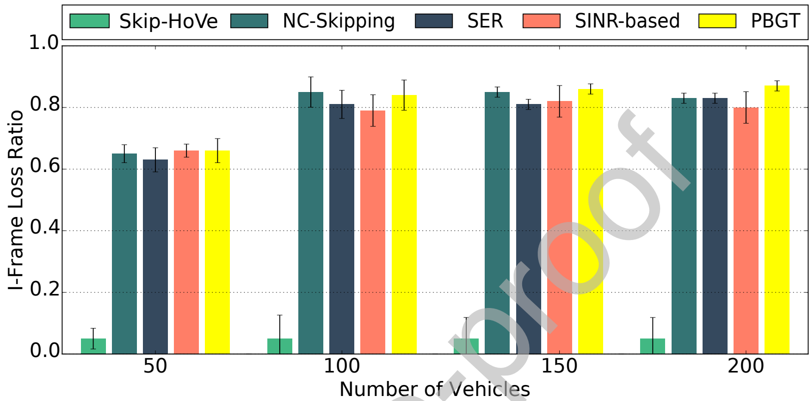


Figure 5: I-Frame loss ratio for videos delivered by different handover algorithms

We selected random frames (*e.g.*, frame number 683) from the Highway video sequence with the highest (Figures 6(b) to 6(f)) and lowest (Figures 6(g) to 6(k)) MOS values for each handover algorithm in order to show the impact of handover decision executed based on the user perspective, as shown in Figure 6. Specifically, the frame number 683, from the highway video sequence, is a P-frame retrieved by a camera in a car driving in a highway with a black car on the left highway lane, as shown in Figure 6(a). In both cases, *i.e.*, video with the highest and lowest MOS values, the frame delivered by Skip-HoVe has the same quality compared to the original frame as can be seen in Figures 6(b) and 6(g), which clearly show the benefits of Skip-HoVe algorithm for video delivery over ultra-dense VANET scenario. On the other hand, the frame number 683 captured from the video with the highest MOS value has few distortions compared to the original frame, which was transmitted by NC-Skipping, SER, SINR-based, and PGBT handover algorithms. However, the black on the left highway lane does not appear, since this frame was lost and it was reconstructed based on the previously received one. For instance, Skip-HoVe, NC-Skipping, SER, SINR-based, and PGBT handover algorithms delivered the video with an I-frame loss ratio of 4.48%, 97.03%, 98.51%, 13.43%, and 97.01%, respectively. Finally, for the frame from the video with the lowest MOS value, the frame transmitted by NC-Skipping, SER, SINR-based, and PGBT handover algorithms are very impaired compared to the original frame, which makes it impossible to see anything. This is because this frame was lost, and also many previous ones, making it impossible to reconstruct the frame based on the previously received frames. For instance, the video with the lowest MOS value delivered by Skip-HoVe, NC-Skipping, SER, SINR-based, and PGBT handover algorithms experienced an I-frame loss ratio of 19.4%, 100%, 100%, 16.19%, and 100%, respectively. Note that even in the best cases, videos usually are not graded with the best score, this is because the resolution of the original video is already limited. As mentioned before, the loss of an I-frame causes severe video distortions based on the user perspective, since QoE only recovers when the decoder receives an unimpaired I-frame. Since the I-Frames contain the most amount of information for the image, and given that the videos were reconstructed using the frame-copy method, algorithms NC-Skipping, SER, and PBGT only reconstruct the image with the information that changes from one frame to the other, decreasing QoE. Hence, we can conclude that Skip-HoVe performs well to deliver videos with the excellent quality compared to state-of-the-art handover algorithms.

Figure 7 displays the SSIM of each frame that composes the video sequences used in Figure 6 transmitted by the evaluated handover algorithms and helps to explain the results of Figure 6. When analyzing the results, we can observe that Skip-HoVe algorithm provided seamless and reliable handover decisions for vehicles to download the video in both cases, *i.e.*, Skip-HoVe algorithm delivered almost all frames with SSIM close to 1, and all above 0.8. For the video with the highest MOS value, existing handover algorithms started with a bad connection (*i.e.*, SSIM below 0.7), after some handover decisions, such algorithms increased the SSIM up to 0.9, but the SSIM reduced afterward. Finally, such handover algorithms delivered the frames with SSIM raging from 0.3 to 0.7 for the video with the worst MOS value. This is because state-of-the-art algorithms experience many handovers, especially ping-pong handovers, which worsen the QoE of delivered videos. For results of Figure 7(a), Skip-HoVe, NC-Skipping, SER, SINR-based, and PGBT handover algorithms experienced 25, 7, 35, 25, and 2 handovers, respectively. Out of these handovers, 5, 2, 13, 7, and 0 were considered ping-pong handovers for Skip-HoVe, NC-Skipping, SER, SINR-based, and PGBT handover, respectively. Besides, state-of-the-art algorithms do not consider multiple metrics coupled with a skipping-based handover decision to perform

(a) Original

Frames from video with the highest MOS value:

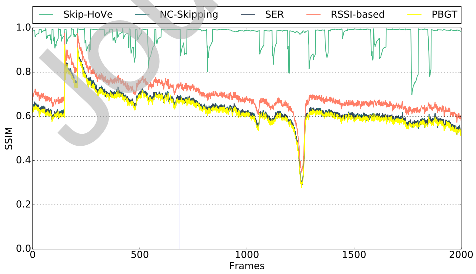
(b) Skip-HoVe (c) NC-Skipping (d) SER (e) SINR-based (f) PBGT

Frames from video with the lowest MOS value:

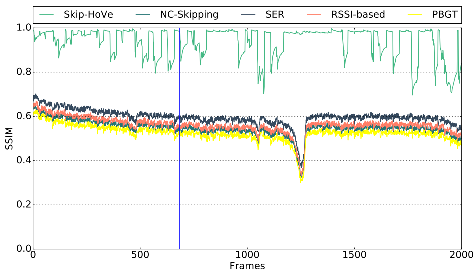
(g) Skip-HoVe (h) NC-Skipping (i) SER (j) SINR-based (k) PBGT

Figure 6: 683th frame from highway video transmitted via different handover algorithms

reliable handover decisions. Hence, we can see that Skip-HoVe is the only algorithm capable of providing a seamless experience, with no QoE drops at all for the evaluated scenarios, by delivering the essential packets and assuring high fidelity to the original video sequence.



(a) Highest MOS value



(b) Lowest MOS value

Figure 7: SSIM for all frames that compose the Highway video sequence delivered by different handover algorithms, with the frame depicted in Figure 6 marked in blue

Figure 8 shows the number of handovers executed during the simulation by each handover algorithm. We can see that performing the least amount of handovers is not necessarily the best approach, as PBGT delivers videos with poor QoE while performing almost no handovers since it keeps users connected to the full macrocell in the scenario. On the other hand, the skipping technique employed by NC-Skipping is inefficient in providing acceptable QoE without a multi-criteria decision. SER has a QoE-aware handover decision, but it does not consider the skipping-based scheme, accumulating the negative effect of the high number of handovers. SINR-based, on the other hand, performs fewer handovers than Skip-HoVe but is highly susceptible to the occurrence of ping-pong. Interestingly, this causes SINR-based to have similar results to the ones of SER, showing the significant impact of frequent handovers even in SER's QoE-based decision. Finally, we can see that even though NC-Skipping and Skip-HoVe perform roughly the same amount of handovers, NC-Skipping fails to deliver acceptable QoE and QoS levels.

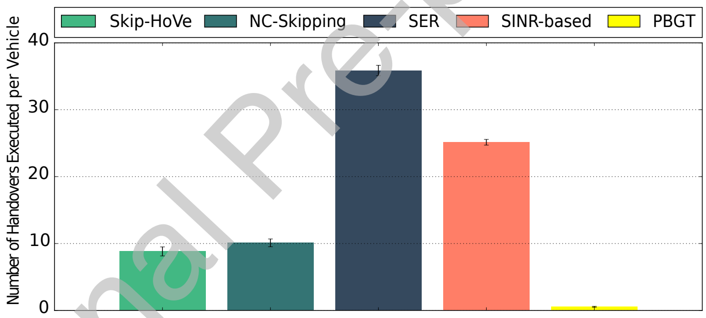


Figure 8: Number of handovers executed by different handover algorithms

Figure 9 shows the ping-pong handover rate by Skip-HoVe, NC-Skipping, SER, SINR-based, and PGBT handover algorithms. It is essential to highlight that we consider a ping-pong handover as soon as a user leaves a cell and returns to it within a window of 4 seconds. By analyzing the results, we can conclude that Skip-HoVe keeps the ping-pong rate around 2%, which is an indication of a better decision policy that avoids such a phenomenon. As mentioned before, PBGT performs a smaller amount of handovers, and, consequently, has a smaller ping-pong probability within the considered window. On the other hand, NC-Skipping, SER, and SINR-based algorithms have higher ping-pongs, due to the fact they do not have a transparent barrier against it. Even with a skipping mechanism, these approaches are not coupled with a multiple criteria strategy and are then also susceptible to ping-pong.

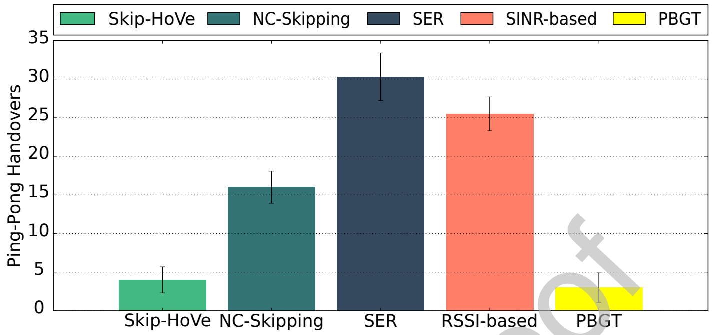


Figure 9: Ping-Pong Handover ratio by different handover algorithms

Table 4 summarizes the experimental results obtained for each of handover algorithms for the case of one randomly sampled vehicle. We can see that in terms of QoE, given in MOS, Skip-HoVe had the highest score out of all the tested algorithms. Followed by SINR-based, PBGT, SER, and NC-Skipping, respectively. This happens because Skip-HoVe performs a QoE-based decision, and also only Skip-HoVe's decision supports the particularities of ultra-dense networks, such as the high number of cells. On average, Skip-HoVe performed fewer handovers, except the PBGT algorithm, in which vehicles only left one macrocell for another. Skip-hove, out of the 38 possible connections, Skip-Hove only made 8 handovers, this is because these handovers were evaluated in order to maintain high QoE, while performing the fewest possible handovers. NC-Skipping performs almost the same amount of handovers as Skip-HoVe, but fails to maintain acceptable QoE and QoS. In the case of SER, the algorithm is very sensitive to fluctuations on QoE, performing then, a great number of disconnections and ping-pong handovers. As well as a high I-Frame loss ratio. The SINR-based algorithm, on the other hand, is very sensitive to random signal fluctuations. Under this algorithm, when a node is in overlapping coverage areas, handovers are very frequent. The PBGT algorithm is less sensitive to fluctuations, and generally prefers macrocells, under this algorithm, the two macrocells that the vehicle crossed triggered a connection.

Table 4: Results Summary for a Vehicle in the Scenario

Algorithm	MOS	Number of Handovers	Ping-Pong Handovers	I-Frame Loss Ratio	Small Cells Passed	Macrocells Passed
Skip-HoVe	8	8	0	5%	38	2
NC-Skipping	1	10	3	66%	44	1
SER	1	36	21	64%	43	1
SINR-based	2	25	13	67%	43	2
PBGT	2	2	0	67%	39	2

Skip-HoVe prevents unnecessary handovers and delivers a seamless experience to end-users.

5. Conclusion

This article introduced a multi-criteria skipping-based handover algorithm for video distribution over ultra-dense VANET scenarios, called Skip-HoVe. Skip-HoVe provides seamless handover decisions, by coupling a handover skipping technique and a multi-criteria handover decision to improve the QoE of video transmissions and reduce the ping-pong rates. In this article, Skip-HoVe considers ARIMA for vehicles mobility prediction, PDR as a QoS criterion, hybrid QoE estimation as the QoE parameter, and RSRQ as the radio parameter. For the handover decision, Skip-HoVe computes the quality level for each cell to select the appropriate cell for the vehicle to connect to by considering AHP to assign different degrees of importance for each criterion. Through these approaches, Skip-HoVe prevents unnecessary handovers and delivers a seamless experience to end-users. Our performance evaluation analysis revealed that Skip-HoVe improved the video delivery up to 14% in SSIM compared to NC-Skipping, SER, SINR-based, and PBGT handover algorithm, and MOS results showed up to 30% better subjective evaluation, while kept the ping-pong rate lower than 2%. For future work, we plan to extend the Skip-HoVe in the following directions: Extend the mobility prediction technique and integrate the handover algorithm for all users on the network, either pedestrians or vehicles; and analyze and correlate the mobility patterns of several users to predict the area congestion and perform efficient offloading of cells and edge services. Finally, another direction is to design integrated solutions where applications can benefit from the Skip-HoVe algorithm and assess their better performance.

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Declaration of interests

✓ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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