ABSTRACT
The performance of haptic interaction across communication networks critically depends on the successful reconstruction of the bidirectionally transmitted haptic signals, and hence on the quality of the communication channel. We propose a novel error-resilient data reduction scheme for haptic communication which exploits known limits of human haptic perception. Particularly, we show that missing haptic information due to packet loss may strongly impair the user’s experience during haptic interaction. We present and compare methods that eliminate the disturbing artifacts resulting out of packet loss. Our approach keeps the estimated impact of packet losses below human perception thresholds. A tree of possible cases (packets received or not received) and their respective occurrence probabilities is maintained at the sender side, and the system predicts unacceptable error cases to decide whether extra packets should be sent. We introduce different criteria that can be employed to trigger additional packets. In our experiments, we evaluate both the objective data reduction performance and the subjective system transparency by performing extensive tests using packet loss probability and round trip time as parameters. The proposed scheme shows excellent performances in terms of data reduction while sustaining good subjective ratings for a wide range of packet loss values and round trip times.

Categories and Subject Descriptors
E.4 [Coding and Information Theory]: Data compression; H.5.2 [User Interfaces]: Haptic I/O

General Terms
Human Factors, Algorithms, Performance, Reliability

Keywords
haptic technology and interaction, haptic communication, perceptual coding, telepresence, telemanipulation, data reduction, error resilience

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Figure 1: Schematic overview of a visual-haptic telepresence and telemanipulation system (adapted from [3]).

The human exteroceptive perception system (namely faculties that perceive external stimuli) relating specifically to haptics is mainly composed of two senses: kinaesthetic and tactile. The former is responsible for determining movement, force and torque through muscle activity and body position in space and time. The tactile sense is responsible for a broad variety of perceptions such as touch, pressure, temperature, texture, pain, etc. Hence, introducing haptics to multimedia communications enables a new range of applications wherein the user can physically manipulate, explore and feel a remote or virtual environment. Furthermore, TPTA systems wherein haptics can be successfully
employed concern applications in which real physical presence in the target scenario is simply not possible, practical, comfortable, accessible or even safe. Some examples are: remote surgeries, minimally invasive medical interventions, mine disposal or disarming, on-orbit or underwater servicing, assisted learning of manual skills, collaborative human task completion, etc.

The transparency of a TPTA system signifies the user’s immersion level. The more transparent the system is, the more realistic is the experience. To reproduce a remote scenario with good accuracy, a high haptic sampling and display rates are required due to the high temporal resolution of human haptic perception. In a real-time application, the sampling frequency and transmission rate on the haptic channel are typically 1 kHz (1000 packets per second) which may cause packet congestion and loss in the communication network. In contrast, the transmission of audio and video usually exhibits significantly lower update/packet rates due to relaxed delay constraints and block-based processing and transmission. To address the issue of high packet rates, a data reduction scheme is required.

Block-based coding schemes, traditionally and efficiently applied in audio and video compression, cannot be used for real-time haptic communication. Haptic data is highly sensitive to additional delay as it can impair the system transparency and additionally compromises the stability of the control loops. Thus, applicable data reduction schemes must be specifically designed for haptic data communication. First approaches on haptic data reduction can be found in [8, 9], where different sampling and quantization techniques for haptic data are introduced. The state-of-the-art in haptic data reduction for lossless data transmission is the deadband-based scheme presented in [5, 7]. This perceptual data reduction approach will be described in the following subsection.

1.1 Perceptual Haptic Data Reduction

Inherently, the human perception system works under limitations. In every sense, such as sight, hearing, taste, smell and touch, there are limits in the natural ability of perceiving external stimuli. According to psychophysical studies, an important and vastly documented limitation concerns the magnitude variation of subsequent inputs within haptic scenarios. In this context, the well-known Weber’s Law of Just Noticeable Differences [1, 4, 10] describes the relation between the initial stimulus and the perceivable intensity of the following stimulus, attesting that

$$\Delta I = K I \quad \text{or} \quad \Delta I = K I$$

where \( I \) is the initial stimulus, \( \Delta I \) is the perceivable variation threshold, or the so-called Just Noticeable Difference (JND), and \( K \) is the threshold parameter describing the linear relationship between the JND and the stimulus \( I \). This relationship describes the smallest amount of change in the stimulus \( I \) that can be detected as often as it cannot be detected.

Exploiting Weber’s Law of the JND, the samples to be sent can be analyzed on-the-fly at the sender accounting for the current perception interval - called the deadband. Within the deadband thresholds, signal variations are expected to be imperceptible for the user. As a simple example, let us assume that \( x_i \) is the current haptic sample, \( x_{ref} \geq 0 \) is the most recent sent sample value and \([x_{ref} - K x_{ref} ; x_{ref} + K x_{ref}]\) describes the deadband interval. In case \( x_i \) falls within the aforementioned interval, it would not be sent, hence the signal would be reconstructed using \( x_{ref} \). In case \( x_i \) falls outside, \( x_i \) will be sent and used to update \( x_{ref} \). The samples that are transmitted to the receiver are identified as updates.

This process can be extended to multiple dimensions (multiple degrees-of-freedom). It requires the redefinition of the perceptual threshold regions within which no changes in the signal can be perceived. For simplicity, isotropic regions centered at the tip of the sample vectors can be displayed as the so called deadzones. For the two-dimensional case, such isotropic region results in a circle and for the three-dimensional case a spherical deadzone is employed.

As an alternative to the simple Hold Last Sample prediction [5], a first order linear prediction (FOLP) can be employed showing improved efficiency along with simplicity [6]. Figure 2 shows the principle of the deadband-based perceptual data reduction scheme using FOLP.

The FOLP considers the last two update samples and can be described as

$$\bar{v}_i = \overline{u}_j - \overline{u}_{j-1}(t'_{j} - t_{j}) + \overline{u}_j$$

where \( \bar{v}_i \) is the \( i \)-th predicted sample, \( \overline{u}_j \) is the \( j \)-th update sample, \( t_j \) is the sampling time of the \( j \)-th update and \( t'_{j} \) is the current time for the \( i \)-th sample.

Whenever the input sample \( \bar{x}_i \) violates the perception thresholds defined by the predicted value \( \bar{v}_i \), then \( \bar{x}_i \), or analogously a new update \( \overline{u}_j \), is transmitted. Otherwise, the sample \( \bar{x}_i \) is dropped and the signal is reconstructed with the prediction \( \bar{v}_i \). The results in [6] show that the perceptual haptic data reduction scheme employing Weber’s Law in combination with a FOLP can reduce the amount of samples (and hence packets) to be sent by up to 90% without impairing the transparency of the haptic interaction system.

1.2 Lossy Transmission

In wired or wireless packet-switched communication, a transmitted packet may or may not reach its destination in time. During deadband-based data reduction, the signal re-
jointly addressed. The state-of-the-art haptic data reduction switched transmission over lossy channels have not been 2. PACKET LOSS IN HAPTIC COMMUNI-

uation the validity of the proposed scheme are presented described. In the remaining sections, the experiments eval-

dications. According to Equation 2, a prediction is correct using the two most recent updates, thus, it takes two fol-

Since the transmission of packets is temporally irregular, the receiver will never know when it is supposed to receive a new update, making it hard to check in real-time if the predictions are in fact aligned with the sender’s estimate. Similarly, the situation at the receiver is unknown at the sender side until the acknowledgments (ACKs) are received. For error-resilient haptic communication, the scheme has to estimate the situation at the receiver taking into account all possible events of successful and unsuccessful transmissions of update packets.

The scenario of sender-driven retransmission with feedback for packetized media streaming is addressed in [2]. A Markov decision process using a binary tree is employed to decide over the retransmission of the same packet. This approach aims to improve the rate-distortion performance in the presence of packet loss. An example trellis is depicted in Figure 3.

In addition to packet loss, communication latency strongly impairs the transparency of haptic interaction sessions. Hence, in comparison to the approach in [2], retransmission of packets or waiting for ACKs to make further decisions becomes impractical. In this paper, we present a novel approach for error-resilient haptic communication which is inspired by [2], but specifically adapted to the properties and demands of networked haptic interaction.

The remainder of this paper is organized as follows. In the next section, the possible effects that can be observed when losing packets in the presence of deadband-based haptic data reduction are discussed. In Section 3, the proposed error-resilient perceptual haptic data reduction scheme is described. In the remaining sections, the experiments evaluating the validity of the proposed scheme are presented followed by a discussion of the results.

2. PACKET LOSS IN HAPTIC COMMUNICATION

So far, perceptual data reduction for haptics and packet-switched transmission over lossy channels have not been jointly addressed. The state-of-the-art haptic data reduction methods [5, 6, 7] assume an error-free communication channel. In this section, the possible effects encountered when losing update packets are described. For every case shown in the following subsections, the packet loss adds undue energy to the displayed signal and compromises the overall passivity of the system and hence its stability.

2.1 Effects of Packet Loss

When running a deadband-based data reduction scheme with first order linear prediction, mainly three kinds of disturbing artifacts can be observed. All of them are caused by packet loss, but the number of lost packets and their disposition within the signal have a direct impact on the force-feedback displayed to the user. For simplicity, the packet loss artifacts will be presented along a single degree-of-freedom (DoF), however, they can be extended to three DoF scenarios.

In Figure 4, 5 and 6, red circles represent the received updates. Yellow circles represent the updates not received due to packet loss. Green circles illustrate the original samples that are not violating the deadband at the encoder and, therefore, are not sent and should be predicted at the decoder. The incorrect predictions due to packet losses at the decoder are represented by the unfilled black dashed circles while the correct ones are depicted as unfilled black solid circles.

2.1.1 Bouncing

In Figure 4, the effect of losing a sample critical in changing the slope of the prediction profile is shown.

2.1.2 Surface Roughness

Similarly to bouncing, in this case, packets are lost when running a deadband-based data reduction scheme. For every case shown in Figure 4, 5 and 6, red circles represent the received updates. Yellow circles represent the updates not received due to packet loss. Green circles illustrate the original samples that are not violating the deadband at the encoder and, therefore, are not sent and should be predicted at the decoder. The incorrect predictions due to packet losses at the decoder are represented by the unfilled black dashed circles while the correct ones are depicted as unfilled black solid circles.

Figure 4: Packet loss in haptic force-feedback causing the bouncing effect.

Whenever a packet that should strongly change the prediction’s direction of an increasing force is lost, the display of the incorrect following estimates violently pushes the user away from the touched object. This repulsion usually occurs on the contact event. It does not only impair the transparency of the system but it also interferes directly with the operator’s activity, fiercely changing its intended position and velocity. This artifact is strongly disturbing.

2.1.2 Surface Roughness

Similarly to bouncing, in this case, packets are lost when they should adjust the course of the prediction. This artifact is less aggressive than bouncing and it does not necessarily interfere strongly with the user’s motion.

Figure 5: Packet loss in haptic force-feedback causing the sensation of an irregularly rough object surface.
This phenomenon is usually perceived by the user when he or she continuously touches the surface of a remote object. Compared to a single contact event, the continuous surface contact naturally triggers more updates within a time interval, therefore, more updates can be successfully received, thus alleviating its effects (see Figure 5). This artifact impairs the user with a feeling of an irregularly rough object surface. This artifact causes a moderate disturbance.

2.1.3 Inverted Force (“Glue Effect”)

The packet loss in this case considerably impairs the interaction since it does not only strongly displace the user, but also exerts an attractive force provoking a "glue effect". In other words, when the user tries to move away from the object, the wrong prediction (inverted force) keeps pulling the user back towards the object with increasing force intensity.

At the encoder, both the original and the compressed signals are known, however, the reconstructed signal at the decoder is not known and can be only estimated. The proposed error-resilient data reduction scheme takes these estimates and makes decisions about sending additional updates to minimize the perceivable distortion.

The proposed error-resilient scheme strongly relies on the tree construction shown in Figure 7. With every transmitted update a new state $s_n$ and its respective new branches are added to the tree. Thus the number of branches grows in the proportion to $2^n$, where $n$ is the number of update packets sent since the initial state. This exponential growth rapidly results in a very large tree size. If the high haptic sampling rate (1 kHz) is taken into consideration, within some milliseconds the tree could admit millions of branches.

When the tree does not receive a new state (i.e. no update is sent), most calculations still need to be performed within the sampling time interval (usually 1 ms) in order to bring predictions and deviations up to date. Therefore, large trees are not only challenging because of their rapid growth but also because the system needs to compute new values at every sample instant.

Whenever a packet acknowledgment arrives, the initial state node is promptly transferred to the acknowledged update state in order to keep the tree size reasonable. The ACK carries information about the two most recent successfully received updates which allows the sender to identify the correct branch in the tree. In other words, the states before the acknowledged update are dropped and the binary tree has its values (probabilities, predictions and deviations) recalculated based on the new initial state. This process is illustrated in Figure 8(b). Nevertheless, latency in the network delays the transmission of ACKs which leads to an increased tree size.

An additional approach for controlling the tree size is to define a maximum tree depth (i.e. maximum number of states). Whenever the tree reaches this depth $s_{max}$, a new initial state $s_0$ is calculated and the tree is reset. The new $s_0$ is defined as the expected value of the current branches as seen in Equation 3.
where \(k\) of the \(k\) probability of that \(k\) estimated sample at the new initial state
dditional uncertainty about the receiver side deviation. The
process is shown in Figure 8(b).

 resets in the meanwhile, those are also recalculated. This
whenever an ACK reaches the sender, the initial state is
until an ACK arrives. As explained earlier in this section,

 After resetting, the tree has only one node again (\(n = 0\)),
therefore it can keep growing as seen in Figure 8(a). If the
tree reaches its maximum depth again, the reset is applied
once more.

 Moreover, the tree can be reset as many times as required
until an ACK arrives. As explained earlier in this section,
whenever an ACK reaches the sender, the initial state is
moved to the acknowledged update state. If there were tree
resets in the meanwhile, those are also recalculated. This
process is shown in Figure 8(b).

 The tree reset operation due to maximum depth adds ad-
tional uncertainty about the receiver side deviation. The estimated sample at the new initial state \(s'_0\) is used to cal-
culate the subsequent predictions, and hence, it plays a pri-
mary role in the computation of the respective deviations
and consequently in the amount of triggered packets. As
will be shown later in the experimental evaluation, the tree
resetting does not significantly impair the data reduction
performance. Please note that in principle there are differ-
ent ways of resetting the tree including intermediate merges
of branches. However, the resetting to more than one start-
ing node is not in the scope of this work; here we always
reset the tree to a single node for rebuilding the tree.

 Three update trigger criteria are proposed in this work,
namely expected deviation, maximum deviation and sum of
probabilities. In addition, a tree-independent periodic update
transmission is also included in this work for comparison.

 The aim of all these approaches is to increase the subjective
quality (system transparency) in the presence of packet loss
without substantially impairing the data reduction perfor-

### 3.1 Expected Deviation

Deviation is a common measure that indicates the dif-
ference between a reference value and its respective ob-
ervations. The reference value which represents the correct
sample to be displayed is available at the sender side. At
every instant of time, each branch of the aforementioned
tree will generate a distinct prediction on the basis of the
last two received updates. The expected deviation can then
be computed as the sum of absolute deviations of each of the
predictions from the reference value, multiplied by its corre-
spanding occurrence probability as shown in Equation 4.

\[
E[d_i] = \sum_k [||\vec{y}_i - \vec{v}_{i,k}|| \cdot p_{i,k}]
\]

where \(E[d_i]\) is the expected deviation for the \(i\)-th sample,
\(\vec{y}_i\) is the sample to be displayed (the correct prediction \(\vec{v}_i\)
or the update \(\vec{u}_i\) if such is being currently triggered), \(\vec{v}_{i,k}\)
is the \(k\)-th prediction for the \(i\)-th sample (i.e. the current prediction
of the \(k\)-th tree branch) and, similarly, \(p_{i,k}\) is the occurrence
probability of that \(k\)-th branch at the time instant \(i\).

At the sender, the error-resilient data reduction scheme
performs a two-step procedure. The first step is the tra-
ditional perceptual analysis that decides about the trans-
mission of an update based on the occurrence of deadband
violation between the prediction \(\vec{v}_i\) and the original sample
\(\vec{x}_i\) as described in Section 1.1. The second step is the com-
putation of the current deviations for each branch and its
occurrence probabilities. Although deviations change from
sample to sample, probabilities change only when new up-
dates are sent (i.e. a new state is added to the tree). Fur-
thermore, the expected deviation \(E[d_i]\) is determined, which
is then compared to the deadband thresholds. Only if the
expected deviation violates the deadband, a subsequent up-
date is triggered. Otherwise, the transmission is kept un-
changed.

 It is important to notice that whenever a violation of the
deadband during the second step occurs, a flag is raised
marking the immediate next sample for transmission (i.e.
the following sample will be an update). In case of non-
violation during the second step, the system continues to run
as usual and thus the next sample will go through the same
aforementioned steps. A diagram of the proposed scheme
can be seen in Figure 9.

Since this approach takes into account both absolute de-
viations and their occurrence probabilities, it is an efficient
way of weighting the decision whether to trigger updates.
As will be shown later, this approach triggers a moderate
number of additional packets.

### 3.2 Maximum Deviation

This approach analyzes all the branches of the current tree
to gauge the maximum deviation between a given prediction
\(\vec{v}_{i,k}\) and the current sample to be displayed \(\vec{y}_i\) (correct pre-
prediction \(\vec{v}_i\) or update \(\vec{u}_i\)) as shown in the following expression.

\[
d_{i,k}^{max} = \arg \max_k [||\vec{y}_i - \vec{v}_{i,k}||]
\]

When the maximum deviation \(||\vec{y}_i - \vec{v}_{i,k}||\) is determined,
wherein \( d_{\text{max}} \) is compared to a second adjustable threshold based on the current sample to be displayed \( \vec{y}_i \). If the maximum deviation violates the new threshold, it triggers an update, otherwise, there is no additional transmission.

Similar to the previous case, if an update is triggered by the maximum deviation criterion, a flag is raised marking the immediate next sample for transmission. If no violation occurs, the system proceeds to evaluate the following input sample for change. The deadband analysis will be performed once again, the branches will be updated with the new predictions, the new deviations are analyzed and so on.

The main goal of this approach is to avoid incorrect predictions gravely exceeding the acceptable perception thresholds, even if they have a low occurrence probability.

### 3.3 Sum of Probabilities

In this criterion, the absolute deviation \(|\vec{y}_i - \vec{v}_{i,k}|\) is evaluated for every \( k \) branch at every time instance \( i \). If the deviation is greater than the deadzone (defined by the current sample to be displayed \( \vec{y}_i \)) then a violation is detected and the respective probability \( p_{i,k} \) is added to a partial probability summation \( P_i \) as seen in the following Equation 6.

\[
P_i = \sum_k p_{i,k}, \quad \forall k: |\vec{y}_i - \vec{v}_{i,k}| > |\vec{y}_i| \cdot K
\] (6)

wherein \(|\vec{v}_{i,k}||\) defines the deadband and \( K \) is the deadband parameter.

After \( P_i \) is calculated, it is compared to a threshold \( P_{\text{max}} \) previously defined by the user. If \( P_i > P_{\text{max}} \), the update flag is raised marking the immediate next sample as an update. Otherwise, the system continues to run and to perform the violation tests until the traditional deadzone is exceeded or the sum of probabilities \( P_i \) infringes its particular threshold.

The **sum of probabilities** criterion is used to control the maximum occurrence probability of incorrect predictions at the receiver side. With this criterion the absolute deviation does not play any role in the decision process.

### 3.4 Periodic Update Transmission

The periodic update transmission runs independently from the traditional deadband approach. The resulting transmission rate can be properly tuned to take the channel loss probability into account. The periodic update happens at every \( r \) samples, where \( r \) can be adjusted to different \( p \) functions such as seen in Equation 7.

\[
r = 1/p^q
\] (7)

where \( p \) is the channel loss probability and \( q \geq 0 \) is a parameter defined by the user.

This criterion is especially interesting because of its simplicity. It may as well enable a better synchronicity between encoder and decoder since the receiver knows when it should receive the updates (except those triggered by the deadband) and therefore can ask for a new transmission in case it does not receive those that are due. However, it is important to observe that the periodic transmission does not consider potential deviations, nor its probabilities and most notably, the user’s activity.

### 4. EXPERIMENTS

Our goal in this work is to improve the rate-distortion performance for haptic communication in the presence of packet loss. The proposed error-resilient data reduction scheme aims to decrease the amount of perceivable packet loss artifacts in the signal displayed at the receiver trying not to significantly impair the data reduction performance. Thus, we propose three different criteria to trigger new updates along with the traditional deadband approach. In addition, for the purposes of comparison, two more approaches are presented in this experiment: the **stand-alone original deadband approach and periodic update transmission**. These five approaches were tested in online and offline experiments to evaluate their performance with respect to transparency and transmission rate.

#### 4.1 Experimental Setup

In our experimental TPTA system, a three-dimensional virtual environment containing a static toroidal object is employed. The SensAble PHANTOM Omni haptic interface device is used to interact with the virtual environment. The operator can explore the remote environment via a virtual end effector (white sphere). A simulated lossy communication channel links the operator to the simulated environment. The experimental setup is illustrated in Figure 10.

The experiments are divided into two parts: offline and online evaluation. In the experiments, we sample the three...
The analysis of different round trip delays reveals that latency does not significantly impair the average compression performance during the offline experiment. The transmission rate slightly increases when longer delays are applied, however, taking into account the considerably higher tree reset recurrence due to longer delays, the rate increase is nearly negligible. This indicates that the limited tree depth does not strongly interfere with the triggering operation, and therefore, a reasonable fixed maximum tree size is able to maintain a stable objective outcome.

The only method that suffers from a substantial change between different RTTs is the maximum deviation approach. This behavior is coherent given that when the delay is short, the ACKs are rapidly received, the tree is promptly recalculated, and the predictions do not become severely incorrect. Hence, it triggers less updates. On the other hand, when there are a longer delays (see Figures 11(b) and 11(c)), they used as a reference in the rating process. The references could be freely accessed at any time during the experiment.

The data reduction performance is also evaluated in this experiment since the displayed artifacts can directly interfere with the user’s position/velocity, and consequently, the respective force-feedback.

Twenty subjects, mostly right-handed male between 20 and 30 years old, evaluated our system. The subjects evaluated 40 sessions, explicitly divided into two different test sets of 20 sessions each. Within both sets, individual sessions (five approaches, four different parameter values) were randomly and blindly presented to the subjects. The first 20 sessions use the packet loss probability as the variable parameter while the round trip time (RTT) is fixed at 20 ms. The loss probability assumes four different values: 10%, 20%, 40% and 60%. The second test set uses the RTT as its parameter while the packet loss was fixed at 10%. The delay could be set to 5, 20, 50 and 100 ms.

5. RESULTS

The following subsections present and discuss the experimental results.

5.1 Offline Experiment

Our results show that higher packet loss probabilities force the proposed scheme to trigger more updates packets in order to preserve the system transparency, decreasing the overall data reduction performance.

As shown in Figure 11, the packet rates for the standalone deadband scheme is kept low and unchanged since the scheme operates independently of packet loss probability or round trip time.

For periodic transmission the packet rate increases significantly with increasing loss probability. In particular, this approach triggers new packets independently from the user’s activity. Therefore, even during motion inactivity or contact free periods new packets are being unnecessarily transmitted.

Table 1: Subjective rating scheme.

<table>
<thead>
<tr>
<th>Description</th>
<th>Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>no difference</td>
<td>100</td>
</tr>
<tr>
<td>perceptible, but not disturbing</td>
<td>75</td>
</tr>
<tr>
<td>slightly disturbing</td>
<td>50</td>
</tr>
<tr>
<td>disturbing</td>
<td>25</td>
</tr>
<tr>
<td>strongly disturbing</td>
<td>0</td>
</tr>
</tbody>
</table>

Figure 10: Experimental setup. On the left, the OP controls the haptic device and receives force-feedback from it. On the right, the virtual environment is shown. A static object within the simulated environment can be haptically accessed with the end effector (white sphere) manipulated by the operator.

DoFs with a sampling rate of 1 kHz. The maximum tree depth \( s_{max} \) is set to 10 states. The deadband parameter \( K \) is kept fixed at 10% for the force-feedback. In the experiments, the position/velocity signal between the OP and the TOP stays unmodified in terms of data reduction and no packet loss is simulated on the forward channel. The proposed error-resilient perceptual coding scheme is only applied to the force-feedback which ensures that introduced distortion is immediately displayed through the haptic device.

4.2 Offline Experiment

In the offline experiment, we evaluate the reduction in packet rate for the proposed error-resilient data reduction scheme. Since the operator is not actively interacting with the remote environment, the transparency cannot be determined in this experiment. However, the offline tests are interesting since they do not suffer with any runtime external influence from the user and thus the data reduction can be evaluated for all the methods under identical conditions.

We employ a pre-recorded 40 seconds sequence that contains four kinds of motion performed by the virtual end effector (tapping the ring, running along the object’s surface, running and tapping simultaneously, and lastly, being static but partially inserted into the object). In order to simulate the individual behavior of subjects, the pre-recorded position signal is slightly modified in a random manner for each run.

The channel packet loss probability is raised from 0% to 50% in steps of 10%, and further to 70%, 90%, and finally 99%. Three different round trip time values are tested: 5, 20 and 50 ms. The criteria parameters are set as follows: for the maximum deviation criterion the threshold parameter is set to twice the deadband parameter \( K \); the sum of probabilities criterion uses \( P_{max} = 10\% \); and the periodic update transmission uses \( q = 2 \).

4.3 Online Experiment

The online experiment is performed using a real-time simulation of a TPTA system wherein the users actively explore the virtual environment shown in Figure 10. The subjects evaluate each session distinctively identifying and rating the artifacts mentioned in the Section 2 of this paper. The used rating system is shown in Table 1.

The artifacts were previously explained to the subjects and demonstrated with three reference sessions. The subjects could also explore a session without any artifacts which they used as a reference in the rating process. The references could be freely accessed at any time during the experiment.
the scheme immediately jumps to a higher rate. This phenomenon occurs since this approach does not directly consider the loss probability, so whenever a prediction violates the second deadband, it triggers a packet (even if its occurrence probability is low). In particular, when the loss probability is greater than 50%, the rate strongly increases due to resets of the tree. As explained in Section 3, when the tree is reset, it creates a new initial state value taking into account prediction values and their probabilities. Therefore, with higher packet loss values, the initial state is already relatively off course and the maximum deviation quickly violates the given thresholds.

Based on the obtained results, the most efficient method from the ones discussed in Section 3 would be the tree-based scheme with the expected deviation criterion, closely followed by the sum of probabilities criterion. The transparency aspect is evaluated in the following online experiment.

5.2 Online Experiment
The results for the online experiment are separated in two subsections which respectively reflect the use of packet loss probability and round trip time as variable parameters.

5.2.1 Packet Loss Test Set
In Figure 12(a), it can be observed that the stand-alone deadband approach undoubtedly exhibits the worst subjective quality. This result is not surprising given the fact that packet losses do not trigger new transmissions. Therefore the number of sent packets stays mostly constant as seen in Figure 12(b) and the user increasingly suffers from the artifacts described in Section 2 as the packet loss probability increases.

The periodic update transmission leads to very good ratings even for high packet loss probabilities. However, the number of transmitted packets increases considerably with increasing packet loss probability. This approach demonstrates a poor trade-off between the number of sent packets and the subjective ratings. Even when the transmission rate is similar to the other proposed approaches (see Figure 12(b) when packet loss ≤ 20%), its ratings are evidently inferior to the others. This shows that not only the number of sent packets is significant, but also the moment in which they are triggered is crucial to the subjective performance.

The maximum deviation approach leads to considerably higher transmission rates. In line with this observation, the subjective ratings for this scheme are also better than most of the other approaches signifying improved overall user experience.

Both expected deviation and sum of probabilities perform comparably in terms of number of packets transmitted, although the sum of probabilities approach outperforms expected deviation with respect to subjective quality.

The results are jointly presented in Figure 13. The higher a given curve is on this chart, the superior the subjective quality ratings are for it. Furthermore, the more towards the right a given curve lays, the better the data reduction performance. The upper right quadrant represents the best performance in terms of both transparency and data reduction. Black arrows along the curves indicate the direction in which the packet loss probability increases. It is evident that the tree-based scheme using the sum of probabilities as criterion performs best for the wide range of packet loss probabilities, closely followed by the tree-based scheme employing the expected deviation, as shown in Figure 13.

5.2.2 Round Trip Time Test Set
Even though the delay issue is not the main focus of this work, it is shown that if higher RTT values are applied to the system, the overall results of the proposed approaches
outperform the stand-alone deadband and the periodic transmission approaches.

In Figure 14(a), the user ratings show a descending trend for all the tested methods. This phenomenon occurs due to longer delay artifacts. Besides the artifacts explained in Section 2, another artifact that may be observed in this experiment is "soft bouncing". This phenomenon is different from the one introduced in Section 2, in that it is far less aggressive. In other words, this artifact does not present an erratic behavior as in the case of packet loss.

In Figure 14(b), we can observe that the number of triggered packets for most of the approaches is fairly constant since the packet loss probability is fixed for this experiment. Additionally, it is shown that even with an increasing number of tree resets (due to longer delays), the overall data reduction performance is not compromised. This proves that the delay itself and the tree reset operation do not play a relevant role for triggering additional updates in the tested approaches. The only exception is the case when the maximum deviation criterion is employed. Here, as explained in Section 5.1, with greater RTT values, an increased amount of tree resetting events rapidly leads to incorrect predictions which violate the respective thresholds.

The results for this experiment are jointly presented in Figure 15. Once again, the upper right quadrant represents the best results jointly for data reduction performance as well subjective quality. The round trip times increase along the directions signified by the black arrows. Although most of the approaches present similar average data reduction performance, the tree-based scheme using the expected deviation as criterion has a slight performance ledge.

6. CONCLUSIONS

In this paper we proposed a novel scheme that addresses the so far unexplored issue of perceptual coding for lossy haptic communication. We present a number of approaches to prevent artifacts arising out of packet loss on the haptic communication channel. The state-of-the-art deadband approach for haptic data reduction was shown to be very efficient for lossless transmission. However, its performance strongly deteriorates when it faces a lossy communication channel.

Our approach for error-resilient haptic data reduction is based on a binary tree built on-the-fly at the encoder in order to estimate all possible signal reconstruction states at the receiver. Moreover, the binary tree takes the channel packet loss probability and the deviation of different predictions into account in order to trigger new update transmissions. The decision of sending additional updates is made at every sampling instant and can be based on different criteria. In this work, three different criteria are presented and tested, namely expected deviation, maximum deviation and sum of probabilities. An experimental evaluation compares our proposed schemes to the periodic update transmission and the stand-alone deadband approach with respect to rate-distortion performance.

Our results show that the proposed error-resilient haptic data reduction scheme maintains the system transparency for an extensive range of packet loss probability values and round trip times. In this way, even with higher packet loss probabilities on the communication channel it is possible to provide a high immersion level for the user with a simultaneous efficient compression of haptic data. Particularly, two of the tree-based trigger criteria (expected deviation and sum of probabilities) exhibit considerably better performances in terms of data reduction while maintaining good subjective
ratings. Moreover, it is shown that the tree reset operation employing a reasonable maximum tree size does not significantly impair the overall data reduction performance. The stand-alone deadband approach shows the worst performance, followed by the periodic transmission approach which has a poor trade-off between data reduction performance and subjective quality. Notably, the latter is completely independent of the user’s activities. Even during motion inactivity or free contact period, it was observed to trigger new packets unnecessarily.

In summary, the proposed tree-based scheme has proven to be an efficient way of applying perceptual deadband-based haptic data reduction while operating under adverse communication channel conditions, while maintaining good system transparency.

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8. REFERENCES