Passive Haptic Data-Compression Methods With Perceptual Coding for Bilateral Presence Systems

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***Abstract*—In this paper, lossy-compression methods for haptic (velocity and force) data as exchanged in telepresence or virtual reality systems are introduced. Based on the proposed interpolative and extrapolative compression strategies, arbitrary passive compression algorithms can be implemented. The derived algorithms do not affect the stability of the presence system. Two algorithms were implemented and experimentally evaluated. The results show that constant data-rate savings of 89% still lead to a perceptually transparent presence system.**

***Index Terms*—Compression, haptic telepresence, robotics.**

I. Introduction

PRESENCE systems allow humans to operate in two kinds of target environments: *Virtual reality systems* allow humans to immerse in an artificially generated environment, and *telepresence systems* allow humans to immerse in a real but inaccessible environment. The inaccessibility can be due to distance, scaling, or living conditions. A presence system consists of a *human operator* who commands an *avatar/teleoperator* (TO) in the *virtual/remote environment*. A multimodal *human–system interface* (HSI) is used for the operator to command the TO and, concurrently, to display the target environment. Signals are exchanged over a *communication channel* (COM) (see Fig. 1 for an illustration).

Presence systems that enable realistic immersive experiences of complex tasks are usually equipped with bimanual highly dexterous facilities to perform and display kinesthetic–haptic stimuli. In such a system, HSI and TO are equipped with haptic devices that have several degrees of freedom (> 20), each using highly accurate sensors (> 14 bits) and actuators controlled at high sampling rates (> 1 kHz). Hence, for the synchronization of HSI and TO, a large amount of data has to be exchanged over the COM. However, bandwidth is generally limited (e.g., existing bus systems) or costly (e.g., space communication). This results in increasing communication delay, information loss, or—as in most cases—in a mixture of both. Consequently,

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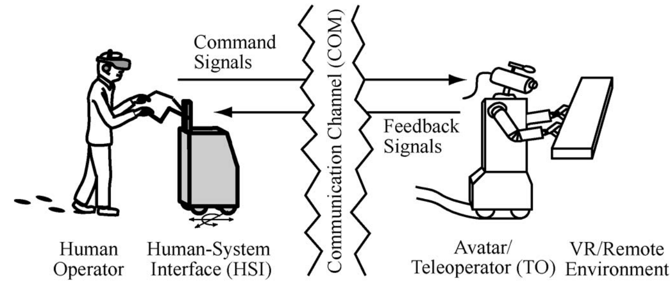

Fig. 1. Multimodal presence system. A virtual or remote environment is mediated via technological equipment.

the need for effective compression algorithms for haptic information is obvious.

In bilateral kinesthetic–haptic (by now "haptic") telepresence systems, force- and position-based signals are commanded from the human operator to the TO, and sensed information from the remote environment is reflected and displayed by the HSI. Thereby, a control loop is closed between HSI and TO. Main objectives in the control-system design are stability and transparency. Ideal transparency means that the operator does not perceive the presence-mediating technology (HSI, COM, TO) when experiencing the target environment.

Compression algorithms reduce the amount of data to be stored, processed, or transmitted. The design of compression algorithms for haptic data raises three main issues. First, high data-rate savings are desired. Second, the compression should not be observable by the human operator, i.e., it should not reduce the transparency of the system. Third, the compression should not destabilize the telepresence system. While the first two issues are typical for all compression problems, the third issue does only arise in compression problems for haptic data in bilateral presence systems.

The lossless-compression scheme for haptic data proposed in [1] results in a tradeoff between compression efficiency and delay required for compression. Differential pulse-code modulation (DPCM), together with a fixed-rate quantization, was proposed in [2]. Adaptive DPCM, together with Huffman coding, was considered in [3]. General considerations about haptic lossy-compression methods and perceptual performance were presented in [4]. A compression method that was designed to not affect the stability of the overall system is *deadband control* introduced in [5]. Therein, the compression is achieved by deadband that defines a deviation from a sample value. Each submitted sample defines a deadband. If the next sample is within the deadband, it will be discarded. If it exceeds the deadband, it will be submitted. Stability is assured by designing the algorithms as passive. This means that the reconstructed velocity and force samples have equal or less energy than their initial correlates. This is conducted by a passive hold-last-sample algorithm for instantaneous telepresence [6]. A passive hold-last sample for delayed telepresence was introduced in [5] and [7]. The implementation can be deployed in telepresence systems with arbitrarily constant communication delay. The authors reported average data-compression rates up to 90% without transparency loss. The main drawback of the algorithm is its inability to maintain an upper bandwidth limitation. If force or velocity signals are subject to fast changes, the compression savings can decrease to zero. Different extensions of deadband control have been proposed such as incorporation of perceptual Kalman filtering [8], additional use of prediction algorithms [9], and application to 3-D data [7]. However, extensions suffer from not being passive and, therefore, possibly causing instability of the overall system. Recently, an extension was published in which a perceptual-coding method was introduced [10].

In this paper, we present a new comprehensive description and analysis of compression methods for haptic data, which were partly published in [11]. Two passive lossy-compression methods are proposed. The first method is based on a passive interpolative compression strategy. The second method is based on a passive extrapolative compression strategy. The algorithms derived from these methods can be arbitrarily complex and do not affect the stability of a presence system in velocity–force architecture. Interpolative and extrapolative lossy-data-compression (LDC) algorithms were implemented, and their impact was analyzed experimentally. As a result, the implementations provided perceptually transparent compression up to a ratio of 9 : 1 (89% data-rate savings).

The remainder is organized as follows. In Section II, background information is given about compression, stability, and transparency. In Section III, the two strategies are proposed based on a comprehensive classification. Algorithms are derived in Section IV. A psychophysical analysis to identify the maximum compression is presented in Section V.

II. Theoretical Background

A. Data-Compression Ratio

The data-compression ratio is defined by the ratio of the original data rate [in bits per second] to the reduced data rate

$$CR = \frac{\text{Uncompressed Data}}{\text{Compressed Data}}. \tag{1}$$

It is usually denoted as an explicit ratio, e.g., 5:1 (read "five to one"). High compression ratios are desirable $CR \gg 1$. Data-rate savings are expressed by

$$DRS = \frac{CR - 1}{CR} \tag{2}$$

and denoted in percent. The relation between CR and DRS is shown in Fig. 2 and reveals that every additionally saved sample yields less data-rate savings.

B. Perceptual Transparency

A presence system is called *transparent* if the human operator can "look through" the technology, directly perceiving the target environment. For haptic presence systems objective criteria like the equality of the impedances of the target and the displayed environment [12]

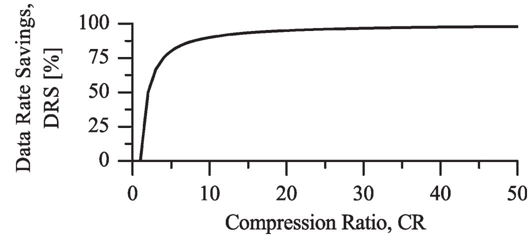

Fig. 2. Data-rate savings. Marginal data-rate savings decrease when the compression ratio is increasing linearly, indicating that each additionally saved sample yields less relative data-rate savings.

$$Z_d = Z_e \tag{3}$$

give advice whether a certain system is transparent or not in terms of a dynamical residual (see Fig. 3 for an illustration of the impedance structure of a telepresence system). Residuals are caused by all involved subsystems. Kinematical and dynamical restrictions are imposed by the robotical devices (HSI, TO). Communication delay, noise, or bandwidth constraints are caused by the COM. In telepresence applications, particularly the stabilization of communication delay T severely affects transparency.

In data compression, the residuals are called *artifacts*. Hence, an LDC algorithm is called *transparent* if it does not cause any artifacts. Artifacts have two origins. First, they can be caused by the loss of information leading to reconstruction failures (*approximation artifacts*). Second, artifacts can be caused by the delay introduced by the compression algorithm (*phase artifacts*). Although the transparency criteria (3) gives objective advice whether a certain compression affects transparency or not, the human operator has to be taken into account, and psychophysical experiments have to be conducted to determine whether artifacts are perceivable or not. Due to a lack of standardized transparency-measurement methods, in this paper, the transparency of an LDC algorithm is evaluated with respect to its psychophysical detectability. The statistics governing psychophysical-signal detectability is called *empirical threshold*. The empirical threshold defines a compression rate at which human operators are able to detect the compression algorithm. Henceforth, an algorithm is called *perceptually transparent* if its compression ratio is equal or lower than the detection threshold (DT) defined for this algorithm.

C. Passivity for Haptic Compression Algorithms

In contrast to audio and video compressions, haptic compression algorithms are applied within an energy-exchanging closed control loop between operator and environment. The dynamics of the compression algorithm can render the haptic telepresence system instable. To assure stability, the passivity paradigm can be deployed. The argumentation is that a system comprised of passive subsystems remains passive if its subsystems are connected in parallel or feedback structure. The passive subsystems of a telepresence system are shown in the upper diagram of Fig. 3.

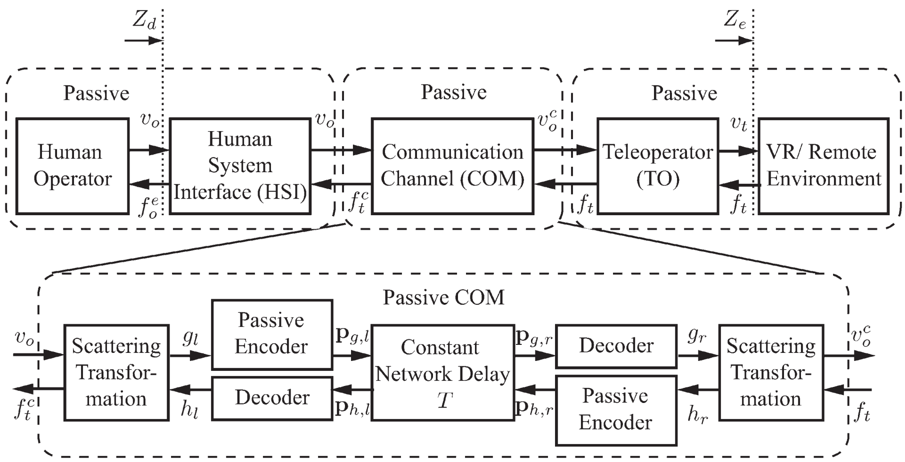

Fig. 3. Presence system in two-port architecture and velocity–force structure. (Upper diagram) If the subsystems [operator-HSI], COM, and [TO-environment] are passive and connected in parallel or feedback connection, the overall system is also passive, i.e., stable. If serial connections occur, the system is not passive but remains stable. Sensor dynamics in HSI and TO are omitted. (Lower diagram) Structure of the COM for passive compression. Encoder and decoder are applied in scattering domain, which assures passivity for arbitrary constant delays. Furthermore, encoder and decoder have to be passive themselves.

A reachable dynamic system with zero initially stored energy is passive if

$$\int_0^t P_{\text{in}}\, d\tau \geq 0 \qquad \forall t \geq 0 \tag{4}$$

where P_{in} is the power input of the system. For the COM of a presence system in velocity–force architecture, the input power is defined as the scalar product of force and velocity

$$P_{\text{in}} = v_o f_t^c - v_o^c f_t \tag{5}$$

where v_o is the velocity commanded by the operator, v_o^c is the commanded velocity on TO side, f_t is the force reflected by the TO, and f_t^c is the reflected force on operator side. The power entering the system is counted positive, and the power leaving the system is counted negative.

In many applications, the COM of a presence system, particularly in telepresence architecture, is afflicted with communication delay (due to delay in the communication networks like the Internet, etc.). Delays are active elements. Therefore, passivity measures for the COM are mandatory. Usually, the scattering transformation is applied to passivate the COM in the presence of constant communication delay (varying delays are buffered to yield a constant delay) mapping power variables (velocity, force) into wave variables. The scattering transformation was introduced in [13] and further described in [14].

The equations are

$$\begin{aligned} g_l &= \frac{b v_o + f_t^c}{\sqrt{2b}}, \\ h_l &= \frac{b v_o - f_t^c}{\sqrt{2b}}, \\ g_r &= \frac{b v_o^c + f_t}{\sqrt{2b}}, \\ h_r &= \frac{b v_o^c - f_t}{\sqrt{2b}}. \end{aligned} \tag{6}$$

Thereby, $g_l, h_r \in \mathbb{R}$ denote the incident wave and $g_r, h_l \in \mathbb{R}$ denote the reflected wave (also called *wave reflections*). The indeces r, l denote signals on the right or on the left side, respectively, of the communication delay. The parameter b (wave impedance) is a positive constant that can be chosen arbitrarily. The transformation is *bijective*, i.e., unique and invertible. Hence, no information is lost or gained by encoding power variables into wave variables or wave variables into power variables. The passivated COM is shown in the lower diagram in Fig. 3.

Applying the scattering transformation (6) to the power input of a telepresence system (5) yields the power input expressed in scattering variables

$$P_{\text{in}} = \frac{1}{2}\left(g_l^2 - g_r^2 + h_r^2 - h_l^2\right) \tag{7}$$

where the index indicates the wave variables on the right- and on the left hand side of the communication delay. Latter equation can be divided into a passivity condition for systems in the command path of the scattering domain

$$\int_0^t g_l^2(\tau)\, d\tau \geq \int_0^t g_r^2(\tau)\, d\tau \tag{8}$$

and a passivity condition for systems in the reflection path of the scattering domain

$$\int_0^t h_l^2(\tau)\, d\tau \leq \int_0^t h_r^2(\tau)\, d\tau. \tag{9}$$

This equation illustrates that waves carry their own power (unit of measurement $\sqrt{W}$). Hence, systems in wave domain remain passive if the output wave does not carry more energy than the input wave.

Because the passivation of the COM is mandatory in haptic telepresence, only LDC methods are considered that preserve passivity of the COM. Hence, the compression algorithms have to be passive in scattering domain. Active dynamics of the LDC algorithms can be caused by processing delays and amplitude change.

Encoder and decoder, as well as the compression strategy itself, cause a constant delay between original wave and reconstructed wave, which is not passive. The delay introduced by encoding and decoding is negligible. Additional measures to passivate the delay caused by the LDC algorithm are not necessary, since the scattering transformation already passivates constant communication delays, which includes the delay introduced by the compression. The passivation causes the phase artifacts of the LDC algorithm. According to [15] and [16], the phase artifacts depend on the dynamics of the target environment. For example, when operating in free space, the passivation of the delay causes an inertial effect proportional to the length of the retardation $Z_d \sim bTs$ (where s is the complex frequency and T is the constant delay in one direction). Additionally, when operating in a rigid environment, the passivation of the delay introduces an additional compliance effect, which is again proportional to the length of the retardation $Z_d \sim (b/Ts)$. Hence, low communication delays are highly desirable for transparent operation.

The amplitude change caused by compressing the signal is not passive either but is not passivated by the scattering transformation. Hence, it has to be passivated by additional measures to obey the passivity conditions in wave domain (8), (9).

III. New Compression Strategies

A. Classification

Data-compression algorithms can be divided into lossless and lossy compressions. *Lossless-compression* algorithms exploit statistical redundancies to achieve the reduction. The decoded data equal the original data. On the other hand, *lossy-compression* algorithm retrieve data that are different from the original data but close enough to be useful in some way. Only lossy-compression strategies are considered in the following.

Since phase artifacts decrease transparency, a classification is proposed that divides the methods in strategies that store a certain part of the incoming wave to apply the compression and strategies that achieve compression without inducing a delay. These different classes are called *frame-based* and *sample-based*. Frame-based strategies can further be divided into frequency-based and interpolative strategies. The *frequency-based* strategy performs a mathematical transformation to achieve the compression (e.g., frequency or wavelet transformation). The *interpolative* strategy performs the compression directly on the signal frame. Sample-based strategies can be subdivided into a strategy that performs an extrapolation. This strategy is called *extrapolative*. Eventually, sample-based schemes can be subdivided into a strategy that achieves the compression on each sample directly. This strategy is called *direct*. This classification is shown in Fig. 4.

Frequency-based strategies are based on reasonably large frames introducing large additional delay, which severely deteriorates transparency. Hence, the frequency-based compression strategy is considered not suitable for transparently reducing haptic data. It is not considered in the following. Direct algorithms have been treated frequently in terms of deadband control, as described in Section I. They are also not considered in this paper. In the following, interpolative and extrapolative strategies are introduced.

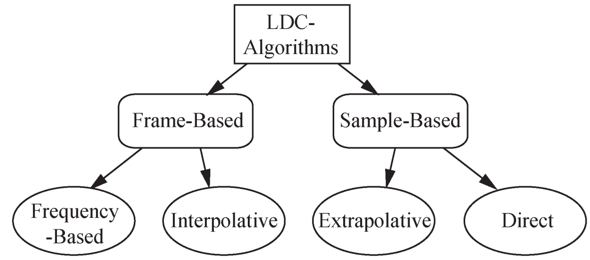

Fig. 4. Classification of compression algorithms. Frame-based algorithms insert a delay due to storing samples into a frame. They can further be divided into frequency-based and interpolative algorithms. Sample-based algorithms insert no delay and can be further divided into extrapolative and direct algorithms.

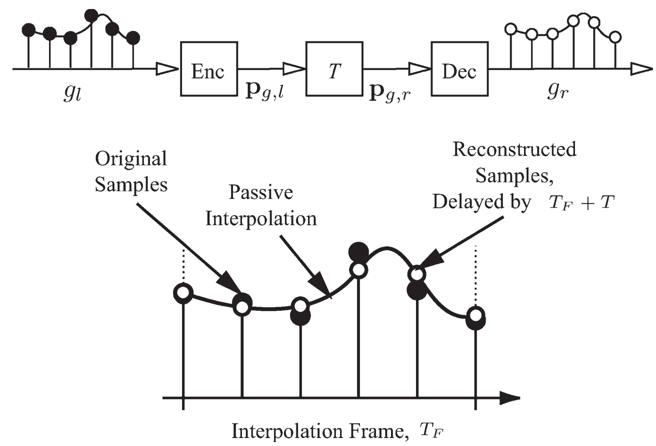

Fig. 5. Principle of the interpolative compression strategy. The interpolated signal is computed to have equal or less energy than its original correlate.

B. Interpolative Compression Strategy

The interpolative compression strategy approximates the incoming signal within an *interpolation frame* T_F. The encoder works as follows: k_F samples are accumulated to a frame, an approximation algorithm (linear or spline interpolation) is applied, and the resulting parameter vector $\mathbf{p}$ is transmitted over the network. The decoder reconstructs the signal using the parameter vector $\mathbf{p}$. The compression principle is shown in Fig. 5. The delay introduced by the interpolation frame amounts to

$$T_F = \frac{k_F}{f_s} \tag{10}$$

where f_s is the sampling frequency. According to the conditions (8) and (9), passivity can be assured by forcing the interpolated wave to contain equal or less energy than the original wave. Hence, the *passivity criterion for the interpolative compression strategy*[1] is

$$\int_{t_j}^{t_j+T_F} g_l(t)^2 \, dt \geq \int_{t_j+T_F+T}^{t_j+2T_F+T} g_r^2(t) \, dt \tag{11}$$

with t_j denoting the starting time of frame j.

[1] The proposed passivity criteria are denoted for the command path only. The conditions for the reflection path are straightforward due to the similarity of the conditions (8) and (9).

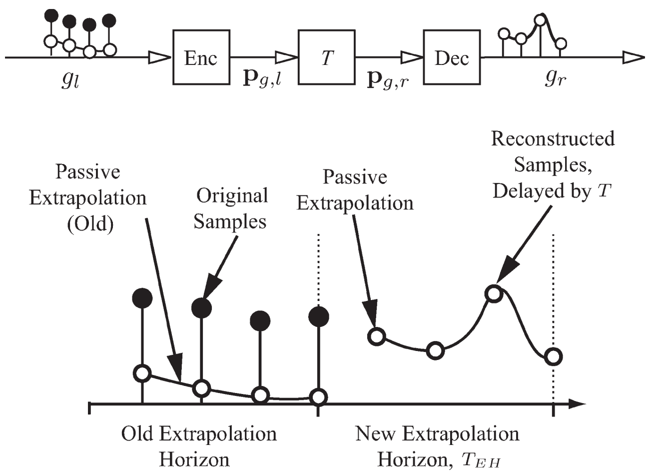

Fig. 6. Principle of the extrapolative compression strategy. The signal within the extrapolation horizon is modeled with the residual energy difference between precedent extrapolations and its real correlates.

The compression ratio is

$$CR = \frac{k_F}{\dim(\mathbf{p})}. \tag{12}$$

Compression is only achieved if

$$\dim(\mathbf{p}) < k_F. \tag{13}$$

The larger the frame length k_F, the more data can be saved, but the lower the transparency due to the induced delay T_F (phase artifacts). The smaller the dimension of the parameter vector $\mathbf{p}$, the higher the data-rate savings, but the lower the transparency due to interpolation errors (reconstruction artifacts).

The advantages of the interpolative compression are as follows.

1) A constant freely adjustable data rate, i.e., the instantaneous compression is equal to the average compression for all times. Hence, any communication-bandwidth limits can be satisfied.
2) Arbitrary algorithms are possible as long as condition (11) is satisfied.

C. Extrapolative Compression Strategy

The extrapolative strategy estimates future samples to a certain extent, called *estimation horizon* T_{EH}. The encoder works as follows: k_{EH} samples are estimated, and a signal is constructed based on certain assumptions resulting in the parameter vector $\mathbf{p}$ transmitted over the network and reconstructed by the decoder. For every k_{EH} samples, an estimation of the next k_{EH} samples is performed. The duration of the extrapolation horizon amounts to

$$T_{\mathrm{EH}} = \frac{k_{\mathrm{EH}}}{f_s}. \tag{14}$$

The compression principle is shown in Fig. 6.

The signal approximation depends on the energy difference between the original signal and the estimated signal. If the available energy allows the approximation of the signal, then an average delay of $T_{\mathrm{EH}}/2$ is introduced. If less energy is available, then the approximation cannot directly follow the signal, and an additional delay effect arises. Since both delay effects are grounded in the approximation, the artifacts they produce are approximation artifacts. According to conditions (8) and (9), passivity of the amplitude change can be assured by forcing the extrapolated wave to contain equal or less energy than the difference between the original wave and the preceding extrapolations starting from the beginning. Hence, the *passivity criterion for the extrapolative compression strategy* is

$$\int_0^{t_j} g_l^2\,dt - \int_0^{t_j+T} g_r^2\,dt \geq \int_{t_j+T}^{t_j+T_{\mathrm{EH}}+T} g_r^2\,dt \tag{15}$$

with t_j representing the time when a new estimation is performed and T_{EH} as the length of the estimation horizon.

The compression ratio is

$$CR = \frac{k_{\mathrm{EH}}}{\dim(\mathbf{p})}. \tag{16}$$

Transparency is influenced only by reconstruction artifacts resulting from the extrapolation. Compression is achieved if

$$\dim(\mathbf{p}) < k_{\mathrm{EH}}. \tag{17}$$

The advantages of the extrapolative compression are as follows.

1) A constant freely adjustable data rate. Hence, any communication bandwidth limits can be satisfied.
2) No strategy-inherent delay. Hence, no phase artifacts will deteriorate transparency.
3) Arbitrary algorithms are possible as long condition (15) is satisfied.

IV. Algorithms

A. iDS

An implementation of the interpolative compression strategy, as introduced in Section III-B, is called *passive interpolative downsampling* (iDS). The main idea is to interpolate the original signal by its mean value

$$p_{g,l} = \frac{1}{T_F}\int_{t_j}^{t_j+T_F} g_l(t) \qquad \forall t = [t_j, t_j + T_F]. \tag{18}$$

The parameter vector contains a single element, which is the mean value of the signal within the interpolation frame. Interpolating with the mean value naturally yields minimal energy if the sum of the waves should remain constant during the interpolation frame. Therefore, the passivity condition for the interpolative compression strategy (11) is already satisfied. The compression ratio is determined as

$$CR_{\mathrm{iDS}} = k_F : 1. \tag{19}$$

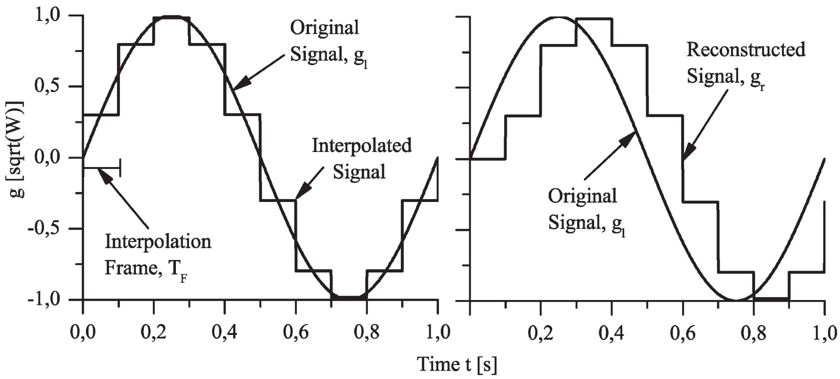

Fig. 7. Operation mode of iDS (simulated at $T_F = 0.1$ s, $f_s = 1$ kHz). An interpolation is calculated as the mean of (right diagram) a wave signal in an interpolation frame. The interpolation causes the delay T_F, hence, (left diagram) the reconstructed signal is delayed by T_F. (Network delay was $T = 0$.)

Simulation results for interpolation frames $k_F = 100$ at a sampling frequency $f_s = 1$ kHz yielding $T_F = 0.1$ s are shown in Fig. 7. Since the original samples are replaced by their mean, the compression ratio is $CR = 100 : 1$, and the data-rate savings are 99%. Depending on the length of the interpolation frame, higher frequencies will be filtered out. Hence, the compression algorithm has low-pass-filter characteristics. Phase artifacts are caused by the interpolation frame. Reconstruction artifacts are caused by the deviation between the original signal and its mean value.

B. eDS

An implementation using the extrapolative compression strategy introduced in Section III-C is *passive extrapolative downsampling* (eDS). The main idea is to extrapolate the future signal by a single value. The extrapolation is performed in two modes. If the last value measured, already satisfies the passivity criterion for the extrapolative compression strategy (15), then it is taken as extrapolation throughout a certain extrapolation horizon. This mode is termed *extrapolate-last-sample* (ELS). If the ELS value does not satisfy the passivity criterion, then a value reduced in energy is computed such that (15) is satisfied. This mode is termed *active passivation*. The equations are

$$p_{g,l} = \begin{cases} g_l(t-1) & \text{if (15) holds} \\ g_l & \text{such that (15) holds.} \end{cases}$$
$$\forall t = [t_j, t_j + T_{\mathrm{EH}}]. \tag{20}$$

The parameter vector contains a single element, which is either the most recent sample measured or a passivated value. The compression ratio is

$$CR_{\mathrm{eDS}} = k_{\mathrm{EH}} : 1. \tag{21}$$

Simulation results for an extrapolation horizon of $k_{\mathrm{EH}} = 100$ at a sampling frequency $f_s = 1$ kHz yielding $T_{\mathrm{EH}} = 0.1$ s are shown in Fig. 8. Since the extrapolation results in a single value, the compression ratio is $CR = 100 : 1$, and the data-rate savings are 99%.

A new extrapolation value for the actual extrapolation horizon is calculated based on the energy difference between old extrapolation and its real correlate. As shown in Fig. 8, the

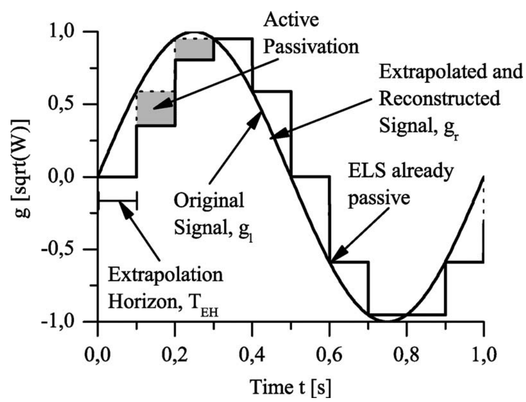

Fig. 8. Operation mode of eDS (simulated at $T_F = 0.1$ s, $f_s = 1$ kHz). A new extrapolation horizon is calculated based on the energy difference between old extrapolations and its real correlates. If the last original sample before a new extrapolation satisfies the passivity criterion, it is taken for the extrapolation (ELS). Otherwise, this sample is reduced in energy such that it satisfies condition (15). (Network delay was $T = 0$).

reconstructed signal is mostly retarded if not enough energy is available for the extrapolation to predict the original signal using the ELS mode. Depending on the length of the estimation horizon, higher frequencies will be filtered out. The algorithm has low-pass-filter characteristics. The performance of the eDS solely depends on the quality of the extrapolation.

A comparison between the eDS and the iDS (e.g., by comparing the left diagram shown in Fig. 7 to the diagram shown in Fig. 8) shows that the eDS causes less artifacts, since no interpolation delay T_F occurs.

V. Psychophysical Evaluation

The application of the proposed interpolative and extrapolative algorithms (iDS, eDS) causes artifacts, which have complex dynamical characteristics depending on the target environment. In general, the higher the compression ratio, the larger the artifacts (see Section II-B for details on transparency). A comparison of the different algorithms based on mathematical evidence is not feasible, because the human operator is not able to exactly repeat an experimental condition that would be needed for an analytic comparison of the signals. Hence, an experimental study was performed that analyzed the perceptual performance of different human operators in detecting LDC

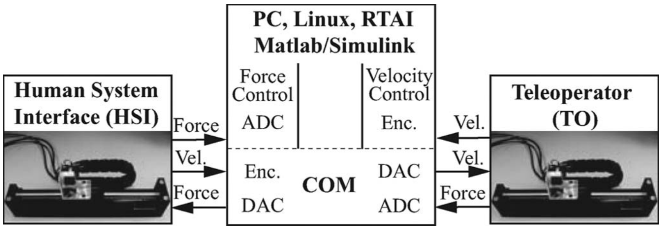

Fig. 9. Presence system to evaluate LDC algorithms. The telepresence system consisted of a haptic HSI, a haptic TO, and a real-time processing unit that emulated the COM. Velocities and forces were exchanged (velocity was calculated based on position measurements). The COM was passivated for constant delays.

artifacts and thereby evaluated the perceptual transparency of the compression algorithms.

Two general questions were answered by the experimental study.

1) Which algorithm (iDS, eDS) yields higher performance, i.e., a lower psychophysical detection performance?
2) What is the greatest compression ratio still leading to perceptual transparency of the compression algorithm?

Therefore, the two algorithms were applied to a telepresence system. Two hypotheses were tested.

H1: "The detection performance is better when telepresence with haptic data compression is performed in a rigid environment than in a soft environment." Since artifacts deteriorate transparency by increasing the compliance of a rigid environment (as described in Section II-C), the lowest DT should be measured in an infinite-stiff environment. In a softer environment, the additional artifactual compliance increase should be concealed.

H2: "eDS provides better performance than iDS." Due to the phase artifacts caused by the frame delay T_F of interpolative methods, iDS is likely to reveal a lower DT than eDS.

A. Method

1) Presence System: A telepresence system was used that provided haptic feedback at high accuracy. The system consisted of two identical linear actuators. One was used as HSI and equipped with a knob for the human operator. The other one was used as TO, and its end-effector interacted with the remote environment, which was represented by different springs. The springs were directly connected to the end-effector of the TO and fixed to a support plate on the other side. An illustration is shown in Fig. 9.

The linear actuators provided a workspace of 310 mm and position resolution of 1 μm. The continuous force amounted to 43 N, and the peak force output was 312 N. The carriage, including force sensor and end-effector, weighted 2.5 kg. A friction compensation was used to reduce the inherent damping. The system operated in a velocity–force architecture. Velocity was commanded from the operator to the TO, and force was reflected from the TO to the operator, as shown in Fig 3. The HSI was controlled by force control, and the TO was controlled by velocity control. The COM was passivated for constant communication delays by the scattering transformation. The sampling frequency was $f_s = 1$ kHz. The control bandwidths were high enough, such that no inertia effects or residual friction effects of HSI and TO were perceivable. Hence, transparency was only deteriorated by artifacts due to the LDC algorithms. The system operated under real-time conditions and was programmed by MATLAB/Simulink. During the psychophysical experiments, participants reported their answers using a response box operated with their nondominant hand.

2) Participants: From the Technische Universität München, 12 students participated in this study. This has been a common sample size for psychophysical evaluations dealing with haptic stimuli. All participants were right-handed. Participants were paid for the participation.

3) Stimuli: The stimuli were generated by the human operator actively exploring the different remote environments by the telepresence system. Thereby, different parametrizations of the compression algorithms yielded differently transparent operation of the presence system. The interpolative algorithm iDS was parametrized by the framelengths

$$T_F = [1, 2, 4, 7, 10, 15, 20] \text{ ms} \tag{22}$$

resulting in compression ratios

$$CR = [1:1; 2:1; 4:1; 7:1; 10:1; 15:1; 20:1]. \tag{23}$$

The extrapolative algorithm eDS was parametrized by the estimation horizons

$$T_{\mathrm{EH}} = [1, 2, 4, 7, 10, 15, 20] \text{ ms} \tag{24}$$

resulting in compression ratios

$$CR = [1:1; 2:1; 4:1; 7:1; 10:1; 15:1; 20:1]. \tag{25}$$

Three remote environments were used. A wooden plate was used as stiff environment. Three spiral springs were used to generate a medium-stiff environment. Moreover, a single spiral spring was used as soft environment. The compliances rendered were

$$Z_e^{-1} = [0, 4, 13] \text{ mm/N}. \tag{26}$$

4) Procedure: Participants were seated in front of the HSI with their right hand grasping the HSI. They were carefully instructed. A short training had to be completed, before the test session started. We used a two-factorial repeated measurements design to test the two compression algorithms in three different environments. The task was a two-interval-two-alternative-forced-choice-task (2IFC2AFC-task) that measured participant's detection performance in terms of a psychometric function. One trial consisted of the sequential presentation of two stimuli: the standard and the comparison stimuli; the sequencing of standard stimulus, and comparison stimulus differed randomly. Duration of each stimulus presentation was 2 s with an interstimulus interval of 2 s and an intertrial interval of 4 s. The standard stimulus was always generated by the telepresence system with no compression algorithm applied ($CR = 1:1$). The comparison stimuli had a compression algorithm applied parametrized as defined earlier. Subjects had to compare both sequentially presented stimuli and to decide whether the second stimulus was more compliant than the first

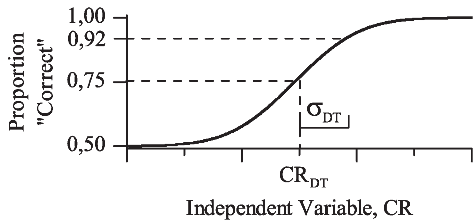

Fig. 10. AFC-task psychometric function to model LDC-algorithm detection performance. Detection performance was assumed Gaussian-distributed and dependent on the compression ratio of the algorithm (independent variable). The dependent variable was the DT compression ratio CR_{DT} at 0.75 proportion "correct." The standard deviation of the perceptual performance σ_{DT} was calculated as the difference between DT and the x value at $F_{\Psi} = 0.92$.

one. The correct detection of trials with LDC algorithm applied was recorded.

5) Data Analysis: Detection performance was assumed to be Gaussian distributed. Therefore, cumulative Gaussians were fit to the experimental data (so-called *psychometric functions* [17], see also Fig. 10). In this experiment, the psychometric function related an operator's performance in detecting the compression algorithm (dependent variable) to the parametrized compression ratio (independent variable). Thereby, the performance was expressed as the proportion of human operators correctly detecting the interval with a compression algorithm applied. The psychometric function for a 2AFC-task starts at proportion 0.5 (*guess rate*), for imperceivable stimuli, and settles at proportion 1.0 for arbitrary large stimuli. For each participant, six psychometric functions were fitted using "psignifit" software, version 2.5.6, described in [18] and MATLAB/Simulink. Hence, 72 psychometric functions were fitted in total. The DT was considered as the CR that lead to the 75%-correct value of the psychometric function.[2]

$$CR_{\mathrm{DT}} = F_{\Psi}^{-1}(0.75). \tag{27}$$

Hence, the DT represents the level at which 50% of human operators correctly detect the compression algorithm.

The standard deviation underlying the perceptual performance of the human operator was calculated as the difference between the value of the independent variable at $F_{\Psi} = 0.92$ and DT[3]

$$\sigma_{\mathrm{DT}} = F_{\Psi}(0.92)^{-1} - CR_{\mathrm{DT}}. \tag{28}$$

B. Results

The experimental analysis provided clear evidence that the passive compression algorithms do not deteriorate the stability of the overall presence system. Stable operation was observed in all trials. Furthermore, detecting the LDC algorithms with our setup was found to produce reliable psychometric functions.

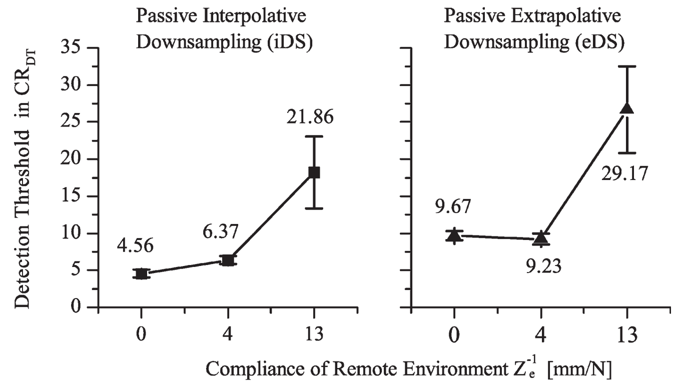

Fig. 11. DT CR_{DT} of compression algorithms with standard error. Participants showed the highest detection performance in the stiff and the medium-stiff environment, i.e., in stiff and in medium-stiff environments, the compression algorithms have the highest impact on transparency. Furthermore, participants showed higher detection performance when detecting the interpolative algorithm, i.e., iDS had a higher impact on transparency than eDS. Based on this result, the perceptual transparent compression ratio was defined to be $CR^*_{\mathrm{iDS}} \approx 5:1$ and $CR^*_{\mathrm{eDS}} \approx 9:1$.

The resulting DTs are shown in Fig. 11. A two-factorial repeated measures ANOVA became significant at $p < 0.05$ for both factors *environment* and *algorithm*. Mauchly's test indicated that the assumption of sphericity had been violated for the factor *environment* $\chi^2(2) = 43.075$, $p < 0.001$. Therefore, degrees of freedom were corrected using Greenhouse–Geisser estimates of sphericity ($\epsilon = 0.503$). The factor *environment* became significant with $F(1.007, 11.75) = 18.92$, $p = 0.001$, $\eta^2 = 0.632$. Bonferroni-adjusted pairwise comparisons indicated a significant difference between the stiff environment and the soft environment ($p = 0.002$) and between the medium-stiff environment and the soft environment ($p = 0.005$) but not between the stiff and the medium-stiff environment. This means that participants performed equally in the stiff and in the medium-stiff environment. In both environments, they detected the LDC algorithms easier than in the soft environment. Hence, they were less sensitive in the soft environment. Since no difference could be observed in the stiff- and in the medium-stiff environment, the hypotheses H1 was partly convalidated. The factor *algorithm* became significant with $F(1, 11) = 8.606$, $p = 0.001$, and $\eta^2 = 0.439$. This means that participants revealed higher detection performance when the iDS algorithm was used to compress velocity and force information. Consequently, eDS was less detectable than iDS. Therefore, eDS provided the highest performance, and hypotheses H2 was convalidated. The interaction between two factors (environment, algorithm) did not reach significance. Based on this analysis, we defined the performance of both algorithms based on the environment in which participants showed greatest detection performance. The minimal average DT for eDS was $CR = 9.23$ (medium-stiff environment). Hence, perceptually transparent telepresence is possible up to data-rate savings of 89% when the extrapolative algorithm

$$\boxed{CR^*_{\mathrm{eDS}} \approx 9:1 \quad (DRS_{\mathrm{eDS}} = 89\%).} \tag{29}$$

The minimal average DT for iDS was $CR = 4.56$ (rigid environment); hence, perceptually transparent telepresence is

[2]Since a 2AFC-task was used, the performance criterion *proportion correct* could be considered bias independent. Participants most likely adopted a symmetric-decision rule (see [19] for detailed information on DT and psychometric function).

[3]In a normal cumulative Gaussian, with proportions ranging from zero to one, the standard deviation is calculated between the mean and the x value at $F_{\Psi} = 0.84$. However, since the psychometric function of a 2AFC-task ranges from 0.5 to 1, this x value changes to $F_{\Psi} = 0.92$ (see Fig. 10).

possible up to data-rate savings of 80% when the interpolative algorithm is used

$$\boxed{CR^*_{\text{iDS}} \approx 5:1 \quad (DRS_{\text{iDS}} = 80\%).} \tag{30}$$

C. Summary

The experiment assessed the performance of human operators who perceived remote environments through a telepresence system with passive haptic compression algorithms applied in command and reflection paths. Two algorithms were analyzed: passive iDS and passive eDS. A high-performance telepresence system was used. DTs were assessed by recoding psychometric functions (proportion "correct") via a 2IFC2AFC-task.

The results gave reliable information to which proportion compression algorithms at different compression ratios could be detected. eDS provided best performance: Perceptually transparent compression at data-rate savings of $DRS_{\text{eDS}} \approx 89\%$.

VI. Conclusion

In this paper, new lossy methods to compress haptic data as exchanged in telepresence systems were proposed. Perceptually transparent constant network traffic reduction of 89% was achieved by applying the proposed passive explorative compression algorithm for haptic information.

The proposed methods open new ways to haptic LDC. Following benefits are provided.

1) The proposed passivity criteria are sufficient and necessary for passive compression algorithms in scattering domain. Passivity criteria were proposed for the interpolative and extrapolative compressions. The criteria allow the design of arbitrary algorithms, which are passive.
2) Two algorithms were implemented. The interpolative algorithm (iDS) performs an interpolation of a certain part of the signal (interpolation frame) by its mean value. The extrapolative algorithm uses a modified ELS strategy to passively forecast the original signal within the extrapolation horizon. Both algorithms provide a constant freely adjustable compression ratio, i.e., the instantaneous compression ratio is equal to the average compression ratio for all times. Hence, any hard communication bandwidth constraints can be satisfied.
3) A psychophysical evaluation clearly indicated that eDS was superior to iDS. The extrapolative algorithm achieved 89% data-rate savings without perceivably imparing transparency when used in our experimental setup. Thereby, our setup was ideally suited to detect any LDC-algorithm artifacts (simple kinematic, capable to rendering nearly infinite stiffness). In multidegree-of-freedom lightweight robotic systems, so-called *flexible joint robots* such as the *LWR* systems by the DLR and KUKA Roboter GmbH, imperceivable compression ratios are very likely to be greater due to intrinsic flexibilities and kinematical effects of the robot that will partly cover the LDC-algorithm artifacts. This claim is bolstered by a property of human stiffness perception: The softer the environment, the greater the standard deviation, i.e., the greater the uncertainty of the human operator about his/her percept. This was reported, e.g., in [20] and can also be seen in the values for σ_{DT} recorded in our experiment (see Table I).

TABLE I
STANDARD DEVIATION OF PERCEPTUAL PERFORMANCE σ_{DT} INCREASES WITH INCREASING COMPLIANCE

Environment	σ_{DT} iDS	σ_{DT} eDS
0 mm/N	4.6 mm/N	4.4 mm/N
4 mm/N	5.9 mm/N	6.9 mm/N
13 mm/N	12.8 mm/N	18.2 mm/N

The passive eDS provided a comparable compression performance to deadband control (see Section I). However, in contrast to deadband control, the proposed algorithms provide deterministic data-rate savings, whereas the performance of deadband control is only an estimate based on the average data-rate savings (instantaneous data-rate savings can drop to zero if signal changes exceed the deadband in short succession). Therefore, the proposed methods are, in contrast to deadband control, particularly suited for data compression in networks with hard bandwidth constraints.

Further improvements can be obtained in particular by improving the extrapolation. The extrapolation is generally limited by its low-pass-filter characteristics. In fast changing environments (e.g., free space to rigid wall), high frequencies will be filtered out depending on the length of the extrapolation horizon. A perceptual transparent implementation is, therefore, constraint, and the compression is not efficient if the environment is changing slowly. A remedy could be an event-based extrapolation, where the extrapolation horizon can be triggered by fast changes in the environment (events). This could enable longer average extrapolation horizons and, therefore, possibly greater data-rate savings.

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