

Haptic Data Compression Based on a Linear Prediction Model and Quadratic Curve Reconstruction

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Abstract—In this paper, a new haptic data compression algorithm is presented. The algorithm partitions haptic data samples into subsets based on knowledge from human haptic perception. To reduce the number of data subsets, a prediction model based on a tangential direction concept is derived that adapts to local geometric changes of haptic signals. Furthermore, to improve signal approximation precision, each haptic data subset is fitted by a quadratic curve. Accordingly, only the coefficients of the quadratic curves are encoded. Experiments are performed on datasets acquired using a six-degrees-of-freedom haptic-enabled telepresence system. The experimental results demonstrate that the proposed haptic data compression algorithm can potentially outperform existed methods in the literature.

Index Terms—haptics, linear prediction, compression, curve reconstruction

I. INTRODUCTION

Recently, haptic technology has been recognized as being compelling to further augment human-to-human and human-to-machine interaction [1]. Many haptic applications involve the transmission, storage, and management of haptic data, which depict trajectory, cutaneous, and kinesthetic information (i.e., force, torque, position, orientation, velocity, etc). The multidimensional, high-frequency, and data intensive nature of haptic media motivates the research and development of both online and offline haptic data compression algorithms. In particular, online compression (e.g., haptic enabled telepresence [2–4]) is restricted by strict delay constraints in order to guarantee control loop stability. Moreover, in

online compression, every set of sample data is transmitted in individual packets to limit packetization and transmission delays. In contrast, offline compression algorithms can process blocks of haptic samples as stability (due to delay) is not a concern. Moreover, offline compression techniques primarily address file size reduction. Examples of applications in which haptic data compression is of great importance include: (1) In telehaptic environments (i.e., online compression), it is highly desirable to use compression techniques to reduce haptic data traffic and improve system performance while maintaining a high-quality telehaptic user experience (e.g., real-time remote haptic collaboration [31]); (2) The compression of voluminous haptic data files typically produced during a haptic session (i.e., offline compression). For example, a haptic training session where the user learns handwriting can be stored to be later analyzed, or even replayed [32].

Haptic data compression is a fairly new research area that has attracted much interest in recent years. The techniques currently available in the literature can be classified into three distinct categories: (1) lossless compression; (2) lossy compression without a model of human haptic perception; and (3) perceptual compression (lossy compression with a model of human haptic perception). Methods that fall in the third category exploit the limitations of human haptic perception to efficiently and transparently compress haptic data in online and offline conditions (e.g., in haptic playback or telepresence systems). All three categories of methods in the literature have been exploited for both online and offline haptic data compression [2,3,5–14]. The related research work discussed here is focused primarily on offline haptic data compression methods as this is the primary application of the proposed algorithm. In [5,6], low-delay compression methods were introduced that exploit Differential Pulse

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Code Modulation (DPCM) and quantization methods, together with Huffman entropy coding. Similarly, in [7] a method is proposed that combines adaptive sampling and adaptive DPCM for the reduction of haptic data samples. In [8], a data reduction technique based on lossy uniform and nonuniform quantization of first-order differences is used. This is performed to explore the potential data reduction rate that may be achieved before compression-induced artifacts are haptically perceived. In more recent work[9], Sakr *et al.* presented a linear predictor that relies on an autoregressive model to predict haptic data; the method's application in an offline haptic data compression scheme is discussed in [10]. In [15], an offline coding technique for haptic data is introduced. It is intended primarily for the compression of haptic data files used in haptic playback applications. Similar to [10], it is a compression algorithm that relies on the concept of the Just Noticeable Differences as well as predictive and entropy coding modules. In particular, the method encodes strictly perceptually significant haptic data samples using a minimum number of bits. For a detailed review of recent literature on haptic data compression refer to [1,28].

In this paper, a new haptic data reduction algorithm is proposed. The algorithm relies on a basic concept that exploits tangential directions at different haptic data points to construct a high-accuracy linear predictor. The linear predictor is used to partition haptic data samples into subsets, while relying on knowledge from human haptic perception. Moreover, in order to further improve approximation precision, each haptic data subset is fitted by a quadratic curve. Accordingly, only the coefficients of the quadratic curves are encoded rather than the original haptic data samples.

The rest of the paper is organized as follows. In Section II the proposed haptic data compression technique is presented. Section III discusses the experimental settings. Section IV presents the experimental results. Finally, conclusive remarks are outlined in Section V.

II. HAPTIC DATA COMPRESSION

In this section, the proposed haptic data compression method is presented. The objective is to enable a high data reduction performance and approximation precision, while preserving a high-quality haptic experience during playback of the compressed haptic data streams. The suggested data compression strategy relies on linear prediction combined with quadratic curve reconstruction. Knowledge from human haptic perception is incorporated into the architecture to assess the perceptual quality of the compressed haptic signals.

A. Haptic Perceptibility

The suggested data compression method relies on the limitations of human haptic perception. In particular, human haptic perception is analyzed using Weber's law of Just Noticeable Differences (JND). The JND consists of the minimum amount of change in stimulus intensity

which results in a noticeable variation in sensory experience. This relation can be expressed as

$$\Delta I / I = k , \tag{1}$$

where I is the stimulus intensity, ΔI is the so-called difference threshold or the JND and k is a constant called the Weber fraction. Generally, the JND for human haptic perception ranges from 5% to 15% [16–18]. This suggests that, if a change in haptic force (or movement) magnitude is less than the JND, the user would not perceive a force-feedback (or movement variation). Weber's law defines a very simple mathematical model to characterise human haptic perception. It essentially provides an approximate model that allows the detection of perceptible changes in haptic signals. In the haptic data compression literature, a haptic perception threshold is often referred to as a *deadband* [2]. Generally, the deadband principle states that haptic signal changes (e.g., due to prediction) do not need to be stored or transmitted, unless they exceed a certain perceptual threshold.

The proposed algorithm relies on a general formulation of the deadband principle intended for multiple multidimensional haptic data types (e.g., force, torque) [1,2,4]. This is due to the fact that the algorithm in Section IV will be evaluated using 6-DoF haptic datasets which consist of force feedback (force/torque) information. It should be emphasized that with minor or no modifications, the algorithm can be easily applied to haptic datasets acquired from devices with fewer or more degrees-of-freedom.

To determine which haptic force-feedback data samples should be encoded, human haptic perceptual limitations with respect to the exerted force and torque must be considered together as follows:

If $(D_F(\mathbf{F}_{pred}, \mathbf{F}_{real}) > f(\mathbf{F}_{real}))$ or $(D_T(\mathbf{T}_{pred}, \mathbf{T}_{real}) > f(\mathbf{T}_{real}))$

Then $\mathbf{F}_{real}, \mathbf{T}_{real}$ must be encoded, can not be predicted

Else $\mathbf{F}_{real}, \mathbf{T}_{real}$ can be predicted.

where \mathbf{F}_{pred} and \mathbf{F}_{real} denote the predicted and actual force vectors, whereas \mathbf{T}_{pred} and \mathbf{T}_{real} correspond to the predicted and actual torque vectors, $D_F(\cdot)$ and $D_T(\cdot)$ consist of distance metrics used to measure the proximity between force and torque vectors respectively, whereas the functions $f(\mathbf{F}_{real})$ and $f(\mathbf{T}_{real})$ define the human perceptual thresholds for different force and torque values. More specifically, the method relies on a force deadband d_f and torque deadband d_t . Also, $f(\mathbf{h}) = d_h \cdot |\mathbf{h}|$, and $\mathbf{h} \in [\mathbf{F}, \mathbf{T}]$. It should be observed that $f(\mathbf{h})$ is defined using Weber's law.

B. Distance Measurement

In order to measure the proximity of two haptic vectors \mathbf{V}_{pred} and \mathbf{V}_{real} ($\mathbf{V} \in [\mathbf{F}, \mathbf{T}]$), different distance measurements are considered. The Euclidean distance is very commonly used in the haptic compression literature [1,2,4,19]. In the proposed haptic data compression method, the orthogonal distance is exploited when

evaluating prediction errors. The orthogonal distance consists of the smallest Euclidean distance among all

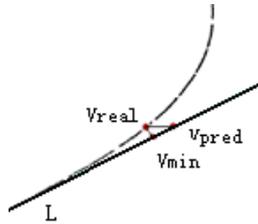


Figure 1. A visual illustration of the difference between the Euclidean and Orthogonal distances (adapted from [14]).

distances between a haptic vector V_{real} ($V \in [F, T]$) and the line which represents the output of the linear predictor. Fig. 1 provides a visual depiction of the difference between the Euclidean distance and the orthogonal distance. Specifically, point V_{real} denotes the original haptic data sample, line L is the output of the linear predictor, whereas point $V_{predict}$ (equivalent to V_{pred}) is its predicted point (that falls on line L). Generally, the nonlinear nature of a haptic signal makes it difficult to predict (with high accuracy) using a linear prediction model. Moreover, the Euclidean distance $|V_{pred} - V_{real}|$ does not represent the true minimal distance between V_{real} and the potential predictor output. In fact, the minimal distance corresponds to the orthogonal distance from V_{real} to the prediction line L (point V_{min}). Consequently, using the orthogonal distance approach, haptic data reduction performance improvement should be expected.

C. Tangential Direction-based Linear Prediction

Several haptic prediction techniques have already been exploited in the haptic data compression literature. In [2,15,20], prediction is performed using a simple linear extrapolation procedure, which solely relies on two previously received sample values. In [21], Clarke *et al.* presented a haptic data prediction method based on a double exponential smoothing approach which essentially models a time series using a basic linear regression equation. In [9], Sakr *et al.* presented a linear predictor that relies on an autoregressive model to predict haptic data; a small number of the initial data is normally required in order to initiate the prediction process. In more recent work [3,4,11,19], a haptic prediction model is introduced that relies on the least-squares estimation method (referred to in this paper as LSE-LP). The authors evaluated their algorithm in both, offline and networked haptic applications. In this paper, a linear prediction model based on curve reconstruction and a tangential direction concept is presented. The details of the algorithm are as follows.

Curve reconstruction has been widely studied in computer graphics and geometric modeling in the past decade and it has various applications in CAD/CAM, computer vision, and many other disciplines [22,23,33, 34]. Quadratic curves and surfaces own a lot of elegant properties which make them a powerful tool for shape

modeling [24–26]. In this paper, quadratic curves are used to derive the haptic linear predictor and to improve

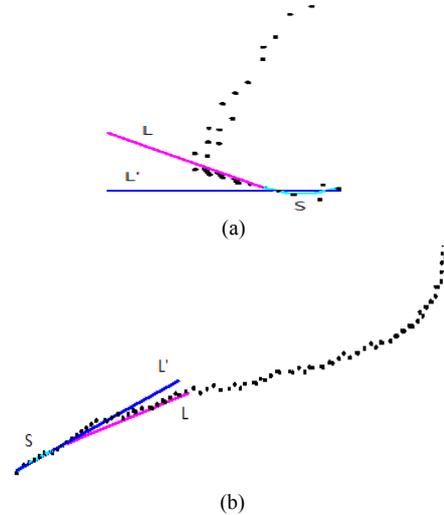


Figure 2. Two examples illustrating the differences between the least square estimation-based linear prediction (LSE-LP) approach and linear prediction based on the tangential directions concept (adapted from [14]).

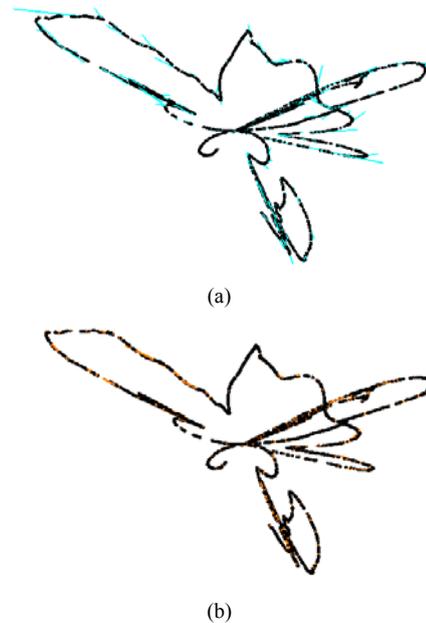


Figure 3. Plots showing the difference in prediction performance between the Least Square Estimation-based linear predictor (LSE-LP) method (a), and the tangential directions-based prediction model (b), when force data are considered.

approximation precision. Specifically, based on M data samples V_0, V_1, \dots, V_{M-1} ($V \in [F, T]$), a short smooth quadratic curve segment

$$S(u) = d_0 + d_1u + d_2u^2 \tag{2}$$

is initially fitted on the data, where d_0, d_1, d_2 are the coefficients and $u \in [0, 1]$ is the parameter. The linear predictor is defined as follows

$$Q(t) = b_0 + b_1t \tag{3}$$

where $\mathbf{b}_0 = \mathbf{V}_{M-1}$, $\mathbf{b}_1 = \mathbf{S}'(u=1)$. As illustrated in Fig. 2, haptic data samples are first fitted with a curve segment S . Regardless of whether S has a significant curvature (Fig. 2(a)) or a relatively small curvature (Fig. 2(b)), the linear predictor (L) based on this tangential direction concept will follow the local geometry of the point cloud [27]. Compared with the LSE-LP method (\hat{L} , which is directly fitted with the same M data samples $\mathbf{V}_0, \mathbf{V}_1, \dots, \mathbf{V}_{M-1}$), the linear predictor based on tangential directions can be expected to predict more accurately. For example, a visual comparison between the linear predictor based on the tangential direction concept and the Least Square Estimation based linear predictor (LSE-LP, as aforementioned this is a popular prediction method used in numerous recent papers in the offline and online haptic data compression literature [3,4,11,19]) is shown in Fig.3. Both algorithms are evaluated in off-line settings. It can be clearly seen that with the same force perception threshold (tolerable signal distortion threshold), the proposed linear predictor (based on the tangential direction concept, the orthogonal distance and quadratic curve reconstruction) outperforms the LSE-LP/Euclidean distance approach. A more detailed analysis of the proposed data reduction algorithm will be provided in Section IV.

D. The Proposed Algorithm

A detailed description of the proposed algorithm is as follows. First, the algorithm constructs a linear predictor. The predictor is then used to divide a haptic signal into subsets, i.e., haptic data samples in the same subset are those that can be predicted within a tolerable perceptual error. Subsequently, samples in each subset are fitted by a quadratic curve. The procedure of the proposed method is divided into the following steps. Given the predefined perception thresholds (deadbands for force and torque) and a haptic dataset, repeat the following three steps until there are no more haptic data samples left (these steps are repeated for each subset).

1- Given the ordered haptic data samples set, the algorithm uses the techniques presented in Section C to construct a quadratic curve based on the initial M data points $\mathbf{V}_0, \mathbf{V}_1, \dots, \mathbf{V}_{M-1}$ ($\mathbf{V} \in [\mathbf{F}, \mathbf{T}]$), and subsequently compute the linear predictors L_v based on the tangential directions of the corresponding curve segments. Each predictor L_v is represented by a parametric line $\mathbf{W}(u) = \mathbf{c}_0 + \mathbf{c}_1 u$, where $\mathbf{c}_0, \mathbf{c}_1$ are the coefficients of the line and u is a parameter that denotes the index of each sample in the sequence.

2- For the successive sample \mathbf{F}_{real} and \mathbf{T}_{real} in the haptic dataset do the following:

If (the distance from \mathbf{F}_{real} to line L_F [linear predictor] is less than $d_F \cdot |\mathbf{F}_{real}|$ AND the distance from \mathbf{T}_{real} to line L_T is less than $d_T \cdot |\mathbf{T}_{real}|$;

Then \mathbf{F}_{real} and \mathbf{T}_{real} can be approximated or predicted by the linear equations L_F and L_T respectively, go to step 2;

Else \mathbf{F}_{real} and \mathbf{T}_{real} cannot be approximated [or predicted] by the linear equations L_F and L_T , \mathbf{F}_{real} and \mathbf{T}_{real} will be the first points of the next point subset.

3- All the data samples in the subset which can be approximated by a linear equation (i.e., the predictor) L_v (where $\mathbf{V} \in [\mathbf{F}, \mathbf{T}]$) are fitted by a new parametric quadratic curve $S(u) = \mathbf{a}_0 + \mathbf{a}_1 u + \dots + \mathbf{a}_n u^n$ where $\mathbf{a}_0, \mathbf{a}_1, \dots, \mathbf{a}_n$ are the coefficients of the curve ($n=2$), u is a parameter that denotes the index of each sample in the subset sequence. Then store (or transmit) only $\mathbf{a}_0, \mathbf{a}_1, \dots, \mathbf{a}_n$ and the number of data samples in the subset. Accordingly, the haptic subset can be reconstructed by simply using the curve coefficients $\mathbf{a}_0, \mathbf{a}_1, \dots, \mathbf{a}_n$ and the number of data samples in the subset.

In order to obtain a precise quadratic parametric curve, the least-squares method is used. A quadratic parametric curve is computed in the suggested formulation and it can be expressed as follows:

$$S(u) = \sum_{i=0}^2 \mathbf{a}_i u^i, \tag{4}$$

where $\mathbf{a}_i, i \in [0,2]$ are the coefficients. The quadratic parametric curve that would best fit the original haptic data samples $S = [S_0, S_1, \dots, S_{l-1}]^T$ where $S \in [\mathbf{F}, \mathbf{T}]$ in the least square sense is derived. The equation is then formulated as

$$\phi A = S, \tag{5}$$

where,

$$\phi = \begin{bmatrix} 1 & u_0 & \dots & u_0^n \\ 1 & u_1 & \dots & u_1^n \\ \vdots & \vdots & \vdots & \vdots \\ 1 & u_{l-1} & \dots & u_{l-1}^n \end{bmatrix}, A = \begin{bmatrix} \mathbf{a}_0 \\ \mathbf{a}_1 \\ \vdots \\ \mathbf{a}_n \end{bmatrix}, S = \begin{bmatrix} S_0 \\ S_1 \\ \vdots \\ S_{l-1} \end{bmatrix},$$

A is the unknown to be solved, u_0, u_1, \dots, u_{l-1} are the parameter corresponding to haptic data $S = [S_0, S_1, \dots, S_{l-1}]^T$. The solution to (5) in the least-squares sense is

$$A = (\phi^T \phi)^{-1} \phi^T S. \tag{6}$$

It should be emphasized that only the coefficients of the curve segments and the number of data samples in a subset are encoded. Entropy coding (e.g., Huffman, Arithmetic coding, etc.) can be applied as a subsequent step (to the coefficients of the curve segment and the number of data samples in different subsets) to further improve the compression.

III. EXPERIMENTAL SETTINGS

For our evaluation, an experimental telemanipulation is used. On the operator side, an MPB high fidelity haptic device tracks the hand movements which control the teleoperator. The haptic device is a six-axis force-feedback hand controller that can generate both translational force and rotational torque (twist force). The

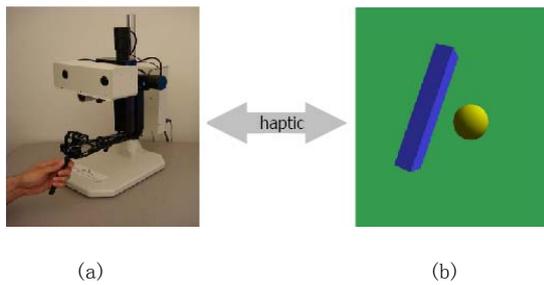


Figure 4. Experimental setup which consists of (a) an MPB Freedom 6S haptic device used by the operator, to interact with (b) a remote virtual environment (adapted from [4]).

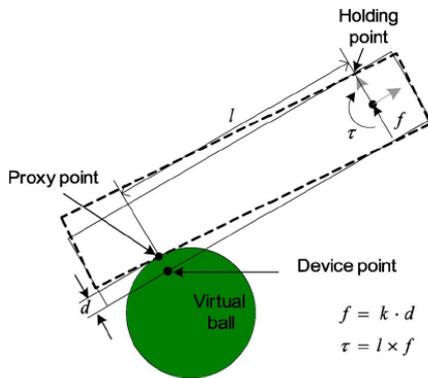


Figure 4. Force/torque feedback in 6-DoF haptic rendering (adapted from [30]).

remote environment is a virtual environment consisting of a stick-on-ball application. Fig. 4 shows a snapshot of the telemanipulation setup. As soon as the virtual 3D stick is in contact with the virtual 3D ball, corresponding force feedback is generated and displayed to the human operator. Furthermore, the force/torque computation to enable 6-DoF haptic rendering is performed while using the direct rendering method [29]. This technique is illustrated in Fig. 5, where a virtual 3D stick mimics the motion of the device stylus (device tool) in free space, but is constrained to the surface of the virtual 3D ball when a collision between the two objects is detected. Moreover, when the 3D stick is in contact with the virtual 3D ball, the deepest penetration point (device point) and its corresponding contact point located at the surface of the ball (proxy point) are first acquired. A feedback force $\mathbf{F}(F_x, F_y, F_z) \in \mathbb{R}^3$ is then calculated using the Hooke's (linear) law $\mathbf{F} = k \cdot \mathbf{d}$ where $\mathbf{d} \in \mathbb{R}^3$ is the penetration vector between the two points and $k \in \mathbb{R}$ is the stiffness constant. The force \mathbf{F} is then used to generate a torque $\mathbf{T} = l \times \mathbf{F}$ around a predefined holding point on the virtual tool where $\mathbf{T} \in \mathbb{R}^3$, l is the distance between the predefined user holding point and the collision point between the 3D stick and the 3D ball. The resulting contact force/torque pair is then directly displayed (haptically) back to the user.

Before the conducted evaluation, we recorded 10 telemanipulation sessions of the described telepresence setup.

In order to ensure stable and realistic haptic interaction, exerted force (force/torque) data acquisition is performed at 1 kHz. Specifically, 10 haptic datasets were recorded, each consists of 6000 instances. Moreover, each instance of haptic force feedback signal encompasses 6 data samples, i.e., 3D force (F_x, F_y, F_z) and torque (T_x, T_y, T_z) data. Therefore, each dataset encompasses $6 \times 6000 = 36000$ force/torque samples.

Haptic compression experiments using the proposed algorithm are performed on all 10 datasets. Force-feedback (force/torque) samples in each dataset are compressed using different deadband values. The purpose is to achieve a high compression ratio while ensuring that perceptual haptic distortions introduced by the algorithm remain relatively imperceptible (if a user chooses to decode the haptic data and play back the signals using a 6-DoF haptic device, e.g., the MPB Freedom 6S device). Accordingly, the haptic compression method was evaluated using eight different force/torque (%/%) deadband values: 0.5/0.5, 1.0/1.0, 1.5/1.5, 3.0/3.0, 5.0/5.0, 7.0/7.0, 10.0/9.0 and 15.0/12.0.

The compression algorithm runs on a Pentium(R) Dual-Core 2.20 GHz PC, with 2.00 GB of RAM and a 32-bit Operating System (Windows 7 Home Basic). The software used for the implementation is Microsoft Visual Studio C++ 2008 and OpenGL.

IV. RESULTS

We are basing the comparison of the proposed algorithm to that of the popular Least Square Estimation-based Linear Prediction (LSE-LP) method which was proofed to deliver perceptually accepted results based on subjective evaluations. Consequently in this paper we objectively compare our results to those of LSE-LP.

Fig. 6 provides a visual performance comparison between the proposed prediction model and the LSE-LP method, using one of the 10 recorded experimental 6-DoF haptic datasets which encompass force/torque data.

Furthermore, Table I compares the haptic data reduction performance of the proposed method with the LSE-LP approach when force feedback (force/torque) data are considered. Specifically, Tables I shows the data reduction rates and the corresponding Mean Square Errors between the original and compressed signals, i.e.,

$$\text{MSE} = \frac{1}{N} \sum_{i=0}^{N-1} (\|\mathbf{V}(i) - \hat{\mathbf{V}}(i)\|)^2, \mathbf{V} \in [\mathbf{F}, \mathbf{T}]$$

using the proposed method and the LSE-LP approach for different force/torque deadband values, respectively. It should be emphasized that Tables I presents the average haptic data compression results obtained upon evaluating the 10 aforementioned 6-DoF datasets. Additionally, data samples encoded (stored) using the proposed compression method consist of 3D coefficients associated with computed/fitted quadratic curves of force, torque data, and the number of data samples in the subsets. Conversely, data samples encoded using the LSE-LP method (as typically performed in the offline and online compression methods that use this approach [3,4,11,19]) consist of the original 3D force, torque data, and the

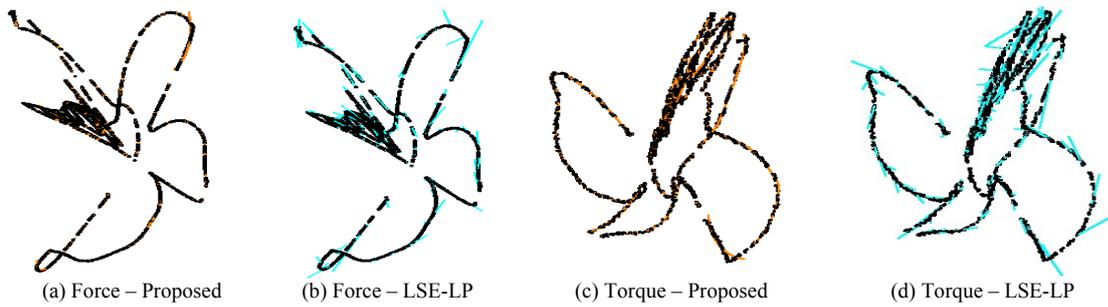


Figure 5. Plots comparing the performance of the proposed prediction model with the LSE-LP method, using force/torque data contained in one of the experimental datasets (force/ torque deadbands = 15%/12%).

TABLE
COMPARISON OF THE PROPOSED COMPRESSION METHOD WITH THE LSE-LP APPROACH WHEN FORCE FEEDBACK (FORCE/TORQUE) DATA ARE CONSIDERED.

Force/Torque Deadband [%/%]	Reduction Ratio Proposed/LSE-LP	Force MSE Proposed/LSE-LP	Torque MSE Proposed/LSE-LP
0.5/0.5	41.41% / 13.91%	$5.3 \cdot 10^{-7} / 6.9 \cdot 10^{-7}$	$3.9 \cdot 10^{-9} / 5.2 \cdot 10^{-9}$
1.0/1.0	53.57% / 35.12%	$1.7 \cdot 10^{-6} / 3.9 \cdot 10^{-6}$	$2.0 \cdot 10^{-8} / 3.5 \cdot 10^{-8}$
1.5/1.5	62.01% / 48.06%	$3.2 \cdot 10^{-6} / 1.0 \cdot 10^{-5}$	$4.4 \cdot 10^{-8} / 1.0 \cdot 10^{-7}$
3.0/3.0	75.70% / 68.87%	$7.9 \cdot 10^{-6} / 4.6 \cdot 10^{-5}$	$1.3 \cdot 10^{-7} / 4.9 \cdot 10^{-7}$
5.0/5.0	83.67% / 80.15%	$1.9 \cdot 10^{-5} / 1.3 \cdot 10^{-4}$	$2.7 \cdot 10^{-7} / 1.4 \cdot 10^{-6}$
7.0/7.0	88.41% / 85.41%	$4.6 \cdot 10^{-5} / 2.9 \cdot 10^{-4}$	$6.1 \cdot 10^{-7} / 2.7 \cdot 10^{-6}$
10.0/9.0	89.74% / 88.33%	$9.4 \cdot 10^{-5} / 5.5 \cdot 10^{-4}$	$9.9 \cdot 10^{-6} / 4.7 \cdot 10^{-6}$
15.0/12.0	91.12% / 90.74%	$1.6 \cdot 10^{-4} / 9.6 \cdot 10^{-4}$	$1.5 \cdot 10^{-6} / 8.2 \cdot 10^{-6}$

lengths of predicted line segments.

From Table I and Fig. 6 (a – d), it can be observed that for different force and torque deadbands, the proposed haptic data compression strategy outperforms the LSE-LP method. For all considered deadbands, the number of encoded data samples is substantially less when the proposed data reduction algorithm is used. For example, for a relative force/torque deadband pair=3.0/3.0¹, the average data reduction rate using the proposed method is 75.70%. Conversely, the average data reduction rate using the LSE-LP method is 68.87%. Moreover, for a relative force/torque deadband=0.5/0.5, the average data reduction rate using the proposed method is 41.41%. For the same relative deadband value pair, the average data reduction rate using the LSE-LP method is 13.91%.

Furthermore, from Table I it can be seen that MSE values obtained when compression is performed using the proposed algorithm are better than those obtained when the LSE-LP method is considered.

V. CONCLUSION

In this paper, an offline haptic data reduction algorithm is proposed. The algorithm is based on a prediction model that exploits tangential directions at different haptic data points and quadratic curve reconstruction to improve haptic data reduction performance and signal approximation precision. Furthermore, the limitations of

human haptic perception are considered in the method to ensure that compression artifacts are imperceptible to the user in haptic playback systems. The experimental results demonstrate that the proposed haptic data reduction strategy can potentially outperform other related methods in the literature which typically rely on a general linear prediction method.

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¹ In [4], it was determined that in haptic data compression of 6-DOF data, force/torque deadbands of 3.0%/3.0% will result in little or no influence on the quality of haptic-enabled interaction.

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