# PERCEPTION-BASED COMPRESSION OF HAPTIC DATA STREAMS USING KALMAN FILTERS

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**ABSTRACT**

In order to realize truly immersive and stable telepresence and teleaction over the Internet it is necessary to keep delay, data rate, and packet rate of haptic data streams as low as possible. In addition, the compression scheme for haptic data, which is necessary to achieve those goals, must be fast enough to work on a sample by sample basis to not add further delay. This paper presents an approach that reduces haptic data traffic in networked telepresence and teleaction systems to a small fraction of the original rate without impairing performance by using fast Kalman filters on the input signals combined with model based prediction of haptic signals. Our approach reduces the number of transmitted packets to 9.8% (velocity) and 6.2% (force) of the original rate without impairing immersiveness.

## 1. INTRODUCTION

In a telepresence and teleaction (TPTA) system a teleoperator (TOP), either a robot equipped with different kinds of sensors and actuators or a virtual simulation thereof, is controlled by an operator (OP), a human being using a human system interface (HSI). The HSI records the position and velocity input by the OP and reflects sensor information acquired by the TOP using displays for visual, auditory and haptic data. While the transmission of video and audio data is mostly unproblematic, haptic data (position/velocity and force/torque) poses a couple of additional challenges. The OP commands the desired TOP position/velocity using the HSI whereas the contact force at the TOP is sent back to the OP side. Therefore a global control loop is closed over the communication system. Because delays in the system may quickly destabilize it [1], the system has to be stabilized by means of sophisticated control measures [2].

Nowadays, the ubiquitous Internet is the medium of choice for the transmission of multimodal data. Unfortunately, high rate real-time data transmission is still a problem and varying delays mostly due to congestions in routers appear as well as packet loss. In order to still use the Internet for TPTA communication makes it imperative to use special data compression and transmission strategies for haptic data streams.

TPTA systems like the one described in [3] normally run update rates of 500–1000 Hz for the local control loops in order to achieve the desired tracking accuracy. Because of increasing stability problems with introduced delay every set of sampled sensor values of a sampling instance has to be transmitted in an individual packet leading to high packet rates (500–1000 packets per second) as well as a poor header to payload ratio because haptic data packets are usually very small depending on the number of degrees of freedom (DoFs) of the system and the sampling resolution. Because of these particular characteristics of packet based transmission of haptic data streams, the only effective way to reduce haptic data traffic is to reduce the rate of which packets are sent.

The Kalman pre-filtering step proposed in this paper enhances the performance of the methods described in [4] and [5] considerably by removing the noise from haptic input signals and therefore making signal prediction much easier and more accurate.

The remainder of this paper is organized as follows. In Section 2 we briefly present previous work on this topic. Section 3 deals with the proposed Kalman pre-filtering of input signals followed by the description of the psychophysical experiment in Section 4 along with its results in Section 5. Section 6 concludes this paper.

## 2. PREVIOUS WORK

In [4] we presented a perception-based deadband transmission approach to reduce the packet rate in TPTA systems. This deadband approach is based on Weber's Law of psychophysics which states that a stimulus has to change for more than a constant percentage in order to be perceivable by human beings [6, 7]. Consequently, data packets are only transmitted when the change of the transmitted stimulus is larger than a given deadband in comparison to the previously transmitted stimulus. This approach leads to a reduction of packet rates between 75% and 90% but is only applicable for 1-DoF devices.

Because of this major disadvantage we extended the deadband approach to 3-DoF applications. This extension is quite straight forward. A 3-dimensional vector of haptic data (mostly velocity or force) is transmitted to the receiver. If the newly sampled vector lies within a spherical deadzone around the tip of the previously sent vector, the new vector is discarded. Only if it lies outside the deadzone, the new vector is sent and used as the new reference vector. The size of the deadzone depends on the chosen deadband percentage. This approach reaches almost the same efficiency as the 1-DoF approach.

In [5] we improve this scheme by introducing a model based signal prediction on both sides of the system. Those predictors (in

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case of this paper linear predictors [LP]) are fed with the same input data on both sides and are therefore always running in parallel. They predict future sample values based on previous ones. Again, a packet carrying new sample information is only sent, if the actual sample value differs by more than the deadband value from the predicted value. This approach leads to an additional 20% to 45% reduction of packet rate in comparison to the 3-DoF approach mentioned before.

## 3. KALMAN FILTERING OF INPUT SIGNALS

Our investigations on typical sensor signals in TPTA systems and predicted signals have shown that prediction of the signals could be much more accurate if there was less noise in the sensor data. Most noise can be observed on velocity signals, which are used for the communication from OP to TOP. The reason for this is simple: Sensors in haptic input/output devices are position sensors and velocity is derived from the position data by differentiation. This differentiation heavily amplifies the noise which is already in the position signals. Force signals, which are transmitted from TOP to OP are less noisy because force is recorded from the sensors directly. This is one of the reasons why the compression of force signals works significantly better than the compression of velocity signals in the three methods reviewed in Section 2.

To denoise the input signal in order to be able to predict future samples more accurately and therefore increase compression performance we introduce a fast Kalman filter. A snapshot of the application of this filter in one of our experiments can be seen in Figure 1.

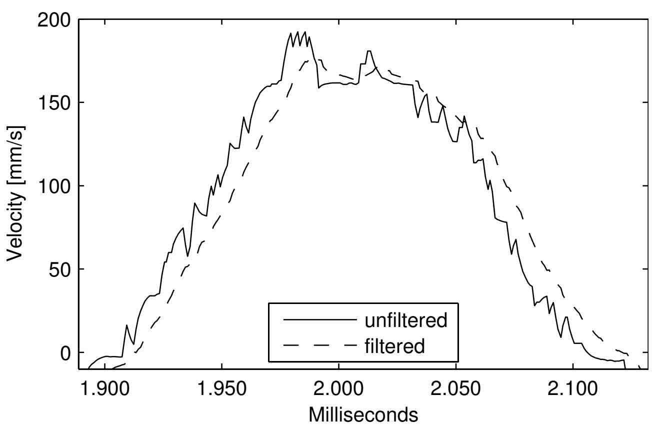


**Fig. 1**. Velocity signal before and after Kalman pre-filtering.

### 3.1. Kalman Filter

To be computationally efficient we need a filter which has a low complexity and can be applied to a signal sample by sample. The Kalman filter [8] in a simplified form does exactly fulfill those needs. We use a scalar Kalman filter for every DoF separately to keep computational complexity low. This is necessary, because filtering has to take place in real time at sampling rates of 1000Hz and many other algorithms (haptic rendering, deadband transmission, prediction models etc.) have to be executed in the one millisecond between samples.

A discrete one dimensional signal of sample values $x_k$ (the real signal without noise) shall be approximated by an estimated signal $\hat{x}_k$. Therefore measurements $z_k$ are taken every sampling instant and the following algorithm is applied:

1. Calculating the innovation $I$, which is the difference between the measurement and the estimation:

$$I = z_k - \hat{x}_{k-1}$$

2. Calculating the variance of the innovation $I$:

$$S = P + R$$

where $P$ is the variance of the prediction error (calculated below) and $R$, the variance of the measurement noise, which is also the only parameter we use to adjust the filter characteristics.

3. After that we calculate the gain $K$ for the estimation step:

$$K = \frac{P}{S}$$

4. Then finally the estimation:

$$\hat{x}_k = \hat{x}_{k-1} + K \cdot I$$

5. and the calculation of the new variance of the prediction error:

$$P = P + Q - K \cdot P$$

where $Q$ is the variance of the process noise. We set it to 1 to have only one filter parameter.

Steps 1 through 5 are executed every sampling instant and the filtered signal values $\hat{x}_k$ are taken as input signals instead of the noisy measurements.

The filter characteristics can be adjusted by changing the parameter $R$, the variance of the measurement noise, which weighs the measured values against the predicted value which in our filter is simply holding the last value. A low $R$ leads to a high confidence that measurements are correct, therefore measurements are weighted more for the filter output than the prediction and vice versa. The example in Figure 1 was recorded using $R = 100$, which was chosen as a good trade off between noise reduction and system response during the preparation phase of the experiment. This was also the value which was used for the velocity signal in the psychophysical experiment in Section 4.

### 3.2. System Design

The signal processing steps in the presented system can be seen in Figure 2.

The sampled velocity values at the HSI are first filtered by the proposed Kalman filter with $R = 100$. The resulting denoised signal is fed into the deadband controller. This deadband controller detects whether the difference of the predicted signal from the prediction model and the Kalman filtered input signal is bigger than the deadband value. If this is the case, a new packet is generated and sent to the TOP side while at the same time the prediction model is updated with the same value. So in consequence the prediction models on both sides run completely symmatrically. In our case a simple first order prediction is used, where future sample values are extrapolated linearly from the last two transmitted sample values (like in [5]). On the TOP side, the system keeps getting new values from the prediction model which is constantly updated by the deadband data from the OP side.

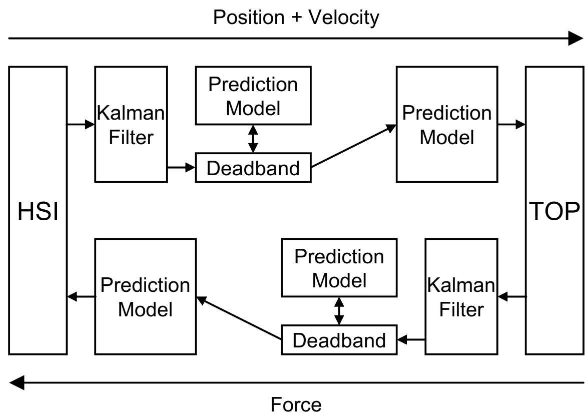


**Fig. 2**. The system signal flow design.

In the direction from TOP to OP signals are handled similarly with the difference that the Kalman filtering only needs to have $R = 5$ (also empirically chosen as a good trade off) because force signals in our case have much less noise than the velocity signals. In other systems the $R$ parameter has of course to be adapted to the noise level of the respective sensors and the desired frequency response. Filtering with higher $R$ leads to a lower cut-off frequency. In consequence this gives us the opportunity to decide the trade-off between compression efficiency and frequency response.

## 4. PSYCHOPHYSICAL EXPERIMENT

In order to prove the efficiency of the proposed algorithm a psychophysical experiment has been conducted.

### 4.1. Setup

The conducted experiment consists of a haptic teleinteraction task with a virtual environment. The hardware and software setup is the following: On the OP side the haptic display device SensAble PHANTOM Omni serves as the HSI. Over a 100Mbit/s Ethernet LAN connection this OP side transmits current position and velocity samples to a simulated haptic environment on another machine in the same LAN and receives force data in return to be displayed to the OP along with a 3D view of the scene rendered in real time.

The task itself is touching and feeling a virtual scene which is simulated by the TOP side. The only object in the virtual environment in this experiment is a sphere in the middle of the virtual workspace. This sphere is of course registered with the sphere in the graphical display on the OP side so that contacts between the cursor and the sphere in the graphical display exactly correspond with contacts in the virtual environment. The virtual sphere is fixed at the center of the workspace and can be touched with the virtual cursor. The resulting force during the interaction is calculated by a simple Hooke's Law

$$F = u \cdot d$$

where $u$ is the stiffness of the sphere and $d$ the amount of penetration into the sphere body. $F$ is the resulting force's magnitude. The direction of the force always points from the sphere's center to the actual cursor position. So in this case it can be calculated as

$$\mathbf{F} = \frac{\mathbf{x} - \mathbf{s}}{|\mathbf{x} - \mathbf{s}|} \cdot (r - |\mathbf{x} - \mathbf{s}|) \cdot u$$

where the resulting force vector $\mathbf{F}$ is calculated from the current position of the user $\mathbf{x}$, the sphere's position in space $\mathbf{s}$, the sphere's radius $r$, and the sphere's stiffness $u$.

The haptic feedback is generated as follows. The OP uses the HSI to command the desired position in space. This position information is transformed into velocity information by differentiation and sent to the TOP after being processed by the transmission system (see Figure 2. Despite filter-, deadband- and prediction algorithms are only used on the velocity signal, current position information is sent along in order to be able to compensate for position errors resulting from the velocity deadband. The position signal coming from position sensors is noisy and so is the velocity signal. On the TOP side the received signal is incorporated into the prediction model and the output force is calculated by the haptic rendering. The resulting force signal has no measurement noise but gets distorted by rapid position corrections caused by the prediction model and the velocity deadband and is therefore processed in the same way as the velocity signal before being sent to the op side. Of course, in real TPTA systems we get noise from the force sensors as well.

### 4.2. Subjects

Five test subjects underwent the procedure described in 4.3. One was female, four were male. All had normal sensory motor capabilities and were 25 to 31 of age.

### 4.3. Procedure

Two sets of evaluations were made with the goal to estimate a perception threshold value for the deadzone in the following three cases:

1. Deadband is applied on velocity values
2. Deadband is applied on force values

To achieve that, the subjects are first presented with a system completely without deadband to get used to handling the device and to learn to know what it feels like. Then a heavily distorted system is shown to the subjects in which they can clearly feel the kind of distortion which is introduced into the system by the deadzone transmission. This phase is called the familiarization phase.

After the subjects feel familiar with the system and the kind of distortion they are presented with, three test runs are conducted each consisting of twelve 30-second intervals (24 intervals in 12 minutes total). In the first run with twelve intervals the deadband is only used for the velocity values which are sent from the OP to the TOP. In the second run the deadband is only used on force values which are sent from TOP to OP. During the tests, the subjects wore a headphone which played loud music so they had to concentrate on their haptic sensations.

The 12 intervals of each run use a randomly chosen order of the following possible deadband values: 0%, 2.5%, 5%, 7.5%, 10%, 12.5%, 15%, 20%, 25%, 30%, 35%, and 40%. The subjects did neither know which value was currently being used nor did they know in which direction the deadband was applied.

After every interval the subject was asked to give a rating for the just perceived interval. If it felt perfectly like the undistorted signal from the familiarization phase, they should give a rating of 10 points. If it feels just as bad as the heavily distorted signal from the familiarization phase, they should give a rating of 1 point. The ratings in between can be chosen according to the quality of the signal where of course higher ratings signify a better quality.

## 5. EXPERIMENTAL RESULTS

The ratings given by the test subjects can be seen in Figure 3. We can see an almost linear decrease in the ratings for both types of data with increasing deadband value. We say that values of 7 and higher represent a good feeling of immersion with the system. Consequently, we can say, that 10% deadband for both velocity and force should not be exceeded to not sacrifice immersion, but lower deadband values are always desirable.

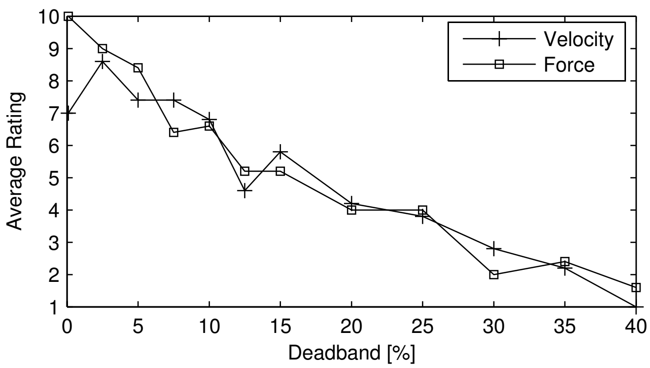


**Fig. 3**. The average ratings given by the test subjects.

Rates of generated packets can be seen in Figure 4. Compared to the results from [5], where no Kalman pre-filtering was applied, we can observe a strong decrease in velocity packet rates, especially with small deadband values. This is exactly the benefit the Kalman pre-filtering was supposed to give. This has two main reasons. Firstly, during motion phases with small velocities the velocity noise constantly triggered the deadband. With less noise in the signal this happens considerably less often. Secondly, less noise makes it easier to estimate and predict signal slopes.

For force packet rates the improvements are not as significant as in the velocity case. The reason for this is the fact that we have considerably lower noise levels on the force signal to begin with. The Kalman pre-filtering step is therefore not as efficient here as for velocity signals. Still we can observe a significant improvement (65%) in packet rate at 2.5% deadband in comparison to the LP case. This means almost 94% packet rate reduction in comparison to the original rate with only a minimal 2.5% deadband applied.

Finally we can state that the proposed Kalman pre-filtering step for prediction based deadband transmission of 3D haptic data works well for velocity and force data. At a combination of 7.5% deadband for velocity and 2.5% deadband for force we achieve a reduction of packet rate to 9.8% of the original rate for velocity and 6.2% for force with barely noticeable influence on immersiveness.

## 6. DISCUSSION AND FUTURE WORK

The Kalman pre-filtering step proposed in this paper improves packet rate reduction in TPTA systems considerably. Despite the example application being relatively simple it still gives an impression how the scheme works. The parameter $R$ gives the user the possibility to adjust the transmission system to his needs of packet rate reduction

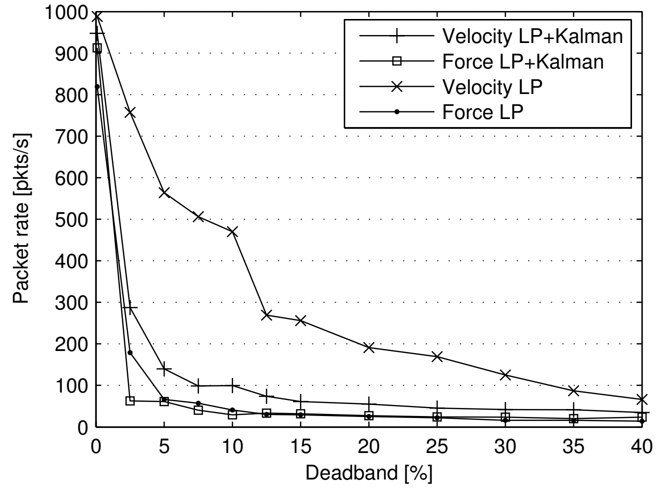


**Fig. 4**. The packet rates measured in the experiment compared to linear signal prediction without Kalman pre-filtering [5].

and frequency response. In our experiments we observe a significant reduction in packet rate in comparison to previous approaches without noticeable impairments of the immersiveness of the system.

## 7. REFERENCES


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