THE WEBER QUANTIZER: PERCEPTUAL CODING FOR NETWORKED TELEPRESENCE AND TELEACTION

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ABSTRACT

We present a theoretical analysis of a perceptual coding approach for networked telepresence and teleaction. Our so called Weber quantizer is based on Weber's Law and can be used in haptic data communication to eliminate changes which can not be perceived by the human operator. The main advantage of the Weber quantizer is that it minimizes the number of samples or packets to be transmitted. Basic properties like the resulting sample rate and the MSE of the proposed Weber quantizer are derived analytically and proven correct by simulation for the case of a uniformly distributed input sequence. The contributions in this paper provide the basis for the analysis of more realistic signal models and constitute a first step towards the understanding of the relationship between the Weber quantizer, statistical error measures and actual human distortion perception.

Index Terms— Quantization, perceptual coding, teleoperation, telepresence, teleaction

1. INTRODUCTION

Extensive studies performed by experimental psychologists and physiologists have unveiled a great number of limitations, properties and dependencies in human perception. Modern signal processing makes it possible to use these findings for the optimization of perceptual signal coding. In this work we study perception-based data reduction for haptic data streams in networked telepresence and teleaction systems.

Quantization is the lossy step in the conversion of analog data into its digital representation. It introduces noise into the signal and makes it impossible, even for band limited signals sampled above the Nyquist-rate, to reconstruct the original signal perfectly.

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The Weber quantizer presented in this work is different to other quantizers in many ways as will be explained later. It exploits one very basic property of human perception which is known as Weber's Law. We analyze the signal behavior of the Weber quantizer in order to derive metrics for the parameters it uses. Our goal is to find connections between the analytical signal distortion it causes and the distortion perceived by humans.

The remainder of this paper is organized as follows. In Section 2 we present previous work on this topic. Section 3 presents the basis for the presented approach followed by a detailed description of the approach itself in Section 4. Some basic properties of the approach are presented in Section 5 and confirmed by simulation results in Section 6. Section 7 concludes this paper.

2. PREVIOUS WORK

Quantization is omnipresent in today's digital technology. For example, Pulse Code Modulation (PCM) as the basic type of digital media signal representation is used with different quantizers depending on the application. For instance, on a Compact Disk (CD) it is used with a uniform scalar quantizer with 16bit resolution. In ISDN it is used with non-linear quantizers (A-law, μ-law, [1]) with 8-bit resolution for telephone speech data. Those two quantizers use a logarithmic scale to match human distortion perception and to optimize signal to noise behavior in speech communication. For this kind of scalar quantization, every sample value is quantized individually. There is no delay introduced by the quantization step. For storage or transmission over a circuit switched connection this approach works fine. For block-based or packet-based transmission typically multiple quantized samples are sent en bloc. The delay encountered corresponds to the block-size used. More recent work on multidimensional logarithmic quantizers which is closely related to the multidimensional extension of the Weber quantizer was presented in [2]. The quantizer in [2] targets at very low delay and hence very small blocks of samples are quantized jointly. If the delay constraint is so strict that every new sample has to be quantized and transmitted immediately, the quantizer in [2] becomes a traditional logarithmic scalar quantizer.

In comparison to these quantizers the quantizer studied in this work introduces no delay and minimizes the number of samples to be sent from a transmitter to a receiver. This property is particularly attractive if every sample has to be sent in a separate packet as it is typically done in networked telepresence and teleaction systems. In such a scenario, the Weber quantizer minimizes the number of packets being generated.

The Weber quantizer presented in this work has already been used for the transmission of haptic data in telepresence and teleaction systems and has been proven to work efficiently [3, 4, 5]. Stability implications and passivation methods for the presented approach have been presented in [6, 7, 8]. In this paper we concentrate on a theoretical analysis of its properties.

3. WEBERS LAW

Human perception has undergone thorough research during the last century. The respective perceptual threshold values for all kinds of stimuli put on the human body have been studied. Apart from very detailed information for every modality a human being can perceive, one major conclusion emerged from these studies: Human perception often follows Weber's Law. Ernst Weber was an experimental physiologist who in 1834 first discovered the following implication

$$\frac{\Delta I}{I} = k \quad \text{or} \quad \Delta I = kI \tag{1}$$

where ΔI is the so called Difference Threshold or the Just Noticeable Difference (JND). It describes the smallest amount of change of an (arbitrary) stimulus which can be detected just as often as it cannot be detected. I is the initial stimulus which is altered by the JND and the constant k, which we call the threshold parameter from now on, describes the linear relationship between the JND and the initial stimulus.

4. THE WEBER QUANTIZER

Generally, a scalar quantizer defines intervals of possible input values and maps them to one output value for each interval, the so called representative value. The time discrete input signal can either be continuous in amplitude or already quantized. The output signal of a quantizer normally consists of 2^n possible representative values for a n-bit quantizer. The Weber quantizer differs from standard quantizers as is explained in the following.

4.1. Principle

The Weber quantizer generates a constant output signal q as long as the input signal does not exceed the perception threshold $q \pm kq$. Once this threshold is exceeded, the output signal is updated to the current signal value and this value is held at the output until the new perception threshold is exceeded.

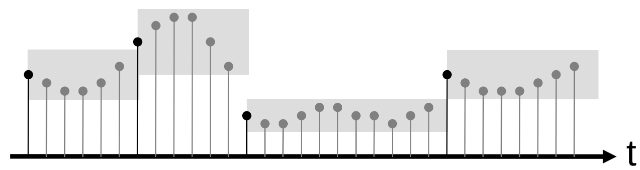

Fig. 1. Principle of the Weber quantizer.

The principle of the Weber quantizer is illustrated in Figure 1. Values in black are the output of the Weber quantizer. Values shown in grey do not violate the threshold and are discarded. The grey zone around the black output signal, the so called deadband, marks the perception threshold. Once it is violated by a new input sample, this input sample becomes the output.

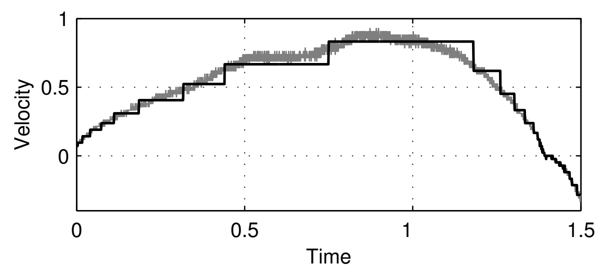

Fig. 2. A haptic signal before and after applying the Weber quantizer. The signal represents the velocity of a haptic device in a telepresence and teleaction experiment [3]. The velocity signal is sampled with 1kHz and represented with 16 bit before quantization with the Weber quantizer.

Figure 2 shows the quantization of a signal in a telepresence and teleaction experiment [3]. In this experiment, the sender is a human operator attached to a human-machine-interface and the receiver is a telerobot. The recorded velocity signal is the noisy signal shown in grey. The quantized signal is the step-shaped signal drawn in black. Note the variable step size depending on the signal magnitude, which corresponds to the JND. As can be seen from Figure 2, the Weber quantizer generates only a very small number of different output samples that are to be signaled between the sender and receiver. In case of a perceivable change it modifies the output without any algorithmic delay.

Whereas other quantizers like scalar and vector quantizers reduce the output alphabet and thereby the sample resolution of the signal, the Weber quantizer adapts the temporal resolution of a signal.

4.2. Input-Output Relationship

The main rule, how the output signal is generated is described in the following. The discrete input signal is defined as:

$$x_i \in [-\infty, +\infty] \tag{2}$$

where i is the sequence number of a sequence of input samples.

The output signal of the quantizer q_i is generated by the following rules:

$$q_i = \begin{cases} x_{i-m} & \text{if} \quad \frac{|x_i - x_{i-m}|}{|x_{i-m}|} < k \\ x_i & \text{else} \end{cases} \tag{3}$$

and

$$q_{i-1} \dots q_{i-m} = x_{i-m} \tag{4}$$

where m samples back in the signal the last threshold violation took place. k is the perception threshold from Equation (1). For human perception k is in most cases in the range from 0.05 to 0.15. We call x_{i-m} the reference value from now on.

5. ANALYSIS

At first we determine the amount of distortion the Weber quantizer introduces. We do this in order to gain a first relationship between measured distortion and perceived distortion. As in other fields of perceptual coding (like video coding) perceptual models are very complex. So although perceived distortion may deviate from measured distortion greatly, simple distortion measures are commonly used to evaluate the performance of coding techniques. In upcoming work, we plan to utilize the knowledge gained from MSE computazion to find metrics that describe how the parameters of the Weber quantizer affect human distortion perception.

5.1. MSE Calculation

5.1.1. Definition of MSE

The MSE of the Weber quantizer introduced up to sample x_i is defined as:

$$\text{MSE} = e = \frac{\sum_{j=0}^{i} (x_j - q_j)^2}{i+1} \tag{5}$$

When the input signal is stationary, we can write the MSE as the expected value:

$$e = E[(x_i - q_i)^2] \tag{6}$$

q_i depends on the last reference value x_{i-m} (the current output value). This value lies m steps back in the input signal. So we have to consider all possible values of m and multiply each respective expected value with the probability that x_{i-m} was the last reference value. This probability is denoted as δ_m in the following. Hence,

$$e = \sum_{m=1}^{\infty} \delta_m E[(x_i - q_{i-m})^2] \tag{7}$$

$m = 0$ is left out because no error is introduced when x_i becomes the new reference value.

5.1.2. MSE for Uniformly Distributed Input Signals

We assume x_i to be uniformly distributed from $-a$ to a:

$$x_i \in \mathcal{U}(-a, a) \tag{8}$$

and signal values are independent:

$$P\{x_i | x_{i-m}\} = P\{x_i\} \in \mathcal{U}(-a, a) \tag{9}$$

Admittedly, this is quite a simple signal model. However, it provides a first step to the theoretical analysis of this novel quantizer to see how it behaves for very basic signals. In upcoming work, we will provide analysis for signal models which more adequately match the encountered signals in bilateral telepresence and teleaction like a Wiener process model or an autoregressive model.

5.1.3. Calculation

For $m = 1$:

$$e = E_{x_{i-1}} \left[E_{x_i}[(x_i - q_{i-1})^2 | x_{i-1}] \right] \tag{10}$$

This means that the MSE in the case $m = 1$ is the expected value of the squared error given the previous value was the reference value.

$$\begin{aligned} & E_{x_i}[(x_i - q_{i-1})^2 | x_{i-1}] = \\ & = \int_{x_{i-1}(1-k)}^{x_{i-1}(1+k)} (x_i - x_{i-1})^2 \cdot P\{x_i | x_{i-1}\} dx_i \end{aligned} \tag{11}$$

To simplify we introduce $v = x_{i-1}$:

$$\frac{1}{2a} \int_{v(1-k)}^{v(1+k)} (x_i - v)^2 dx_i = \frac{1}{2a} \int_{-kv}^{kv} x_i^2 dx_i = \frac{k^3}{3a} v^3 \tag{12}$$

$$E_{x_{i-1}} \left[\frac{k^3}{3a} v^3 \right] = \frac{1}{2a} \frac{k^3}{3a} \int_{-a}^{a} v^3 dv = \frac{k^3 a^2}{12} \tag{13}$$

Under the same assumptions and the same signal model, especially because of the independence of subsequent signal values, we can also say for general m:

$$E_{x_i}[(x_i - q_{i-m})^2 | x_{i-m}] = \frac{k^3}{3a} x_{i-m}^3 \tag{14}$$

and

$$E_{x_{i-m}} \left[E_{x_i}[(x_i - q_{i-m})^2 | x_{i-m}] \right] = \frac{k^3 a^2}{12} \tag{15}$$

Therefore the MSE is:

$$e = \sum_{m=1}^{\infty} \delta_m E[(x_i - q_{i-m})^2] = \frac{k^3 a^2}{12} \sum_{m=1}^{\infty} \delta_m \quad (16)$$

Because one of the preceding input values is certainly the reference value, the sum over the probabilities δ_m is 1. Concluding, we can say:

$$e = \text{MSE} = \frac{k^3 a^2}{12} \quad (17)$$

for the given signal model.

5.2. Update Rate

Since the output signal of the Weber quantizer does not change as long as the input signal stays within the perception bound, no information passes through the quantizer during those times. This property can be used to reduce update rates because only in case of threshold violation updates are necessary. In applications like the transmission of data streams this can be used to significantly lower packet transmission rates as shown in [3, 4, 5] in the context of haptic data communication in telepresence and teleaction systems.

5.2.1. Savings in Update Rate

In general, the savings in update rate can be expressed as the probability α that a new input value does not violate the current threshold.

$$\begin{aligned} \alpha &= P\{x_i \text{ does not violate threshold}\} = \\ &= \sum_{m=1}^{\infty} P\{-k < \frac{x_i - x_{i-m}}{x_{i-m}} < k\}\delta_m \end{aligned} \quad (18)$$

The probability that a new input value x_i does not violate the threshold $x_{i-m} \pm kx_{i-m}$ multiplied with the probability that the value x_{i-m} is the respective reference value is summed up over all possible values of m.

5.2.2. Savings for Uniformly Distributed Input Signals

If we again assume x_i to be uniformly distributed from $-a$ to a, we can calculate the update rate saving as follows.

$$\begin{aligned} \alpha &= \sum_{m=1}^{\infty} P\{-k < \frac{x_i - x_{i-m}}{x_{i-m}} < k\}\delta_m \\ &= \sum_{m=1}^{\infty} \gamma\delta_m = \gamma \sum_{m=1}^{\infty} \delta_m = \\ &= \gamma \end{aligned} \quad (19)$$

Now we have to calculate γ.

$$\gamma = P\{-k < \frac{x_i - x_{i-m}}{x_{i-m}} < k\} \quad (20)$$

Unfortunately this is not trivial. The PDF of the term

$$\beta = \frac{x_i - x_{i-m}}{x_{i-m}} \quad (21)$$

can be seen in Figure 3. Note that the distribution does not depend on a.

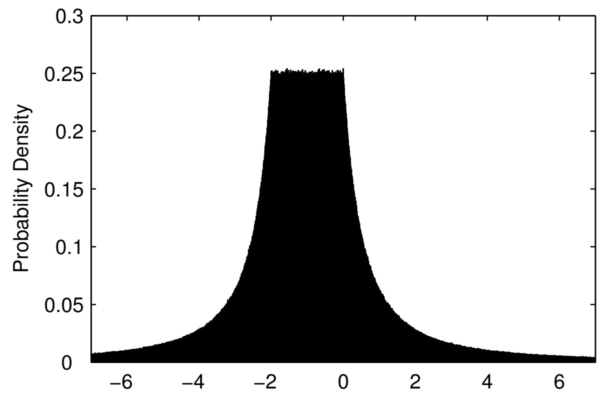

Fig. 3. Probability distribution of β.

The integral under this distribution from $-k$ to k yields γ. Figure 4 shows the curve for γ from $k = 0$ to $k = 1$.

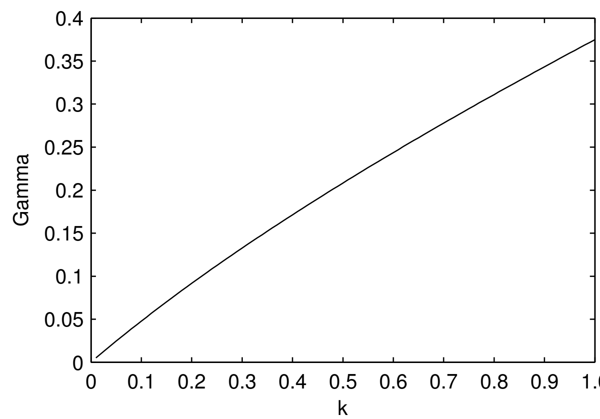

Fig. 4. The update rate savings γ over k.

6. SIMULATION RESULTS

6.1. Calculated MSE

In order to verify the analytical calculations in the last section simulations were conducted. The left plot in Figure 5 shows the MSE as calculated in Equation (17) as a function of the width of the uniform distribution a and the threshold parameter k. Values of a range from 0 to 10, k ranges from 0 to 0.5.

6.2. Simulated MSE

The simulation was done by taking every possible combination of a and k and generating a uniformly distributed random

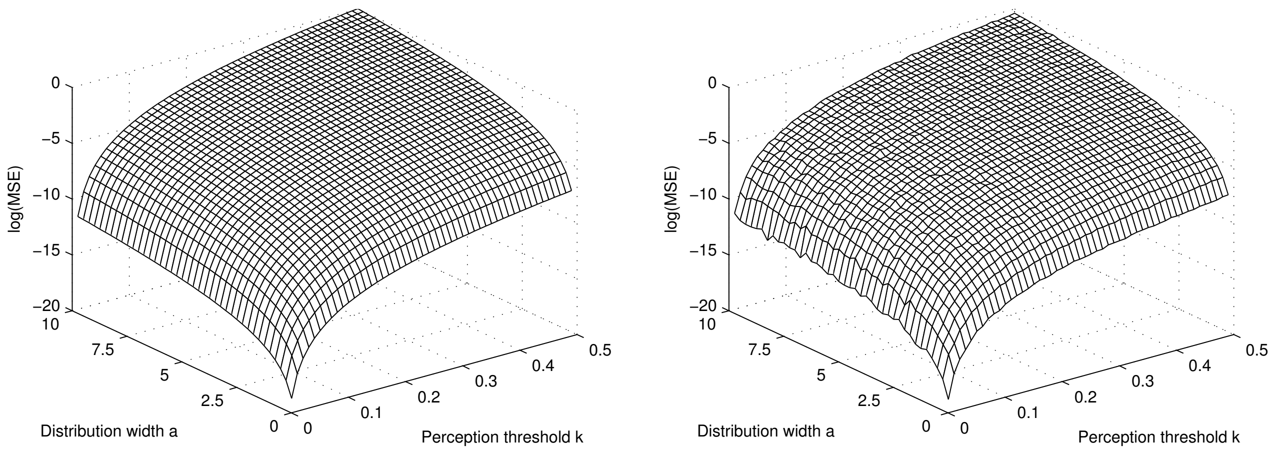

Fig. 5. The calculated (left) and simulated (right) MSE results.

sequence of 1000 samples with the respective a, quantizing this sequence with a Weber quantizer with the threshold parameter k and measuring the resulting MSE. The measurement plot is shown on the right side of Figure 5.

We can see that the plots match very well which indicates that the analytical derivations were correct. However, due to the simplicity of the signal model, implications for real applications are hard to derive.

6.3. Simulated Savings in Update Rate

During the same simulation run a measurement of update rate savings was made. The results of this measurement are shown in Figure 6.

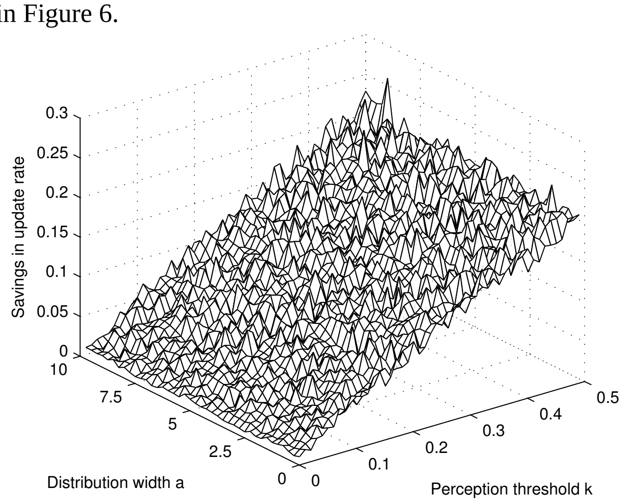

Fig. 6. Simulated savings in update rate.

It can be seen that the savings in update rate are independent from the width of the uniform distribution. And the increase with k matches exactly the calculations from Figure 4. What we can see from this result is that for the given signal model packet rate savings are almost linearly dependent on k, with a saving rate of about 5% for $k = 10\%$ (an empirically reasonable value). Experiments with real telepresence and teleaction systems have shown that for $k = 10\%$ packet rate savings of 90% and more are possible. This leads to the conclusion that a more correlated signal model (like Wiener or autoregressive process) would yield much more realistic results.

7. DISCUSSION AND FUTURE WORK

A new way of perceptual coding is presented in this work. The so called Weber quantizer is introduced. In comparison to well known approaches like scalar- and vector-quantization, the Weber quantizer does not quantize the samples of a signal but its temporal behavior. It can be used to remove imperceptible samples from a signal and, by doing so, adaptively downsample the signal. This work concentrates on the theoretical background of the approach: We present a way of computing the achievable update rate saving along with the analysis of the distortion (MSE) introduced by it for uniformly distributed input sequences both analytically and by simulation.

Since the Weber quantizer gives us the possibility to only update the output signal when a perceivable change of the input signal takes place, it can be used in the packetized transmission of multimedia data as has been shown in earlier work of the authors where haptic data in telepresence and teleaction systems was transmitted. The perception threshold parameter k has to be determined individually for every application. Our experiments with haptic data showed k to be mostly between 0.05 and 0.15.

The multidimensional extension of the Weber quantizer has already been presented in [4] and will be further analyzed in the near future.

8. REFERENCES

[1] ITU-T Recommendation G.711, "Pulse code modulation (pcm) of voice frequencies," November 1988.

[2] J. B. Huber and B. Matschkal, "Spherical logarithmic quantization and its application for dpcm," in *Int. ITG Conf. on Source and Channel Coding*, Erlangen, Germany, January 2004, pp. 349–356.

[3] P. Hinterseer, E. Steinbach, S. Hirche, and M. Buss, "A novel, psychophysically motivated transmission approach for haptic data streams in telepresence and teleaction systems," in *Proc. of the IEEE Int. Conf. on Acoustics, Speech, and Signal Processing*, Philadelphia, PA, USA, March 2005, pp. 1097–1100.

[4] P. Hinterseer, E. Steinbach, and S. Chaudhuri, "Perception-based compression of haptic data streams using kalman filters," in *Proc. of the IEEE Int. Conf. on Acoustics, Speech, and Signal Processing*, Toulouse, France, May 2006.

[5] P. Hinterseer, E. Steinbach, and S. Chaudhuri, "Model based data compression for 3d virtual haptic teleinteraction," in *Digest of Technical Papers at the IEEE Int. Conf. on Consumer Electronics*, Las Vegas, NV, USA, January 2006, pp. 23–24.

[6] S. Hirche, P. Hinterseer, E. Steinbach, and M. Buss, "Towards deadband control in networked teleoperation systems," in *Proceedings IFAC World Congress, International Federation of Automatic Control*, Prague, Czech Republic, 2005.

[7] S. Hirche, P. Hinterseer, E. Steinbach, and M. Buss, "Network traffic reduction in haptic telepresence systems by deadband control," in *Proceedings IFAC World Congress, International Federation of Automatic Control*, Prague, Czech Republic, 2005.

[8] S. Hirche, P. Hinterseer, E. Steinbach, and M. Buss, "Parsimonious data transmission in haptic telepresence systems," in *Proceedings of the Human Centered Robotic Systems (HCRS)*, Munich, Germany, October 2006, pp. 19–24.