Alternative Techniques for the Efficient Acquisition of Haptic Data

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ABSTRACT

Immersive environments are those that surround users in an artificial world. These environments consist of a composition of various types of immersidata: unique data types that are combined to render a virtual experience. Acquisition, for storage and future querying, of information describing sessions in these environments is challenging because of the real-time demands and sizeable amounts of data to be managed. In this paper, we summarize a comparison of techniques for achieving the efficient acquisition of one type of immersidata, the haptic data type, which describes the movement, rotation, and force associated with user-directed objects in an immersive environment. In addition to describing a general process for real-time sampling and recording of this type of data, we propose three distinct sampling strategies: fixed, grouped, and adaptive. We conducted several experiments with a real haptic device and found that there are tradeoffs between the accuracy, efficiency, and complexity of implementation for each of the proposed techniques. While it is possible to use any of these approaches for real-time haptic data acquisition, we found that an adaptive sampling strategy provided the most efficiency without significant loss in accuracy. As immersive environments become more complex and contain more haptic sensors, techniques such as adaptive sampling can be useful for improving scalability of real-time data acquisition.

Categories and Subject Descriptors

H.3.4 [**Information Systems**]: Systems and software – *information networks, performance evaluation (efficiency and effectiveness).*

General Terms

Algorithms, Management, Measurement, Performance.

Keywords

Immersive technologies, immersidata, haptic data acquisition, sampling.

1. INTRODUCTION

Immersive environments are those that surround users in an artificial world, connecting them with other people and objects in an augmented or virtual reality experience. These environments are compelling because they enable the development of applications that simulate reality. For certain application domains, an immersive environment is both cost-effective and practical. Immersive surgical training, for example, could allow aspiring surgeons to repeatedly practice their techniques in a realistic setting – but without requiring a real body.

Immersive environments are composed of various types of *immersidata* [1], unique data types that are combined to render a virtual experience. One such type is the *haptic data* type, which includes information describing the movement, rotation, and force associated with user-directed objects. Haptic data is produced by devices that, analogous to a standard computer mouse, translate user motion, rotation, and forces into a stream of numeric values.

Currently, we are studying the problem of efficient, real-time haptic data acquisition. This mode is important because it allows haptic data to be stored and thus enables it to be replayed, queried, and analyzed. The real-time aspect is important because it enables immersive interactions between multiple participants. The number of sensors involved and the real-time demands represent major challenges in haptic data acquisition. In this paper, we introduce and compare three approaches to sampling of haptic data during acquisition: fixed, grouped, and adaptive sampling. We describe each of these approaches below and summarize our results from experimenting with their deployment.

2. HAPTIC DATA

Haptic data consists of a series of sensory values measured at some point in time. Today, there are commonly three basic types of sensors associated with haptic devices: positional, rotational, and force feedback. Acquiring haptic data means frequently sampling the values of these sensors during an immersive session.

2.1 The CyberGrasp Haptic Device

Haptic devices have only recently become available. We have focused our study on one set of available devices: the CyberGrasp™ interface from Virtual Technologies. This interface includes the CyberGlove™ and a position-tracking device containing a total of 33 different sensors. When users wear the devices one hand, they are able to move a “virtual hand” in an immersive environment. Thus, users are able to touch and experience the virtual attributes of objects encountered, as well the sensations associated with grasping and releasing objects.

CyberGrasp interfaces two subclasses of haptic data: *grasping data* and *kinesthetic data*. The former consists of 22 angle sensors, 3 values for hand coordinates in 3D space, and 3 angles for hand orientation. Kinesthetic data is composed of 5 sensors that measure the force applied by each finger.

3. DATA ACQUISITION

A key challenge in haptic data acquisition is determining the sampling rate for the sensors. A naïve approach might be to sample as often as possible, the intuition being that more samples collected will lead to higher accuracy. On the other hand, due to device limitations or the nature of human motion, the value/status of a sensor might not change as fast as the system samples. In such cases, the sampling rate would be higher than necessary and lead to wasted storage and/or bandwidth. If possible, a lower sampling rate – one that does not sacrifice accuracy – is desirable so that haptic data acquisition can scale to many concurrent users and sensors. This would also reduce the cost and increase the flexibility of immersive environments, since less data captured per time quanta reduces bandwidth demands.

3.1 Basic Sampling Methodology

To maintain accuracy, our sampling techniques are based on the Nyquist theorem, which states that a signal must be sampled with a rate twice as fast as the maximum frequency in the signal in order to reconstruct it:

$$r_{\mathrm{nyquist}} = 2f_{max}$$

Standard discrete Fourier transform, auto-correlation, and minimum square error techniques can be applied to a signal to identify f_{max} within a specified confidence threshold [1]. Our work focuses on determining *when* to make these calculations.

3.2 Fixed Sampling

Fixed sampling involves choosing a sampling rate and then sampling all sensors at that rate. There are two approaches for choosing the sampling rate. The first, *maximum rate sampling*, means simply choosing the default rate permitted by the CPU. That is, the faster the CPU, the more often sampling is possible. A second approach, that we call *modified fixed sampling* (MFS), involves using an initial set to training sessions to find the minimum sampling rate r_0 needed among all device sensors. In our experiments, we found that r_0 for the CyberGrasp/CyberGlove was 67 KHz (compared to an r_{max} rate of 80 KHz).

While there are clear efficiency benefits of MFS, there are two disadvantages. One has to do with the training sessions: they require extra work and the resulting rate may be inappropriate for all sessions that are significantly different than the training set. A second disadvantage is that implementation becomes more complicated when sampling at a rate other than the default rate.

3.3 Grouped Sampling

We propose *grouped sampling* as a method that takes the MFS approach one step further: it identifies minimum sampling rates for different groups of sensors. The intuition here is that haptic devices like CyberGrasp will have natural groups of sensors where each group of sensors has similar sampling demands. For example, moving the CyberGrasp/CyberGlove virtual hand around without grasping anything may require higher sampling rates for the positional sensors than the kinesthetic sensors. Grouped sampling improves MFS by storing less data for those groups of sensors that do not require high sampling rates.

The difficulty in pursuing a grouped sampling strategy in the general case has to do with identifying the groups. Using human intelligence, we can distinguish between positional and kinesthetic sensors and understand why they are different. However, for an arbitrary set of sensors, classifying groups may be more difficult. For example, even though we could conceivably apply standard clustering techniques to identify the sensor groups, such choices are only a reflection of the training session and do not necessary apply to all future sessions.

3.4 Adaptive Sampling

Finally, we define adaptive sampling as a dynamic form of sampling applied to each sensor. Under this approach, we would identify an optimum sampling rate r_{ij} for each sensor i during a given window j of a session. Thus, the sampling rate is determined periodically, at real-time, and negates the need for having apriori training sessions.

Obviously, the main advantage of this approach is the optimality of identifying this rate. Adaptive sampling could potentially reduce bandwidth and storage requirements to far lower levels than achieved by fixed or grouped sampling. In addition, the technique is robust: one-time training sessions do not limit the applicability of the approach. Sampling rates can, therefore, be optimized for each session.

The disadvantage to adaptive sampling is the higher cost of implementation. At run-time, we need to manage the concurrent recording and periodic analysis of data sampled at the maximum rate. Based on this analysis, the buffered data is resampled at the optimum rate and then stored or broadcast to other devices (this assumes that enough memory is available at run-time).

4. CONCLUSIONS

Our experiments have shown that an adaptive sampling approach can significantly reduce storage and bandwidth demands, without sacrificing accuracy [1]. It has robustness advantages over any other approach, except sampling at the maximum rate, because it determines the optimal sampling rate at run-time, not from a set of prior training sessions. While it is more complex to implement, adaptive sampling can lead to a more efficient form of haptic data acquisition. In the future, we are interested in being able to extract semantic information from haptic sessions, so that bandwidth can be further reduced and queries can be processed with greater accuracy.

5. REFERENCES

[1] C. Shahabi, G. Barish, M.R. Kolahdouzan, D. Yao, R. Zimmermann, K. Fu, and L. Zhang. Alternative techniques for the efficient acquisition of haptic data. *USC Computer Science Technical Report TR-0739*. Nov 2000.