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Choice of low resolution sample sets for efficient super-resolution signal reconstruction

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ABSTRACT

In applications such as super-resolution imaging and mosaicking, multiple video sequences are registered to reconstruct video with enhanced resolution. However, not all computed registration is reliable. In addition, not all sequences contribute useful information towards reconstruction from multiple non-uniformly distributed sample sets. In this paper we present two algorithms that can help determine which low resolution sample sets should be combined in order to maximize reconstruction accuracy while minimizing the number of sample sets. The first algorithm computes a confidence measure which is derived as a combination of two objective functions. The second algorithm is an iterative ranked-based method for reconstruction which uses confidence measures to assign priority to sample sets that maximize information gain while minimizing reconstruction error. Experimental results with real and synthetic sequences validate the effectiveness of the proposed algorithms. Application of our work in medical visualization and super-resolution reconstruction of MRI data are also presented.

1. Introduction

Temporal registration, which is the computation of a correspondence in time between two sequences, is an important component in applications such as mosaicking [1], multiview surveillance [2], sprite generation [3], 3D visualization [4], medical imaging [5], time-series alignment [6] and super-resolution imaging [7,8]. In spatio-temporal super-resolution (SR), for example, low resolution (LR) videos from single or multiple sources are combined to generate a super-resolution video. These LR videos can differ from each other in terms of various parameters, such as viewpoint, frame rate (and therefore sampling instances) and spatial resolution. Assuming that spatial viewpoint remains the same or can be estimated using stereo registration algorithms [9], a critical step in SR is to register the LR videos in time. When the frame rates of the videos are low, accuracy of the temporal registration process becomes crucial.

In order to address the abovementioned issues, we use concepts developed in the field of *recurrent non-uniform sample* (RNUS) reconstruction. In RNUS reconstruction, a signal is reconstructed from multiple sample sets which are offset from each other by a *known* time interval [10]. Although RNUS was developed for applications where accurate time stamp information is available, and it is assumed that the sample sets are from the same continuous time signal, this assumption does not always hold true for SR reconstruction. However, it still provides useful insights into some of the factors that must be considered for SR reconstruction.

Given that in SR reconstruction multiple LR sequences are available, it is important to differentiate between LR sequences that have better registration and contribute more towards reconstruction versus LR sequences that have higher uncertainty associated with their registration and may not contribute at all to the reconstruction process. An approach to making this differentiation is to associate with each pair of LR sequences a certain level of confidence so that higher confidence indicates better reconstruction. Confidence measures have been proposed in a variety of fields in the past. In signal processing and pattern recognition, confidence measures have been computed extensively for speech recognition [11,12], where they are used to reliably assess performance of speech recognition systems. These confidence measures are mostly based on probability distributions of likelihood functions of speech utterances, which are derived from Hidden Markov Models. In image processing, confidence measures have been proposed in motion estimation [13,14], stereo matching [15] and moving object extraction [16]. For example, in [15], spatial, temporal and directional confidence measures are developed based on the premise that good motion vectors are those that do not change drastically; hence, a confidence measure based on gradient information is computed that favors smooth gradients.

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Our work is unique as it introduces the concept of a confidence measure in temporal registration and reconstruction from recurrent non-uniform samples. The formulation criterion for the confidence measure is two-fold: (1) it provides an estimate of how much confidence we have in the registration, and (2) it also provides an estimate of how much new information is added to the reconstruction process by the inclusion of a particular sample set. We also present an iterative ranking method that not only prioritizes the sample sets, but given that some registration may be inaccurate, it also introduces a threshold limit beyond which adding more sample sets becomes redundant. Preliminary results of our work have appeared in [17,18]. In this paper, we present a detailed examination of the confidence measure and the various factors that influence it. We also address previously unanswered questions about determining weights for the confidence measure and present quantitative and subjective results of the application of this work in super-resolution magnetic resonance (MR) imaging.

The rest of this paper is organized as follows. In Section 2, we provide some preliminary definitions and review some approaches that are used in this work. In Section 3, we present our confidence measure (along with a detailed discussion of various influencing factors) and an iterative greedy rank based reconstruction method. Evaluation of the confidence measure and ranking algorithm with 1D (synthetic and audio) and 2D (real video) data is presented in Section 4. In Section 5, we discuss the application of the proposed method in SR MR imaging and present performance results for this application. Lastly, conclusions of this work and ideas for future work are presented in Section 6.

2. Preliminary definitions and review

In this section we review some preliminary definitions and methods with regards to recurrent non-uniform sampling, feature extraction, event modeling and super-resolution reconstruction that are used in this work.

2.1. Recurrent non-uniform sampling

Recurrent non-uniform sampling (RNUS) is used to describe the sampling strategy where a signal is sampled below it's Nyquist rate, but multiple such sample sets offset by a time delay are available, i.e. the sampling frequency is fixed, but the sampling time is randomly initialized. Fig. 1 illustrates such recurrent non-uniform sampling, where $x(t)$ is a 1D continuous time signal which is sampled at a sampling rate of T, giving rise to samples at $T, 2T, \ldots, MT$.

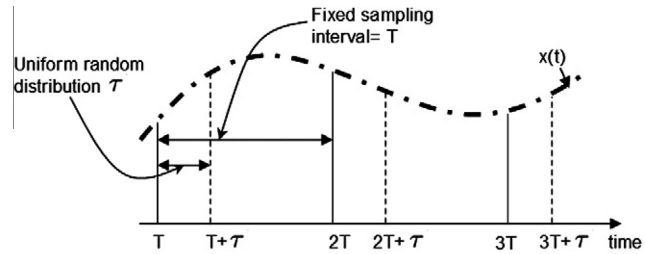

Fig. 1. Illustration of recurrent non-uniform sampling with two sample sets.

Another sample set is also acquired at a sampling rate of T, however, this sample set is offset by a timing offset τ.

Direct reconstruction of a continuous signal from its N non-uniformly sampled sequences [19] can be done as follows:

$$x(t) = \sum_{n=1}^{N} \sum_{k \in \mathcal{Z}} x(kT + \triangle_n)\phi_n(t - (kT + \triangle_n)), \tag{1}$$

where $\triangle_n = \frac{(n-1)T}{N} + \tau_n$ and ϕ_n represents the reconstruction kernels such as splines, Lagrange's polynomials and the cardinal series. An indirect approach to reconstruction from RNUS is to derive uniformly separated samples from the non-uniform signal instances, and then reconstruct using the standard interpolation formula in (2). Suppose a bandlimited signal $x(t)$, is sampled at the Nyquist rate to obtain uniform samples $x(kT)$, $x(t)$ can be reconstructed from the samples using the interpolation formula:

$$x(t) = \sum_{k=-\infty}^{+\infty} x(kT) \frac{\sin \Omega(t - kT)/2}{\Omega(t - kT)/2}, \quad T = 2\pi/\Omega. \tag{2}$$

Let x_0, x_1 and x_2 correspond to three discrete samples of $x(t)$ taken with a uniform time interval at time t_0, t_1, and t_2 (see Fig. 2(a)). Assuming a finite window of reconstruction (instead of the infinite samples in (2)), an approximate reconstructed signal can be computed as:

$$\hat{x}(t) = x_0 \text{sinc}(t - t_0) + x_1 \text{sinc}(t - t_1) + x_2 \text{sinc}(t - t_2). \tag{3}$$

If $x(t)$ was also sampled at non-uniform time instances t'_0, t'_1 and t'_2, as shown in Fig. 2(b), by substituting t with $t'_i (0 \leqslant i \leqslant 2)$ in (3) we can write the following linear equations:

$$x(t'_i) = x_0 \text{sinc}(t'_i - t_0) + x_1 \text{sinc}(t'_i - t_1) + x_2 \text{sinc}(t'_i - t_2) : 0 \leqslant i \leqslant 2, \tag{4}$$

where $x(t'_i)$ are the known non-uniform samples. Eq. (4) can be expressed as a system of linear equations:

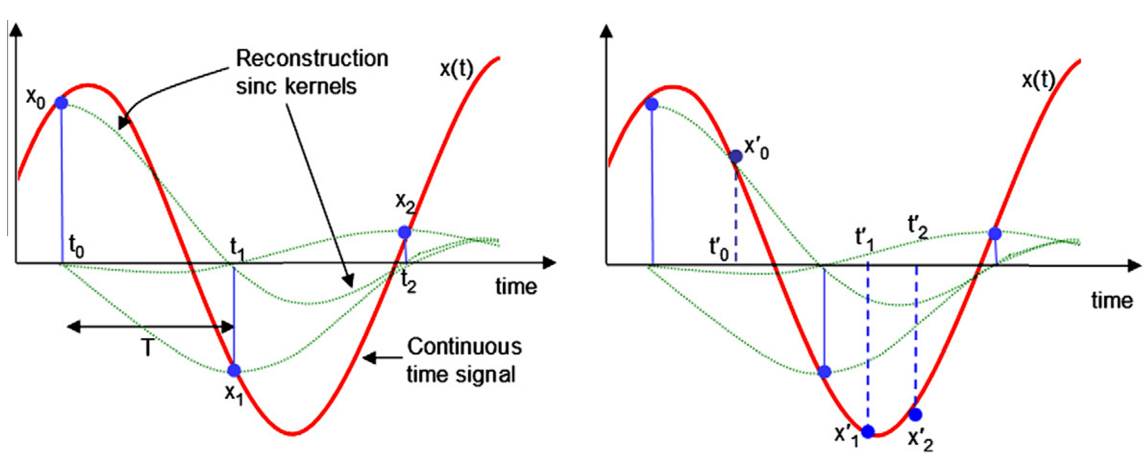

Fig. 2. (a) Reconstruction from uniform samples using sinc kernels. (b) Illustration of non-uniform samples which can be expressed as linear combinations of samples from (a).