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Neurocomputing 38–40 (2001) 1725–1734

NEUROCOMPUTING

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Handling large files of multisite microelectrode recordings for the European VSAMUEL consortium

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Abstract

The EU-funded project VSAMUEL aims to record from up to 128 channels from animal multi-electrode experiments. This will put a significant load on data storage and retrieval. To decrease the file size of 16 bit, 25 kHz recordings, compression algorithms were investigated and compared. Due to the high entropy of the signal, entropy coding was discarded and instead a wavelet based coder implemented. Compression ratios of up to 1 : 20 were achieved, but on the cost of loss of spike events. This was quantified by a new spatio-temporal event detector, which takes the location of electrodes on our silicon probes into account.

Keywords: Multi-site recording; Silicon probes; Wavelet; Compression; Morphological filter; Image processing; Entropy

1. Introduction

Modern neuroscience and our understanding of how the brain and its neural units work, is indisputably connected to the experimental ability of detecting their natural means of communication by electrical activity [6]. Even though extracellular recording from single cells is performed routinely, little is still known about network- and higher level activity. Intercepting this level of information processing requires the technological ability to place a high number of recording sites in close proximity to cells in question [18,20]. The use of standard microelectrodes or even tetrodes not

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0925-2312/01/$ - see front matter
PII: S0925-2312(01)00538-0

only requires extremely difficult surgical procedures, but also traumatizes the penetrated tissue, due to the number of probes with rods of diameters of up to several tens of microns. Additionally, it lacks a high precision of positioning subsequent electrodes [4,17].

The EU-funded project VSAMUEL aims therefore to insert with only *one* single penetration and a *few* thin rods as many recording sites as possible into the area of interest. This will be performed by micro-machined and inexpensive silicon forks, carrying tens of micrometer-sized recording sites on each tine, as already proposed earlier [25] and achieved significantly later [1,15]. Micro-structuring is here performed by a dry etch process, avoiding high temperature boron diffusion etch stops.

Although well established, real widespread, general use of batch fabricated silicon multi-site probes in neuroscience research has not truly been achieved yet. We attribute this, besides the delicate handling of silicon probes, in part, to a lack of appropriate, easy to use and inexpensive data acquisition systems, which relieves the researcher from troublesome technological issues. In order to overcome this limitation and provide a multisite recording system out of one cast VSAMUEL was initiated to specifically tackle these tasks. Further details on the whole project may be found on the Internet under www.vsamuel.de and are described elsewhere [7,8].

2. Characterization of recorded data

Above mentioned overall goals for data acquisition will lead to 128 channel recording with 16 bit A/D resolution and 50 kHz sampling rate by a PC. Streaming such data from the full fledged VSAMUEL system in a "raw" format will fill up every data storage device with 12.8 Mbyte/s. In other words, 1 h of 128 channel recordings will produce a data volume of over 46 Gbyte. This lies technologically well within the current state of the art for data transfer through the utilized PCI-bus (up to 1 Gbyte/s [9]), but requires significant financial efforts in data storage and backup.

In order to minimize these investments, the following study deals with ways to reduce data storage requirements without compromising data quality. For that purpose, we characterized and processed 30 s worth of data from eight channel neuronal recordings from rat SI area [22] by algorithms developed under MATLAB (Mathworks Inc.), utilizing the Wavelet- and the Morphological Filter-Toolbox. Signals had amplitude values in the range of -1.5 to 1 mV with up to 100 μV high frequency noise level. These data are digitally stored in an eight channel SUN audio file comprising 24 Mbyte.

Fig. 1 (left) shows a histogram of discrete values of one channel, resulting from 16 bit sampled raw data. Going from analog, extracellular to digitized signals corresponds to a step called "Pulse Code Modulation" (PCM). Histograms of all channels show wide, but similar distributions over almost the whole bit range and may be quantified by their entropy H [10]:

$$H = -\sum_{x} P(x)\log_2 P(x),$$

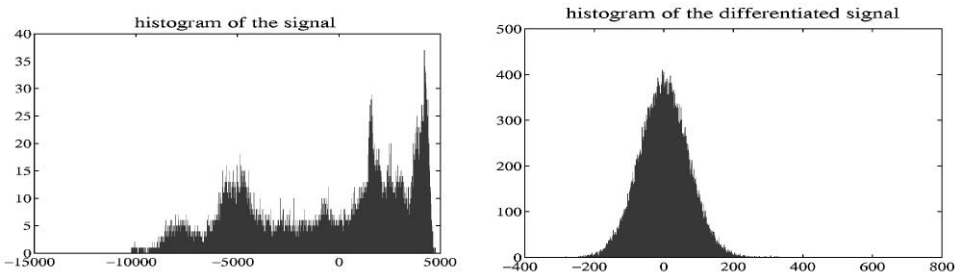

Fig. 1. Histogram of digitized values for 2^{16} data points of one channel of raw, 16 bit sampled (left) and differentiated data (right). Note the change in scale and spread from raw to differentiated data.

where $P(x)$ is the frequency of occurrence of value x, for large data sets this is their probability.

Theoretically, if all recorded values show equal frequency of occurrence, i.e. all bins contain equal numbers of counts and therefore probabilities for all values are equal, the entropy corresponds to the value of sampling precision—here 16 bit. Our real rat data show an entropy value of 13.85 ± 0.04 bit over all channels. This means that a loss-less compression scheme by entropy coding, like the famous Huffman algorithm will optimally yield a compression ratio of 0.86 only [16].

This situation may be improved by storing the differences of subsequent samples instead of their absolute values, a method called "Differential Pulse Code Modulation" (DPCM) [10]: A histogram for one channel may be found on the right of Fig. 1. The clear reduction in entropy to 8.14 ± 0.06 bit may optimally yield a compression ratio of 0.51, still more than half the original file size.

Further improvement may be achieved by storing low-pass filtered "field-potential" data (0–500 Hz) separately from high-pass filtered "action potential" signals (500 Hz–6 kHz). This will obviously introduce losses into the file, but the entropy for a DPCM modulated high-pass signal will drop to 5.21 ± 0.11 bit, making a compression ratio of 0.325 maximally achievable. Bearing the vast amounts of expected neuronal data in mind leads us to conclude, that entropy coding of our data yields insufficient compression ratios and will therefore need to be subsidized by other means of compression, like the following wavelet transformation.

3. Compression by discrete wavelet transformation

Wavelet transformation is a recent implementation of the mathematical concept of orthogonal function systems [5]. In fact, a wavelet is in general a function of Hilbert space with a zero average. In contrast to a Fourier transformation with its infinite extending base functions sine and cosine, in wavelet transformation, a so-called "mother-wavelet" is focused in the time domain, but smeared out in the frequency domain [2,12].

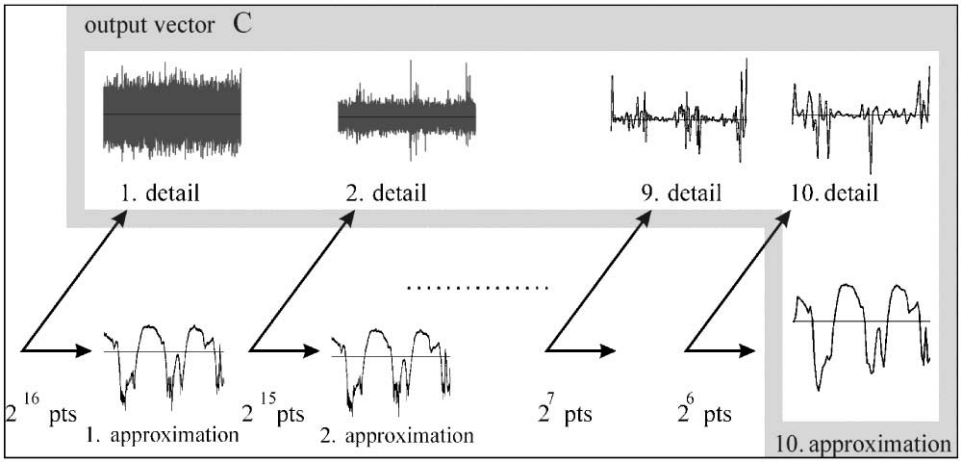

Fig. 2. Illustration of the pyramidal wavelet decomposition on 2^16 sample points with the "Daubechie 2" wavelet.

Technically, a mother-wavelet may be implemented as a filter [11]. Applying this filter to a power of two number of elements of the signal vector leads to two sets of coefficients (each half the original length) which represent the first approximation of the signal and its first detail content (Fig. 2). The values of the detail vector are small and are stored in one new output vector. Skewing the original filter, i.e. wavelet, by $\frac{1}{2}$ and applying this to the approximation vector itself leads to another pair of approximation/detail vectors ($\frac{1}{4}$ length) and so on until the required precision is reached. Each time the detail content is concatenated to the output vector, thus leading to an output vector with as many coefficients as original data points. This scheme is called a pyramidal decomposition algorithm and deconstructs signals based on wavelets rather than the usual sine/cosine (see Fig. 1 of [11]). An exact copy of the original data may be regained if the pyramidal decomposition is used to the nth level assuming 2^n original sample points. Lossy compression of data may simply ignore certain scales and reconstruct the signal only from a fracture of the pyramid [12].

Fortunately, if the original mother-wavelet was chosen wisely, many of the resulting coefficients in output vector $\boldsymbol{C}$ will be small and may then be clipped to zero. This enables us to effectively compact the coefficients vector by a standard entropy coder like UNIX' "bzip2"-routines.

For the compression scheme we implemented for the VSAMUEL project (Fig. 3; the stand-alone version may be downloaded from www.vsamuel.de), we calculate the decomposition pyramid to its n-6th level on each channel based on the "Daubechie 2" wavelet and allow the user to set its own threshold level. In the best case, this will lead to a compression ratio of up to 1 : 20, but will introduce losses in the original data.

In order to quantify this distortion on the data and subsequent loss of spikes, we implemented a new spike detection scheme based not only on the temporal characteristics of the data, but on the spatial structure of the recording sites as well.

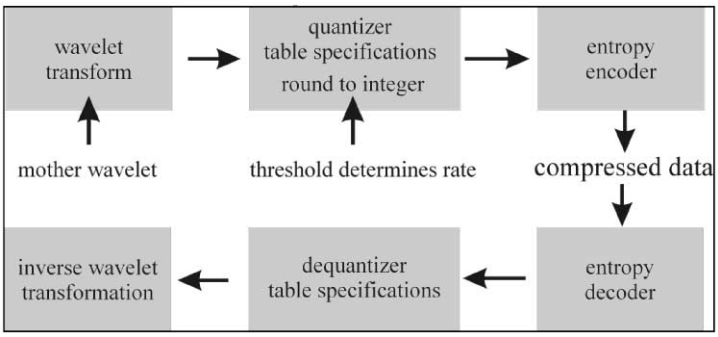

Fig. 3. Schematics of our compression algorithm based on discrete wavelet transform, thresholding and entropy coding.

4. Spatio-temporal event detection by morphological filtering

Standard in vivo microelectrode recording utilizes only a handful of recording sites [19,24], which are located inpredictably from each other. Recorded signals have therefore to be treated as spatially independent.

In spite of this, micro-machined multisite probes have the invaluable advantage, of precise determination of their sites location relative to each other due to their lithographic origin. In our case, electrode sites were distributed along one tine with a center-to-center distance of 50 μm, which we decided to incorporate into a new kind of spike event detector.

For detecting separate events, the obtained signals (Fig. 4A) are represented as gray level images with one line for each channel respectively each recording site. The signal amplitudes are mapped to image intensities by identifying the individual signal means with average intensity. This representation enables us to consider time-correlation among the signals by the local image neighborhoods and to detect spatially separated events occurring at the same time (Fig. 4B). Since events are structures of high intensities, a global clipping suppresses noise and yields potential events (Fig. 4C). The event detection now turns into an image processing problem that can be tackled by means of mathematical morphology, since events occur with characteristic shapes and extends in the image representation.

Mathematical morphology provides powerful nonlinear filters for shape sensitive manipulation of structures [21]. It has been used successfully for many biological and medical tasks [3], such as cytological shape analysis [13] and image segmentation [14].

Since we want to detect structures of high intensity and known shape we perform "opening" filtering with a specially shaped template. Opening of gray level images removes bright structures that are subsets of the template and smoothes contours. The size of the remaining structures is qualitatively preserved since opening is a composition of the dual operators erosion and dilation. The remaining structures represent desired events (Fig. 4D). They are detected by a maximum-transformation that yields

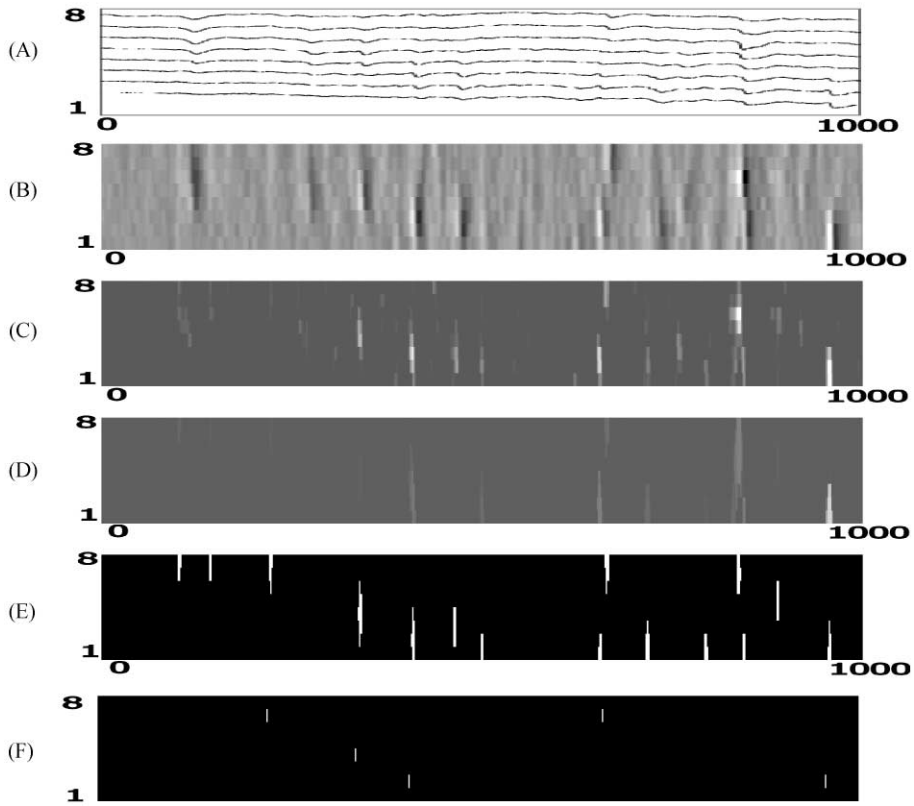

Fig. 4. Illustration of the new spatio-temporal spike detection algorithm: (A) 1000 samples of 8 channels recordings are mapped in (B) according to their amplitude to a grayscale line for each channel. Global clipping of amplitude values yields (C) on which events are detected by morphological opening-filtering. Detection of regional maxima results in (E) and localization of single events by marker extraction is shown in (F). Only events visible on more than 2, but less than 5 electrodes were marked.

a binary image consisting of all regional maxima of certain gray-level dynamics. Gray-level dynamics controls the minimal intensity of the selected region. It is globally subtracted from the image and the subsequent reconstruction-by-dilation yields regional maxima [23]. The final extraction of representative markers to indicate the time of occurrence for each event is subject to ongoing research, but depends on the chosen morphological template.

5. Results

Ultimate goal of this study was to design a compression algorithm, which enables the user to compress acquired data to his wishes while preserving spike information. Although numerical values like a PSNR [10] are useful to compare compression

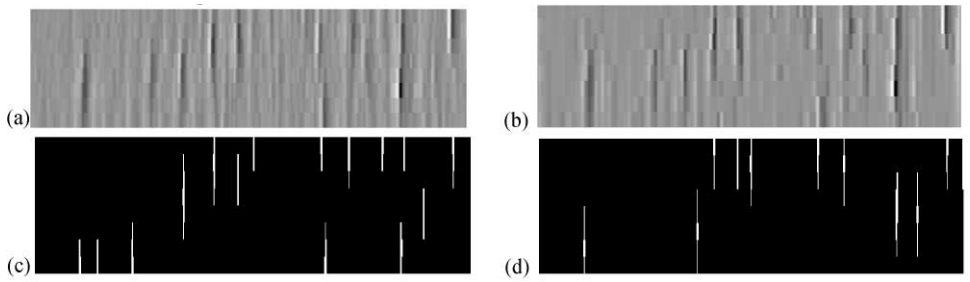

Fig. 5. Comparing our wavelet compression with respect to loss of spike events. The upper pictures show raw (a) and 95% compressed and retrieved data (b) both sets of data were subject to the same spatio-temporal event detector. Regional maxima, correlating to spike events, are shown in the lower row: Events from raw (c) and compressed (d) data.

algorithm on test data, the ultimate requirement is preservation of all those events the user deems important. To achieve this user driven comparison we subjected our test data to a compression and decompression cycle and performed the spatio-temporal event detection on those data. Pictures (c) and (d) in Fig. 5 clearly illustrate a loss of events which is put into perspective by the achieved compression of 1 : 20!

Analysis of several compression ratios showed, that from 1 : 3 on (66% of original size) a loss of events occurs as compared to the raw data set. For our test data, this loss increased almost linearly to 25% for a compression ratio of 1 : 20 (5% of original size). In other words, the user pays for savings in data storage with a reduction in performance and biological meaning. Whether or no this loss is acceptable has to be determined by each user for his specific application.

Clearly, since the VSAMUEL project is work in progress, our algorithm needs further investigations and field testing, in particular with respect to artifactual events and computing performance in a real-time application.

Acknowledgements

With great pleasure we acknowledge the help of Maren Pakura and fruitful discussions with Til Aach. We are indebted to Steve van Hooser and Dave Kewley for their generous sharing of data. Financial support was provided by European Union grant IST-1999-10073.

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