SAMICOS—A Sleep Analyzing Microcomputer System

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Abstract—A microcomputer-based sleep analyzing system capable of real-time waveform detection and storage is presented. A system design methodology necessary to build the real-time, multichannel, multichannel signal detection scheme is described with the crucial steps in algorithm development and implementation. The system performance is comparable to that of a hybrid, older version of a sleep analyzer which was extensively tested with good results.

INTRODUCTION

A SLEEP analyzing hybrid computer (SAHC) was developed several years ago for the routine processing of sleep data [1]. The computer consists of several EEG waveform detectors (alpha, beta, delta, theta, sigma, sleep spindles, rapid eye movements (REM), and muscle artifacts (ARTF)), plus additional logic circuitry for processing the waveform detections. Each waveform detector includes a linear bandpass filter, zero-crossover detector, and pattern recognizer [2]. The original linear filters and zero-crossover detectors were constructed with analog components and the remainder of the system was digital. The development of relatively inexpensive 16 bit microcomputer systems prompted us to study whether or not a SAHC system could be designed using a single microcomputer system interfaced with an analog to digital converter. Digital processing of the sleep EEG/EOG data offers several advantages over the previously used special purpose hybrid system. It is easier to extract more information from the data, such as the amplitude and period of each wave; the SAHC system only determines whether each wave meets a minimum amplitude criterion and the period falls within a specified time window. Also, the all digital system would allow for signal processing techniques not feasible with the analog system; the use of linear phase filters for waveform detection is an example of this. In addition, the use of commercially available systems avoids many of the costly construction and maintenance problems associated with special purpose hardware. Modifications to the digital system are readily made by simply changing the software.

This paper describes the design of an all digital version of the SAHC. The strategy consisted in adopting the SAHC signal processing methodology that has proven very effective, with up to 84 percent agreement with the human sleep stage scorer [1]. Nevertheless, an important engineering effort was required for the drastically different implementation constraints found in the design of a real-time signal processing system with analog and digital hardware. The primary consideration in the digital system design is related to the efficient use of the microprocessor computing resources like speed, memory, and word length. Accordingly, the signal processing algorithm’s implementation uses a multirate sampling scheme, multitasking, and reentrant routines. The all digital system is referred to as SAMICOS (sleep analyzing microcomputer system). SAMICOS’ signal processing architecture consisting of waveform detectors is adapted from [2] and illustrated in Fig. 1.

Waveform detection is the most important and computationally intensive section of SAMICOS. The waveform detection method utilized for this study detects the peaks of the filtered data (except the muscle artifact detector that uses the raw data). The data between two peaks are defined as a wave. The wave amplitude and period, defined respectively as the peak amplitude and as the number of samples between two consecutive peaks with the same slope (normalized by the sampling period), are measured. A waveform is defined as a sequence of waves that meet specified criteria. This methodology is utilized for alpha, sigma, beta spindles, and muscle activity. What distinguishes one detector from another is the center frequency of the filter, the wave period and amplitude thresholds (windows), and the number of waves to define a waveform.

For delta, theta, and EOG activities, the procedure is slightly different. The peak detection is augmented with a zero-crossing algorithm. The data between two consecutive zero-crossings are defined as a halfwave. For these activities, a waveform is defined as a halfwave which meets specified amplitude and duration criteria.

Sleep staging is accomplished by counting the number of phasic events or their duration in each minute of polygraphic recording [3]. The staging rules are all in software and are easily modified for sleep staging with different criteria (such as whether or not EMG activity is used).

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IMPLEMENTATION CONSIDERATIONS

The sampling frequency is the system's primary defining factor. The Nyquist theorem states that a digital signal contains all the information necessary to reconstruct the analog signal from the samples if and only if the analog signal is sampled at a frequency at least twice the highest frequency present in the signal. This theorem is theoretically very important, but the infinite history of the digital signal is required to achieve perfect reconstruction of a signal sampled at the Nyquist rate, which means that not all the information contained in the samples is available locally. Furthermore, it does not describe the errors incurred when finite portions of the signal or even local properties of the digital signal are utilized to make direct measurements.

To illustrate this fact, consider estimating the frequency \( f_0 \) of a sine wave digitized with a sampling frequency of \( f_s \) Hz, by counting the number of samples that exist between three consecutive zero crossings of the digital signal, i.e., \( f_0 = f_s / N \). It is readily shown that the error in frequency \( \Delta f \) is

\[
\frac{\Delta f}{f_0} = \frac{f_0}{f_s}
\]

For example, the frequency of a 25 Hz beta wave after digitization with a sampling frequency of 100 Hz can only be measured with an accuracy of \( \pm 6.25 \) Hz. Therefore, every EEG wave with a frequency between 18.75 and 31.25 Hz after digitization will have the same number of samples between two changes in sign, i.e., will produce the same estimate of the frequency. The error can be reduced with interpolation between samples, but less processing time is required, in microcomputer environments, if the sampling frequency \( f_s \) is increased in order to decrease \( \Delta f \). In fact, oversampling is a very efficient interpolation procedure which does not introduce errors of its own (like interpolation) when the waveshape is not precisely known.

According to (1), if our criterion is to establish a maximum error for frequency measurements, different sampling frequencies can be used in the implementation because the EEG waveforms exist in separate frequency bands as Table I shows.

The frequency error \( \Delta f \) must be acceptable from the signal detection point of view, but according to (1) when \( \Delta f \) is chosen, \( f_s \) is set. Therefore, the limiting factor in the selection of \( \Delta f \) is the throughput of the microcomputer and the overall algorithm execution time because in real-time systems the processing of one sample must be over before the next sample is acquired.

For the microcomputer utilized (the Texas Instruments TI 9900) allowing a maximum frequency measurement error of 7 percent permitted all processing to be accomplished in real time with acceptable performance. If the conventional approach of choosing a single sampling frequency was taken, it would be impossible to keep the real-time operation with the specified hardware and precision.

Table I presents the sampling frequency for each EEG activity that guarantees a maximum 7 percent measurement error together with the sampling frequency actually utilized in SAMICOS in order to efficiently manage the multirate sampling scheme. Notice that the selected frequencies are submultiples of 1 kHz. If the sampling frequencies are chosen such that they are submultiples of a given frequency, they can be generated through division by an integer factor \( M \) which facilitates the control of the
A/D converter, the chaining of processing modules, and the uniformity of the processing load along time. The same rationale was used to assign the sampling frequencies 500 and 83.3 Hz to ARTF and EOG, respectively.

Digital Filtering Considerations

Early work on the automated analysis of EEG data using implementation schemes similar to the one presented in Fig. 1 showed that good detection performance depends on the filter characteristics [2]. The major function of the linear filters in the processing is signal conditioning to guarantee easy implementation and robust performance. The discrimination between EEG activities is done with period measurements at the filter outputs. For alpha, sigma, and beta activities, bandpass filters are used to attenuate both the EEG lower frequency components (delta and theta) as well as the high frequency muscle activity and other artifacts. Low-pass filters are used to attenuate higher frequency components that can appear superimposed on delta and theta waves. All waveform parameters are measured from the filtered EEG data, so the filter should not distort the temporal characteristics of the waveform of interest. In order to avoid waveform distortion, the filters should have a linear phase characteristic which guarantees that the group delay of the network is constant. Another requirement is the filter shape factor. The filter bandwidth must be selected such that the ratio of bandwidth to center frequency is one or less, i.e., the bandpass filters are relatively wide-band (low Q). The center frequencies of the SAMICOS bandpass filters were selected according to the frequency of the corresponding EEG activity, but their bandwidths (listed in Table II) are chosen subject to the Q constraint and are wider than the frequency span of the EEG bands. The need for filters with the above characteristics, which could be implemented in a microcomputer (for real-time operation), prompted work on a design procedure for FIR filters called the stopband design [4].

Table II lists the stopband filter transfer functions in cascade form. The filter structures have integer coefficients (or coefficients that can be obtained with at most two shift and add operations) and can be computed in less than 150 µs when programmed in the TI Assembly language. Fig. 2 illustrates the general shape of the impulse and frequency characteristics that can be expected from this class of filters (sigma filter).

The use of a multiple sampling scheme turned out to be also a simplifying factor in the filter design. The way the filter characteristics are specified as a constant ratio of bandwidth to center frequency, and also the way the sampling frequencies were selected (constant ratio f/d), made the filter transfer functions scalable and enabled the implementation of the six EEG, EOG filters with only two digital filter structures. Therefore, the bandpass digital filters for alpha, sigma, and beta activity can be implemented as the same twelfth-order FIR structure, as Table II shows. The frequency span of delta and theta detectors permitted their implementation with the same eighth-order FIR low-pass structure. EOG waveforms are processed with the same low-pass filter as delta used. The sampling frequencies selected for delta and theta processing (27.7 and 83.3 Hz, respectively) are below the EEG Nyquist rate, so frequency aliasing must be prevented. It is not adequate to analog low-pass filter the input data, because this would remove other information of interest, so the signals are digitally low-pass filtered before reducing the sampling frequency to implement the delta and theta detectors, as will be explained later.

Additional considerations for the digital design include the number of bits required for the A/D conversion process and the computation word length. Previous studies showed that in order to obtain at least a 40-dB signal-to-noise ratio at the output of EEG IIR filters, a 12 bit A/D converter and 16 bit arithmetic [5] are required. Although the class of filters currently used is different from those of the previous study and better noise characteristics are measured, a 12 bit A/D was again selected.

Block Diagram of the Implementation

The implementation of Fig. 1 requires at least seven detectors. They are realized in SAMICOS with a single
microprocessor which sequentially executes the algorithms for each detector.

Early in the research work it was necessary to define the elementary digital signal processing block in order to estimate the computation complexity of the corresponding processing task. (A processing task is a program that controls the CPU at a particular point in time.) For the sake of testability and because it made sense conceptually, it was decided to assign a processing task to each detection algorithm. It was determined that each detection algorithm takes at most 500 μs to execute, so the design problem became one of chaining of tasks such that real-time operation is guaranteed.

The 12 bit A/D converter operates at 1 kHz. As explained, the detector sampling frequencies are obtained using the simple strategy of selective sampling. For instance, to obtain a sampling frequency of 500 Hz, every other sample of the frontal channel data is processed (a division by 2). What is gained with this integer division scheme is the ability to distribute uniformly in time the processing in order to avoid bottlenecks and obtain a repetitive pattern (after 36 clock samples for the sampling frequencies specified in Table I). Fig. 3 shows the temporal distribution for all processing tasks. The frequency clock defines 1 ms time slots. The execution of a particular detector is indicated by an arrow in the corresponding time slot. With the particular arrangement shown in the figure (which is not unique), it is seen that at most two tasks are processed in a 1 ms time frame. The equivalent of one 166.6 Hz, one 83.3 Hz, and two 27.7 Hz time slots are still available for processing additional physiologic variables such as temperature, respiration, and cardiac activity.

The current application of SAMICOS uses the frontal EEG channel (Fp1−Fp2) to analyze delta, theta, and beta activities; sleep spindle activity is analyzed from a central channel (C3−A2 or P1−T3) and alpha activity from the occipital channel (O2−O1). Muscle activity is analyzed from the frontal channel and the EOG channel (outer canthus to ear) is used to detect rapid eye movements. Other data channels can be used, but the present system is limited to four data channels.

Fig. 4 contains a system block diagram of the data flow paths together with the dividing factors utilized to obtain
TABLE III
SLEEP EEG Waveform Definitions

<table>
<thead>
<tr>
<th>EEG WAVES</th>
<th>FREQUENCY</th>
<th>AMPLITUDE</th>
<th># WAVES ON / OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LOW THRES. (Hz)</td>
<td>HIGH THRES. (Hz)</td>
<td>THRES. (uV)</td>
</tr>
<tr>
<td>δ</td>
<td>0.55</td>
<td>1.96</td>
<td>17.5</td>
</tr>
<tr>
<td>θ</td>
<td>1.95</td>
<td>7.85</td>
<td>10</td>
</tr>
<tr>
<td>θ</td>
<td>7.95</td>
<td>11.93</td>
<td>5</td>
</tr>
<tr>
<td>θ</td>
<td>11.91</td>
<td>15.62</td>
<td>5</td>
</tr>
<tr>
<td>θ</td>
<td>15.13</td>
<td>30.27</td>
<td>2.5</td>
</tr>
<tr>
<td>EOG</td>
<td>2.59</td>
<td>8.84</td>
<td>30</td>
</tr>
<tr>
<td>ARTF</td>
<td>50</td>
<td>-</td>
<td>10</td>
</tr>
</tbody>
</table>

The required sampling frequencies. This arrangement avoids aliasing errors in the delta and theta activities. The beta bandpass filter is a cascade of a low-pass and a high-pass filter. The low-pass is implemented first; its output is a low-pass filtered version of the input. For the beta filter, this means a low-pass with -3 dB gain at 45 Hz and a zero (gain) at 55 Hz. Therefore, a frequency division by 2 to 166.6 Hz at the output of the low-pass section can be implemented without aliasing, since the processed signal has negligible energy above 55 Hz. Another low-pass antialiasing filter is implemented for the 166.6 Hz data. It is a linear phase eleventh-order FIR, with a -3 dB frequency of 7 Hz and a zero at 14 Hz. The filter passband is wide enough to accommodate theta and delta activities without aliasing. This arrangement has the drawback of requiring that beta, theta, and delta be detected from the same channel but this is normally the case.

EEG waves are defined by a minimum amplitude and a minimum and maximum frequency (defined as the inverse of the period) windows as Table III shows. For alpha, sigma, and beta, criteria regarding the minimum number of consecutive waves is also used. There are basically two requirements: one to recognize the beginning of the waveform (on criteria); the waveform is said to terminate (off criteria) when the wavecount drops below a threshold [i.e., a sigma spindle ends when the wavecount is less than three out of six waves (6/3)]. The values presented in Table III were arrived at empirically and have been found to work well in conjunction with the filters presented in Table II for a diverse normal subject population between 13 and 79 years of age.

THE PROGRAM STRUCTURE

SAMICOS is a real-time system implemented using the microcomputer interrupt structure driven by a 1 kHz clock. The processing, which includes digital filtering, signal processing, and decision making, is done on a sample by sample basis. For efficiency, the signal processing algorithms are written as routines which may not be single input single output: the effort, both at the development and debugging phases, to handle the pointers to link the several subroutines would be excessive if conventional programming techniques were adopted. Therefore, a systematic approach in the form of a simple multitasking structure is used in the algorithm, where the processing of each EEG activity, EOG, and ARTF represents a task as defined above. The core of the processing algorithm is a fixed task scheduler which controls the A/D converter and implements the chaining of tasks illustrated in Fig. 5 according to the time slot allocation presented in Fig. 3. A simple loop with 12 steps and only one test is sufficient to control the chaining of tasks along time. This is a direct consequence of using integer ratios between sampling frequencies. The task structure is efficiently implemented with the list structure of the TI 9900 microprocessor [6]. Except for the task scheduler, interrupt driver, and the module that packs the number of counts per minute and stores the counts in memory (which are independent of the tasks), every task requires three programming modules (filtering, peak detection, and pattern checking).

Due to the use of reentrant code routines; the uniformity designed into the filtering and the symmetry of the processing tasks, the number of programming modules was reduced from 24 to 12 different modules, occupying a total of 4 kbytes of memory. All of the parameters that change from task to task are kept in the microcomputer.
working registers located in RAM. This feature also enables very simple testing of different waveform criteria.

**System Outputs**

SAMICOS provides three types of outputs. One type uses two 12-bit digital-to-analog converters to observe the filtered EEG signals. Under program control, the filter outputs can be displayed on an EEG polygraph in order to assess digital filter performance. The second output type uses the microcomputer parallel port. When an EEG event is detected, the computer outputs a 5 V signal level which can also be routed to a polygraph for on-line evaluation of system performance. Fig. 6 shows an example of these outputs during a sleep epoch. For alpha, sigma, beta, and muscle artifact, the length of the pulse is related to the duration of the EEG event. These outputs are of paramount importance for system evaluation, since they provide an immediate assessment of the man-machine agreement.

The third type of output is related to how the human scores the sleep record, i.e., by counting the number of waveforms or the time occupied by each EEG activity during a minute (or 30 s) [3]. As SAMICOS detects most of the waveforms that the human identifies for sleep staging, it is possible to arrive automatically at the sleep scoring if the system stores in RAM the number of waveforms (sigma spindles, REM waves) or the cumulative duration of the events (delta, theta, alpha, beta, muscle artifact) per minute.

The data format implemented by the packing routine is illustrated in Fig. 7. A total of 6 bytes are used per minute, so 1440 bytes or roughly 1.5 kbytes of RAM are necessary to store the information detected in an 8 h sleep record (twice as much memory is required if the data are stored for 30 s intervals).

The sleep scoring algorithm is also adapted from the earlier SAHC. It is a small program that runs off-line when the data collection is over, reads the minute data, and arrives at the sleep stage using anthropomimetic rules [7]. The minute detection summaries are sent via a serial line (RS 232) to a larger computer for storage on hard disk, display, and further processing by the sleep scoring algorithm.

**Conclusions**

This paper presents, in a detailed fashion, the implementation of a multibiject, multichannel EEG signal processing system intended for the on-line, ambulatory processing of sleep data. The careful system design, tuned to the requirements of the signal processing methodology, made possible the time sharing of a single 16-bit microprocessor.

The key assumption, which chooses the sampling frequency (above the Nyquist rate) as a function of the signal processing algorithm, departs from the conventional approach, but proved valuable for efficient implementation. The mapping of EEG waveform detectors as independent
processing tasks is also judged useful, mainly for software testability and maintainability.

As was apparent throughout the paper, the emphasis is placed on digital implementation parameters, i.e., how could proven algorithms be implemented efficiently in a microprocessor environment. However, the man–machine agreement was also studied. In the preliminary tests, SAMICOS presented a man–machine agreement identical to the one reported with the SAHC [7], which is to be expected since the signal processing criteria are unchanged. Nevertheless, the two systems have different features. The SAHC is capable of 32 times real-time operation which cannot be achieved with the present SAMICOS hardware; on the other hand, SAMICOS is a much more expandable, versatile system due to the software-based nature of its operation. It is felt that the digital implementation can use other parameters like memory to improve the algorithms. In fact, the ability to use directly the values from the wave parameters can lead to algorithms that use multichannel information.

SAMICOS was programmed in the following off-the-shelf hardware: one 16-bit CPU board (Texas Instruments TMS 990/101M), one 8 kbyte memory board (TMS 990/201), and one 16-channel, 12-bit A/D board (Analog Devices RTI-1241). There are newer single board computer systems with even more computing capacity which could also be used for the system hardware. The system is being tested at the Konigsfelden Clinic (Switzerland), the University of Florida (U.S.A), and Hospital St. Antonio (Portugal).

REFERENCES


Jose C. Principe (M’83), for a photograph and biography, see p. 559 of the June 1986 issue of this Transactions.

Jack R. Smith (S’57–M’58–SM’74), for a photograph and biography, see p. 559 of the June 1986 issue of this Transactions.