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A Parallel Algorithm for Filtering Gravitational Waves from Coalescing Binaries

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Coalescing binary stars are perhaps the most promising sources for the observation of gravitational waves with laser interferometric gravity wave detectors. The waveform from these sources can be predicted with sufficient accuracy for matched filtering techniques to be applied. In this paper we present a parallel algorithm for detecting signals from coalescing compact binaries by the method of matched filtering. We also report the details of its implementation on a 256-node connection machine consisting of a network of transputers. The results of our analysis indicate that parallel processing is a promising approach to on-line analysis of data from gravitational wave detectors to filter out coalescing binary signals. The algorithm described is quite general in that the kernel of the algorithm is applicable to any set of matched filters. © 1993 Academic Press, Inc.

1. INTRODUCTION

The detection of gravitational waves from galactic and extragalactic sources will provide us with an alternative view of the universe hitherto not obtained via the electromagnetic spectrum of radiation. Their detection is important to further our understanding of fundamental theories of physics: confirming the predictions of Einstein's general theory of relativity, providing useful inputs towards the solution to a long-standing theoretical problem of quantizing gravity, obtaining accurate values of certain cosmological parameters like the Hubble constant [1], etc. These are only a few reasons why several groups around the world have been concentrating on building laser interferometric gravitational wave detectors of very high sensitivity, several prototypes of which already exist in different countries [2].

The principle behind such a detector is the following:

An interferometric detector, in its simplest form, is a Michelson interferometer consisting of a corner mirror and two end mirrors. Instead of an ordinary monochromatic light a continuous wave laser is used as the source of light. The beam is first split and reflected by the mirrors several times and then brought together to form a fringe pattern on a photo-diode. A gravitational wave impinging on the detector causes the masses attached to the two end mirrors to oscillate, which results in a shift in the fringe pattern. This shift constitutes the gravitational wave signal.

However, the data from the detector is contaminated with noise from several sources, which limits the sensitivity of the detector. The sensitivity can be expressed in terms of the metric perturbation due to the gravitational waves. The fullscale detectors which have been planned for the future have armlengths 3 to 4 km and expected peak sensitivities $\sim 10^{-22}$ or 10^{-23} [2]. Our current knowledge of astrophysical sources indicates that at such sensitivities several events per year may be observed.

Data from such detectors would be sampled at a rate of ~ 100 kHz and all through the year [3]. Unless on-line data analysis systems which can search for a variety of signals are designed, all the effort in doing such an experiment will be wasteful as the number of expected events are not too large and it is neither desirable nor practical to store all the data. With this view in mind several groups have been concentrating on the design of data analysis systems that can effectively pick out specific signals from noisy detector output. In this paper we present one such algorithm to detect gravitational waves from coalescing binary systems.

Coalescing binary systems are one of the more promising sources for the detection of gravitational waves with broad band detectors [2]. A compact coalescing binary system consists of two stars, typically neutron stars or blackholes, which orbit around each other bound by their mutual gravitational attraction. The general theory of relativity predicts that such a system should radiate energy in the form of gravitational waves [4]. The gravitational waves emitted carry away the energy and the angular momentum of the system, causing the two stars to spiral-in. The wave's frequency is just twice the orbital frequency of the system. With the in-spiral of the two stars, the amplitude and the frequency of gravitational waves increase. Thus, the nature

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of the gravitational waves emitted by the system has a very characteristic waveform—the so-called *chirp waveform*. The power emitted in the process depends not only on the distance between the component stars but also on their individual masses. However, in the Newtonian approximation a certain combination of the masses—the mass parameter—determines the evolution of the system. Such binaries are expected to spiral-in and coalesce over time scales that are much less than the age of the universe. Recent estimates [5] show that the event rate is about three per year in a volume of a sphere of radius 200 Mpc. Near coalescence the physical conditions in the vicinity of the system will be such that an understanding of the nature of the gravitational waves would entail a fully general relativistic treatment of the evolution or at least a certain approximation that incorporates some of the strong field effects of the full theory. Since the fully general relativistic solution to the two-body problem has not been obtained so far, there have been efforts to make use of the well-known post-Newtonian and post-Minkowskian approximations [6] and numerical methods with high resolution grids on fast computers [7]. These investigations indicate that the waveform from coalescing binaries would be different from those based on Newtonian approximation and novel algorithms will have to be employed for the analysis of data.

Parallel processing is a new development in the area of fast computing which overcomes the *von Neumann bottleneck* [8] and promises to be very useful in analysing data from gravity wave detectors. Parallel processors avoid this bottleneck because they are multiple instruction multiple data systems. Development of application software related to data analysis on such systems has become extremely important since, as mentioned above, the present-day physics problems involve formidable amounts of data and sophisticated processing. For instance, the matched filtering technique is a very powerful tool for detecting known signals that are buried in noisy data. This technique makes use of the fact that the waveform of the signal is known accurately. When the noisy output of a detector is correlated with a copy of the expected signal, the correlation is also noisy. When a signal of sufficiently large amplitude is present in the output of a detector, the correlation will peak at a time when the signal arrives at the detector. Because of the random nature of the noise, it is possible that there is a chance large amplitude in the correlation—the so-called false alarm [9]. However, if we choose a sufficiently high threshold so that the chance of a false alarm during a certain time of observation is vanishingly small, then we can be confident of detecting the presence of a signal by looking at the height of the correlation.

Matched filtering is a promising tool for detecting gravitational waves from coalescing binaries [2, 3], although there exist other algorithms to detect them (see, e.g., [10]). Even though the waveforms of certain signals, like coalescing binaries and quasi-normal modes of a black hole, are known, the experimenter will not know beforehand what the values of the parameters are. The method followed then consists of constructing a bank of filters which scans the relevant range of parameters, which correlates a data segment with each of these filters. Since calculation of each correlation is independent of any other, the problem is highly parallelizable; matched filtering is a *multiple instruction single data* problem and therefore parallel processing is the appropriate approach. However, there are other complications. The number of filters needed to search for gravitational waves from coalescing binaries in the astrophysically relevant range of parameters is formidably large—about a couple of thousand. Thus, if one is using a parallel machine like a set of interlinked transputers, due to the large number of templates through which one has to filter the output, data transfer times and communication overhead would be appreciable and every effort should be made to minimize such overhead. This can be achieved by connecting the processors in a judicious manner so that the resulting topology leads to minimization of data transfer times and communication overhead. In this paper we present one such algorithm that is well suited to detecting gravitational waves from coalescing compact binaries and which takes care of the problems mentioned above. We also describe its implementation on a parallel machine consisting of a network of 256 transputers. The code developed here can be modified easily to suit any other set of matched filters, with the basic methodology remaining the same. Similar implementation can also be found in the work of J. Watkins [11].

The paper is organized as follows. In Section 2 we discuss briefly the nature of the coalescing binary waveform. We also discuss a criterion for detecting signals and show how a lattice of filters corresponding to various parameters can be constructed. In Section 3, we present an algorithm to detect chirp signals and describe the implementation of this on a parallel machine.

2. THE COALESCING BINARY SIGNAL

During the final stages of its evolution a binary system of stars emits a burst of gravitational waves with a very characteristic spectrum. There are two independent wave amplitudes corresponding to the two independent polarizations of the wave. However, the response of the detector is a linear combination of the two amplitudes and, therefore, for the purpose of developing data analysis algorithms, it is sufficient to deal with only the normalized response function as shown in [12] (henceforth referred to as paper I). In our discussions we shall use the noise-free *normalized* response $q(t; t_a, \xi, \Phi)$ given by

$$q(t; t_a, \xi, \Phi) = \mathcal{N} a(t)^{-1/4} \cos[\nu_a \xi (1 - a(t)^{5/8}) + \Phi], \tag{2.1a}$$

where

$$a(t; t_a) = (1 - \xi^{-1}(t - t_a)), \tag{2.1b}$$

$$\xi = 3.00 \left[\frac{\mathcal{M}}{M_\odot}\right]^{-5/3} \left[\frac{f_a}{100\text{ Hz}}\right]^{-8/3} \text{s}, \tag{2.1c}$$

$$\nu_a = 320\pi \left[\frac{f_a}{100\text{ Hz}}\right] \text{Hz}. \tag{2.1d}$$

Here $M_\odot = 2 \times 10^{33}$ g is the mass of the Sun; $\mathcal{N}$ is the normalization constant; ξ is the time taken for the two stars to coalesce, starting from the time when the frequency of the gravitational wave is f_a; and $\mathcal{M}$ is called the *mass parameter* and is related to the reduced mass, μ, and the total mass, M, of the binary by $\mathcal{M} = (\mu^3 M^2)^{1/5}$. For a fixed f_a, ξ serves as one of the parameters of the signal instead of $\mathcal{M}$. The time when the gravitational frequency reaches f_a is t_a and is called the time of arrival of the signal. In the context of gravity wave detectors, whose sensitivity has a lower cutoff around 100 Hz, it serves as the second parameter of the signal. Finally, Φ is the phase of the signal at $t = t_a$. Thus, the response or the signal is characterized by three parameters: the coalescence time, the time of arrival, and the phase. It should be noted that the binary system is assumed to consist of point mass stars and the standard quadrupole radiation formula has been used (see, e.g., [13]) in deriving the above waveform. Thus, this waveform will not accurately describe the actual wave emitted by the system when the two stars approach relativistic speeds and/or when the tidal interaction between the two stars becomes important [6]. The waveform can at best be used up to times that are not too close to the coalescence time. Since the sensitivity of laser interferometers is expected to be peaked around 100 Hz this finer point need not concern us in the present paper. We shall treat the waveform to have compact support—it is non-zero only in the frequency range 100–1000 Hz.

The noise in real detectors is expected to be colored and its nature depends on the kind of technique employed to enhance the sensitivity of the detector [2]. However, for the purpose of setting up an algorithm to detect gravitational waves the nature of the noise, while important, is secondary. Thus, we assume that the detector noise is Gaussian with a flat power spectrum. In that case the normalization constant $\mathcal{N}$ is determined by the condition that the maximum of the auto-correlation, divided by the noise power spectral density, S_h, is equal to unity:

$$\frac{1}{S_h} \max_{\Delta t} \int_{-\infty}^{\infty} q(t)\, q(t + \Delta t)\, dt = \frac{1}{S_h} \int_{-\infty}^{\infty} q(t)^2\, dt = 1 \Rightarrow \mathcal{N} = \sqrt{S_h/\xi}. \tag{2.2}$$

This normalization has several advantages (see Ref. [12] for details). Note that the normalization is different for waveforms with different coalescence times. This is permissible since the multiplicative constant for filters is arbitrary and the signal-to-noise ratio is independent of this constant.

We can now express the actual waveform [2, 3] of a coalescing binary including all its dependences on the distance to the binary, etc., in terms of normalized filters. The multiplicative factor S, which we call the *strength* of the signal, will contain the distance to the binary and the coalescence time:

$$h(t; t_a, \xi, \Phi) = Sq(t; t_a, \xi, \Phi). \tag{2.3}$$

The gravitational wave from a coalescing binary located at a distance r and whose coalescence time, starting from a frequency f_a, is ξ, is of strength

$$S(r, \xi, f_a) = 44.3 \left[\frac{r}{100\text{ Mpc}}\right]^{-1} \left[\frac{f_a}{100\text{ Hz}}\right]^{-2} \times \left[\frac{S_h}{10^{-48}\text{ Hz}^{-1}}\right]^{-1/2} \left[\frac{\xi}{3\text{ s}}\right]^{-1/2}, \tag{2.4}$$

where 1 Mpc $= 3.086 \times 10^{24}$ cm.

In the matched filtering technique the statistic used to decide the presence or absence of a signal is the correlation of the output with a filter. Due to the choice of our normalization it turns out that the expected value of the maximum of the correlation is nothing but the signal strength (2.4) itself for a perfectly matched filter. We say that a signal is present if the maximum of the correlation crosses a preset threshold η. The threshold is set by allowing for one false alarm (due to noise) in a year's time. The sampling rate of 2.5 kHz and 100 filters per second implies one crossing in 10^{13} trials. For a Gaussian noise distribution with standard deviation σ this implies $\eta \sim 7\sigma$. The filters will be constructed for a discrete set of values of the parameters while the actual signal could have any values for these parameters. In general, therefore, the values of the parameters of the signal would differ from those of the filters in the set and the expected value of the signal-to-noise ratio will be less than the signal strength. It is therefore possible to detect, with a great confidence level, only those signals that have strengths larger than the threshold by a certain amount. How large the strength should be depends on the spacing between filters in the parameter space. In the context of the detection of chirp signals we essentially need to construct filters for the phase and the mass parameters; the time of arrival is decided when the correlation peaks.

In paper I, we have shown that there is a two-dimensional basis on which a signal of arbitrary phase can be expanded. As a result, the maximum correlation between a signal and a filter of arbitrary phase, for a given mass parameter and arrival time, can be found analytically by using only two filters.

Suppose we are interested in detecting all signals of strengths greater than or equal to a certain minimal strength $S_{\min} = \kappa\eta$, $\kappa > 1$. We begin with a filter with coalescence time $\xi = \xi_1$, corresponding to an initial mass parameter $\mathcal{M}_1$, say $0.5 M_\odot$, at the lower end of the mass parameter range. A signal whose coalescence time is ξ_1 produces a correlation equal to $\kappa\eta$. As we decrease the coalescence time ξ of the signal (this corresponds to an increase in $\mathcal{M}$), the correlation decreases and for some value of the coalescence time, say $\xi_1 + \frac{1}{2}\Delta\xi$, of the signal it hits the threshold level. Further mismatch reduces the correlation still further and another filter is needed to detect such signals. We have shown in paper I that for the astrophysically interesting range of mass parameter values, the correlation (in the stationary phase approximation) depends only on the *differences* in the parameters of the signal and the filter. This implies that the spacing between filters remains a constant. Choosing the filter spacing to be $\Delta\xi$ guarantees that the correlation of a signal of minimal strength always exceeds the threshold (the $\Delta\xi$ defined here is twice that in paper I).

For a given value of κ, the bank of filters is the set characterised by the coalescence times ξ_k, where

$$\xi_k = \xi_1 - (k-1)\,\Delta\xi, \qquad k = 1, 2, ..., n. \tag{2.5}$$

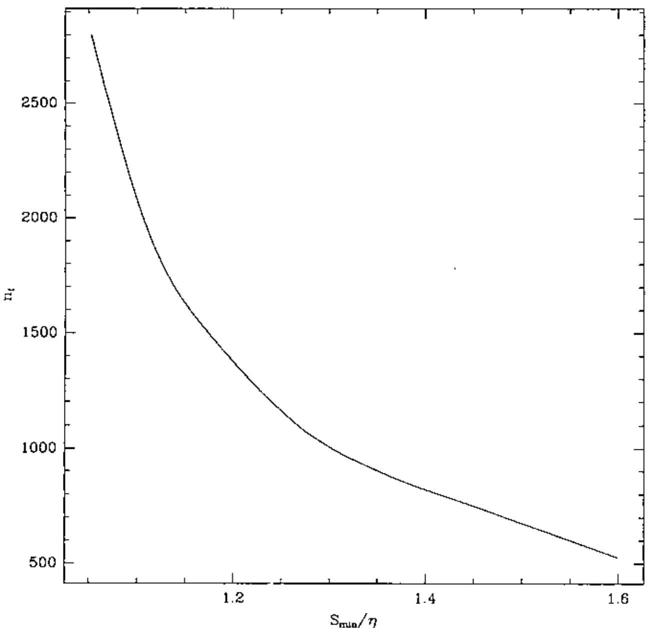

FIG. 1. A plot showing the dependence of the number of filters as a function of $\kappa = S_{\min}/\eta$. Note that for minimal strengths below about 1.1η the number of filters required rises sharply, indicating that it is harder to improve the sensitivity beyond a certain value. This plot is obtained for the initial mass parameter $0.5 M_\odot$.

Note that in the filter bank, there are two filters corresponding to two values of the phases 0 and $\pi/2$, for each value of ξ_k. Thus the bank consists of $n_f = 2n$ filters. We may choose n so that ξ_n is just greater than zero. This ensures a high value for the mass parameter at the upper end of the range.

No simple analytical relation exists between $\Delta\xi$ and κ in the white noise case, as the second derivatives of the correlation at the peak become infinite and no Taylor expansion is possible [14]. However, the relation between $\Delta\xi$ and κ is implicit in Fig. 1. Figure 1 shows the number of filters n_f plotted against $\kappa = S_{\min}/\eta$ for the initial mass parameter $\mathcal{M}_1 = 0.5 M_\odot$ ($\xi_1 = 9.54$ s). We have the relation $\Delta\xi \sim 2\xi_1/n_f$ which connects $\Delta\xi$ to κ through Fig. 1. For example, for $\kappa = 1.25$ we obtain from the figure, $n_f \sim 1150$ and hence $\Delta\xi \sim 16.6$ ms.

3. PARALLEL ALGORITHM FOR MATCHED FILTERING

In this section we first discuss the demands on the computing speeds brought about by the need to filter each data set through several thousand templates and how this affects the volume of space from which we can expect to detect gravitational waves. We then go on to describe the algorithm which we have developed to search for chirp signals by using the matched filtering technique on a network of interlinked transputers. The algorithm reported here is similar to the one found in Ref. [11].

A. *On-line Data Analysis*

The astrophysically relevant range of the mass parameter for coalescing binary systems is $[0.5, 20]\ M_\odot$. If ξ_1 and ξ_2 are the corresponding values of the coalescence times and $\Delta\xi$ is the distance at which the correlation between a filter and a signal of minimal strength falls down to the threshold level, then the total number of filters, n_f, including two basis filters for the phase for each mass parameter filter, is

$$n_f = \frac{2(\xi_1 - \xi_2)}{\Delta\xi}. \tag{3.1}$$

Generally, $\xi_2 \ll \xi_1$ and we can write n_f solely in terms of $\mathcal{M}_1$ using (2.1c):

$$n_f = 300 \left[\frac{\mathcal{M}_1}{M_\odot}\right]^{-5/3} \left[\frac{f_a}{100\ \text{Hz}}\right]^{-8/3} \left[\frac{\Delta\xi}{20\ \text{ms}}\right]^{-1}. \tag{3.2}$$

A graph of the number of filters as a function of $S_{\min}/\eta$ is plotted in Fig. 1 (cf. Table III in paper I) for $\mathcal{M}_1 = 0.5 M_\odot$. It clearly demonstrates that we have here a case of diminishing returns: close to the threshold one has to fight harder to improve upon sensitivity; very little is gained in choosing the minimal strength to be less than about 1.1η while the number of filters, and effectively the cost of computing, increases enormously below this value. Now, the computing speed dictates the coarseness or fineness of the lattice—the greater the available computing speed, the finer the lattice and the weaker the signal strengths that can be detected. Although little gain in sensitivity is brought about at the cost of a heavy investment on computing, it should be remembered that while the signal strength falls off as $1/r$, the number of events is proportional to the volume which scales as r^3. Thus, detecting weaker signals also means an increase in the number of events, which is very important for the detection of gravitational waves. Therefore, a compromise has to be reached on the choice of minimal strength. This brings us to another question in the data analysis problem, in the context of gravitational wave detection, viz., analysis of data in real time. Let Σ be the speed of the computer measured in units of the number of million floating-point operations per second (MFLOPS). It is straightforward to show that such a machine can filter the data on-line through a number of n_f of filters given by

$$n_f = 1000\left[\frac{\Sigma}{100\text{ MFLOPS}}\right]\left[\frac{\Delta^{-1}}{2.5\text{ kHz}}\right]^{-1}. \tag{3.3}$$

Here Δ is the sampling interval between consecutive data points. We now have two equations for the number of filters. Equation (3.2) relates the number of filters to the range of mass parameters in which the search is carried out and the distance between filters. On the other hand, (3.3) relates the number of filters to the demands on computing speed for on-line data analysis. Equating these two expressions, we obtain a very useful relation between computing speed and the spacing between consecutive filters:

$$\Delta\xi = 6\left[\frac{\Sigma}{100\text{ MFLOPS}}\right]^{-1}\left[\frac{\Delta^{-1}}{2.5\text{ kHz}}\right]\left[\frac{\mathcal{M}_1}{M_\odot}\right]^{-5/3} \times\left[\frac{f_a}{100\text{ Hz}}\right]^{-8/3}\text{ ms}. \tag{3.4}$$

The usefulness of this relation is twofold. On one hand, given a spacing between filters it tells us what the minimum computing speed should be in order to do on-line data analysis; on the other hand, given a machine of a certain speed it facilitates a choice for the spacing between filters in order to do on-line data analysis. This has deep implications since the spacing between filters is related to the minimal strength of detectable signals and hence the distance up to which we can see. The smaller the spacing between filters, the lower the minimal strength of detectable signals, implying a greater distance up to which we can see, and hence a greater event rate. For instance, if $\Delta\xi = 16.6$ ms then for $\mathcal{M}_1 = 0.5M_\odot$ we would need a machine of speed 115 MFLOPS to process the data on-line. With this set of filters, the distance up to which the binaries can be detected is ~ 500 Mpc (see paper I for details).

B. *The Numerical Algorithm and Its Implementation*

The computer that we have used for the simulation is a network of 256 INTEL T-800 chips interlinked with one another. It is possible to use any topology for the connection of different processors since there is a hardware link from each transputer in the network to every other via a cross-bar exchange. The only constraint in the present configuration of the machine is that only one transputer in the network can access the host. (We believe this constraint will soon be removed.)

For the simulation of the experiment we have two *tasks*. The first one, henceforth referred to as the *master* task, has access to the host and performs the necessary i/o and bookkeeping. The second task, henceforth referred to as the *worker* task, searches for the coalescing binary signal by the method of matched filtering. A copy of the worker task is placed in the rest of the processors.

While we are using a network of a large number of transputers, data transfer and communication overhead will cost appreciably more if proper care is not taken in setting up the algorithm. However, the availability of concurrent processes—the so-called *threads*—facilitates the choice of a very simple topology while avoiding the overhead. We have connected the processors in a ring topology as shown in Fig. 2. As we shall argue and demonstrate below, such a configuration leads to a linear increase in the machine speed as the number of processors in the network is increased. Moreover, this configuration is immediately portable to a network consisting of any number of transputers without any change in the source code.

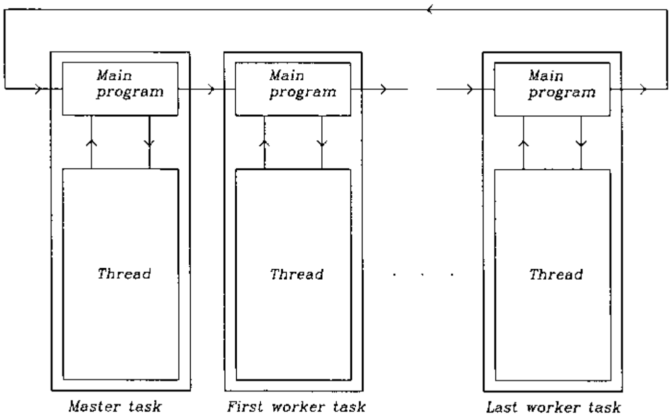

FIG. 2. The topology for communication between processors. On each transputer there is a main program and a thread. The main program in the master task does the necessary i/o and the thread generates the data that mimics the output of a gravity wave detector. The main program in each worker task avoids the accumulation of communication times by having a data set ready for analysis with the help of a thread.

In our algorithm both the master and the worker tasks have threads. A thread in parallel Fortran is a subroutine of the main program that runs concurrently with the main program and has its own *workspace*. A thread can share *common blocks* with the rest of the code and has access to communication *channels* too. Thus, if a serial code has several pieces, each of which can be executed independently of the other, then it is possible to execute each of them concurrently by having those pieces as threads. For instance, in our problem, when the worker task is analysing data we can have a concurrent thread which receives data from its input port and keeps it ready for analysis. We use the following terminology in the description of the algorithm: the main programme will be referred to as the *main thread* and any concurrent processes that are initialized by the main routine will be referred to as *subsidiary threads*.

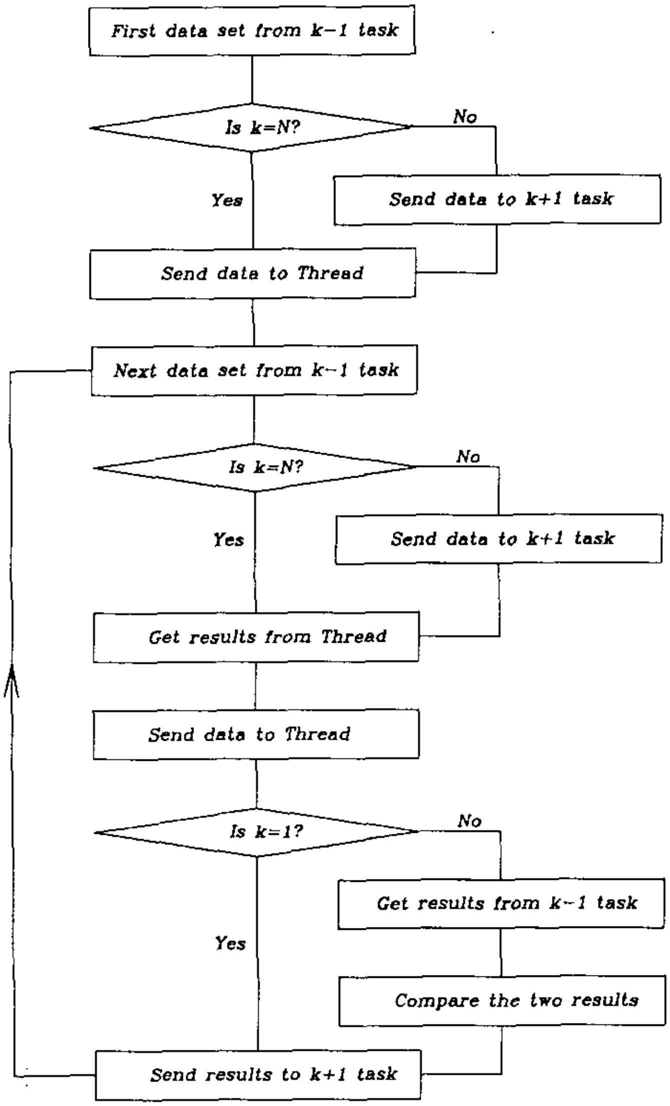

FIG. 3. Flow chart for the main thread in the worker task.

The two tasks together perform data analysis in the following way. Since the programs are intended to be portable to a network consisting of any number of transputers, the master task first sends initialization parameters to the first worker task which in turn passes it on to the next worker and so on. The identity of each task is maintained by an *id* number. The *id* of each task tells it the range of mass parameter values for which it should construct filters. The worker tasks store only the Fourier transforms of the filters to save on the number of operations in computing the correlations. Each computation of a correlation then involves just computing an inverse Fourier transform amounting to $3N \log_2 N$ operations. Since we are placing one task per transputer, given the speed Σ of a transputer, Eq. (3.4) can be used to find the maximum number of filters per task. The sustained speed of a T-800 chip is about 0.5 MFLOPS. Thus, for on-line analysis it is necessary that each task have at the most five filters; in the simulation that we have carried out, 10 filters are placed on each task in order to analyse data for a low value of the minimal strength.

After initialization, the main thread in the master task generates Gaussian, stationary, white noise using the International Mathematical and Scientific Library (IMSL) subroutine GGNML. A chirp waveform sampled at 2.5 kHz is added to the noise with a 50% probability so that a data segment may or may not contain the signal; the values of the mass parameter, phase, and time of arrival are chosen randomly. Finally, the FFT of the data segment is taken using the REALFT routine of *Numerical Recipes* [15]. The data so generated is sent to the main thread in the first worker task which in turn sends it first to the main thread in the second worker and then to *its* subsidiary thread and so on. In Figs. 3 and 4 we have shown the flow charts of the main and the subsidiary threads, respectively, of the worker task. The subsidiary thread in the worker task filters the data

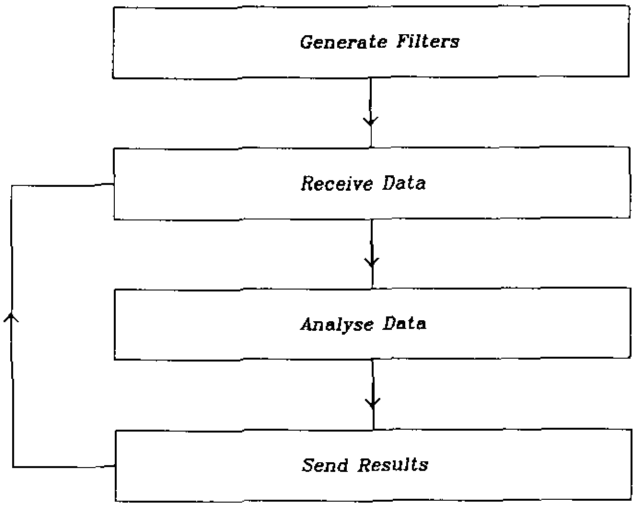

FIG. 4. Flow chart for the subsidiary thread in the worker task.

through the filters that it has built. The filtering involves computation of the correlations and maximization over all the parameters. Maximization over phase-shift is done analytically using the fact that there exists a two-dimensional basis in the phase-space. The maximum over the mass parameter and the time-shift is found numerically. The results of the search that it has carried out, viz., the maximum of the correlation, together with the corresponding values of the parameters, are sent to the main thread, which in turn immediately passes on a fresh data segment. The subsidiary thread then begins analysing the fresh data set. After having sent the data set to the subsidiary thread, the main thread seeks the results of the analysis carried out by a previous worker task, if any, and then sends the results corresponding to the larger of the two correlations to the next worker task. In this way the results of the analysis corresponding to the maximum of the correlation reach the master task which sends an alarm if the signal-to-noise ratio is larger than the threshold. For the purpose of studying the noise characteristics and other housekeeping, all significant events are recorded by the master task.

From the flow charts in Figs. 3 *and* 4 *it is clear that as long as the data transfer rate between processors is less than the rate at which the analysis of data is carried out, the subsidiary thread does not waste its time in either waiting for the data to arrive or sending the results of its analysis through to the main thread.* This is because the main thread in each worker task would have received the data from a previous worker task and sent it to the main thread of the next worker task much before its subsidiary thread can send results since interprocessor data transfer rates are much larger than the rate at which the analysis is carried out. As an example, data transfer rates across hard links of a transputer are ~ 2 Mbytes/s while a typical data set is only as large as 120 kbytes. On the average, such data segments require analysis times ~ 40 s. Thus, if we use a *ring* topology communication, overhead will start delaying the processing only if the number of processors is larger than about 500. In that case a judicious choice of a more complicated topology of processors will be beneficial.

It is quite straightforward to test that the above statements are indeed correct. If the communication overhead is not present in a given algorithm, then as the number of processors is increased the computation time per processor should remain a constant or the effective speed of the machine should increase linearly. We have tested this for numbers varying from 4 to 256 transputers on the network and found that the increase in speed is linear to a very high degree of accuracy.

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