

**LASER INTERFEROMETER GRAVITATIONAL WAVE  
OBSERVATORY**

**- LIGO -**

**CALIFORNIA INSTITUTE OF TECHNOLOGY  
MASSACHUSETTS INSTITUTE OF TECHNOLOGY**

Technical Note	LIGO-T030112-00-D	04/22/2003
<b>A study of the cross-correlation coefficient distribution in the presence of additive signals</b>		
S. Mohanty, R. Rahkola, Sz. Márka, S. Mukherjee, R. Frey		

**Max Planck Institut für  
Gravitationsphysik**  
Am Mühlenberg 1, D14476,  
Germany  
Phone +49-331-567-7220  
Fax +49-331-567-7298  
E-mail: office@aei.mpg.de

**California Institute of  
Technology**  
LIGO Laboratory - MS 18-34  
Pasadena CA 91125  
Phone (626) 395-212  
Fax (626) 304-9834  
E-mail: info@ligo.caltech.edu

**Massachusetts Institute of  
Technology**  
LIGO Laboratory - MS 16NW-145  
Cambridge, MA 01239  
Phone (617) 253-4824  
Fax (617) 253-7014  
E-mail: info@ligo.mit.edu

**www:** <http://www.ligo.caltech.edu/>

This note is a continuation of [1], which should be read for background information.

## 1 Statement of problem

In order to use the cross-correlation coefficient,  $r$ , for confidence interval estimation, we need to know its probability density function,  $p(r; h_x, h_y)$ , given additive signals  $h_x[i]$  and  $h_y[i]$ ,  $i = i_0, \dots, i_0 + M - 1$ , in the two IFO time series  $x[k]$  and  $y[k]$ ,  $k = 0, \dots, N - 1$ , respectively. In the following,  $0 \leq i_0 \leq N - 1$  and  $0 \leq i_0 + M - 1 \leq N$ . We report a study of  $p(r; h_x, h_y)$  in the context of its use in a triggered search.

## 2 Analytical results

For simplicity, we consider only the identical signal case  $h_x[k] = h_y[k] = h[k]$  here. Let the noise in each detector be a Gaussian, zero mean, white random process.

First, we explore how the signal waveform influences the distribution  $p(r; h)$  of  $r$ . The main result is that there are only three gross quantities associated with a waveform that are relevant to this problem. The three quantities are,

1. The signal mean  $\mu_h$ ,

$$\mu_h = \frac{1}{M} \sum_{i=0}^{M-1} h[i + i_0]. \quad (1)$$

2. The signal duty cycle  $\epsilon$ ,

$$\epsilon = \frac{M}{N}. \quad (2)$$

3. The norm  $\rho_h$  of the signal *after mean removal*,

$$\rho_h^2 = \sum_{i=0}^{M-1} (h[i + i_0] - \mu_h)^2. \quad (3)$$

**Theorem** – The distribution  $p(r; h)$  depends only on a single quantity,  $\rho_r$ ,

$$\rho_r^2 = \rho_h^2 + M\mu_h^2(1 - \epsilon). \quad (4)$$

**Proof** – Let  $n_x[k]$  and  $n_y[k]$  denote the noise components of  $x[k]$  and  $y[k]$  respectively. Let  $s[k]$  be the signal component,  $s[k] = h[k]$ ,  $k = i_0, \dots, i_0 + M - 1$  and zero otherwise. Then,

$$r = \frac{\sum_{i=0}^{N-1} (n_x[i] + s[i] - \widehat{\nu}_x - \epsilon\mu_h)(n_y[i] + s[i] - \widehat{\nu}_y - \epsilon\mu_h)}{\|n_x + s - \widehat{\nu}_x - \epsilon\mu_h\| \|n_y + s - \widehat{\nu}_y - \epsilon\mu_h\|},$$

$$\hat{v}_x = \frac{1}{N} \sum_{i=0}^{N-1} n_x[i], \quad (5)$$

$$\hat{v}_y = \frac{1}{N} \sum_{i=0}^{N-1} n_y[i], \quad (6)$$

Temporarily redefine  $n_x[i] \rightarrow n_x[i] - \hat{v}_x$ ,  $n_y[i] \rightarrow n_y[i] - \hat{v}_y$  and  $s[i] \rightarrow s[i] - \epsilon\mu_h$ . Then,

$$r = \frac{\langle n_x, n_y \rangle + \|s\| (\|s\| + \langle n_x, \hat{s} \rangle + \langle n_y, \hat{s} \rangle)}{\sqrt{\|n_x\|^2 + \|s\| (\|s\| + \langle n_x, \hat{s} \rangle)} \sqrt{\|n_y\|^2 + \|s\| (\|s\| + \langle n_y, \hat{s} \rangle)}}, \quad (7)$$

$$\hat{s} = \frac{s}{\|s\|}. \quad (8)$$

Consider the terms  $\langle n_x, \hat{s} \rangle$  and  $\langle n_y, \hat{s} \rangle$ . Reverting back to the original definitions for  $n_x$  and  $n_y$ ,

$$\langle n_x, \hat{s} \rangle \rightarrow \langle n_x, \hat{s} \rangle - \hat{v}_x \sum_{i=0}^{N-1} \hat{s}[i]. \quad (9)$$

But  $\sum_{i=0}^{N-1} \hat{s}[i] = 0$  and the remaining term is the projection of  $n_x$  on some fixed unit vector. However,  $n_x$ , being a white noise sequence will have an isotropic distribution in an  $N$  dimensional vector space. Therefore, the distribution of its projection on a fixed unit vector will not depend on the direction of the unit vector. (The same argument goes through for  $\langle n_y, \hat{s} \rangle$ .) Hence, examining Eq. 7, we see that none of the random variables,  $\langle n_x, n_y \rangle$ ,  $\|n_x\|$ ,  $\|n_y\|$ ,  $\langle n_x, \hat{s} \rangle$  and  $\langle n_y, \hat{s} \rangle$ , depend on the signal in their distribution. The distribution of  $r$ , therefore, only depends on  $\|s\|$ ,

$$\begin{aligned} \|s\|^2 &= \sum_{i=0}^{M-1} (h[i] - \epsilon\mu_h)^2 + \sum_{i=M}^{N-1} (\epsilon\mu_h)^2 \\ &= \rho_h^2 + M\mu_h^2(1 - \epsilon). \end{aligned} \quad (10)$$

Q.E.D.

The above result means that the  $r$  statistic is as efficient for Gaussians as for sine-Gaussians or for any other signal as long as they have the same  $\rho_r$ . It also means that an interval/point estimate of  $\rho_r$  is independent of signal waveform, within random errors, **even if the estimation is done using signal injection with specific waveform types**. The only way we can tune ourselves to one signal type versus another is to first pre-process the data such that only one type of signal survives. For example, band pass filtering the data can choose between sine-Gaussians with different carrier frequencies. However, even with pre-processing, the estimate of  $\rho_r$  applies to *whatever signal survives the processing*.

Thus, the purpose of using signal injection for estimating  $\rho_r$  is *not* to arrive at different limits for different signal types but to arrive at a limit on  $\rho_r$  for

whatever signal is present in the conditioned data, albeit with a different treatment of noise and a different set of assumptions about the data. For instance, the systematic errors may be different for methods that use signal injections from the ones that do not or the response to non-stationarity may be different. The astrophysical interpretation of the signal injection derived limit on  $\rho_r$  will not be any different from waveform independent methods for limiting  $\rho_r$ .

### 3 Numerical results for identical signals

The proof that  $p(r; h)$  depends only on  $\rho_r$  is demonstrated using MC simulation with different signal types. The MC simulation consists of generating pairs,  $x[k]$  and  $y[k]$ ,  $k = 0, \dots, N - 1$ , of white Gaussian noise sequences. Each sequence is zero mean and each sample has unit variance. The *same* signal waveform  $h[k]$ ,  $k = 0, \dots, M - 1$ , ( $M \leq N$ ) is injected into each sequence and  $r$  is calculated repeatedly over  $N_{\text{trials}}$  independent trials. The distribution  $p(r; h)$  is then estimated from this set of  $r$  values. Signals are injected with amplitude  $A$  such that  $\rho_r$  has some prescribed value.

The signal types used are,

#### Gaussian pulse

**DFM waveforms** From the Dimmelmeier, Font, Müller catalog [2, 3].

Figure 1 shows the result. As can be seen,  $p(r; h)$  depends only on  $\rho_r$  within statistical error.

### References

- [1] Soumya D. Mohanty *et al*, LIGO-T030111-00-D.
- [2] Dimmelmeier, H., Font, J.A., and Müller, E., "Relativistic simulations of rotational core collapse. I. Methods, initial models, and code tests", *Astron. Astrophys.*, 388, 917-935 (2002); astro-ph/0204288.
- [3] Dimmelmeier, H., Font, J.A., and Müller, E., "Relativistic simulations of rotational core collapse. II. Collapse dynamics and gravitational radiation", *Astron. Astrophys.*, 393, 523-542 (2002); astro-ph/0204289.

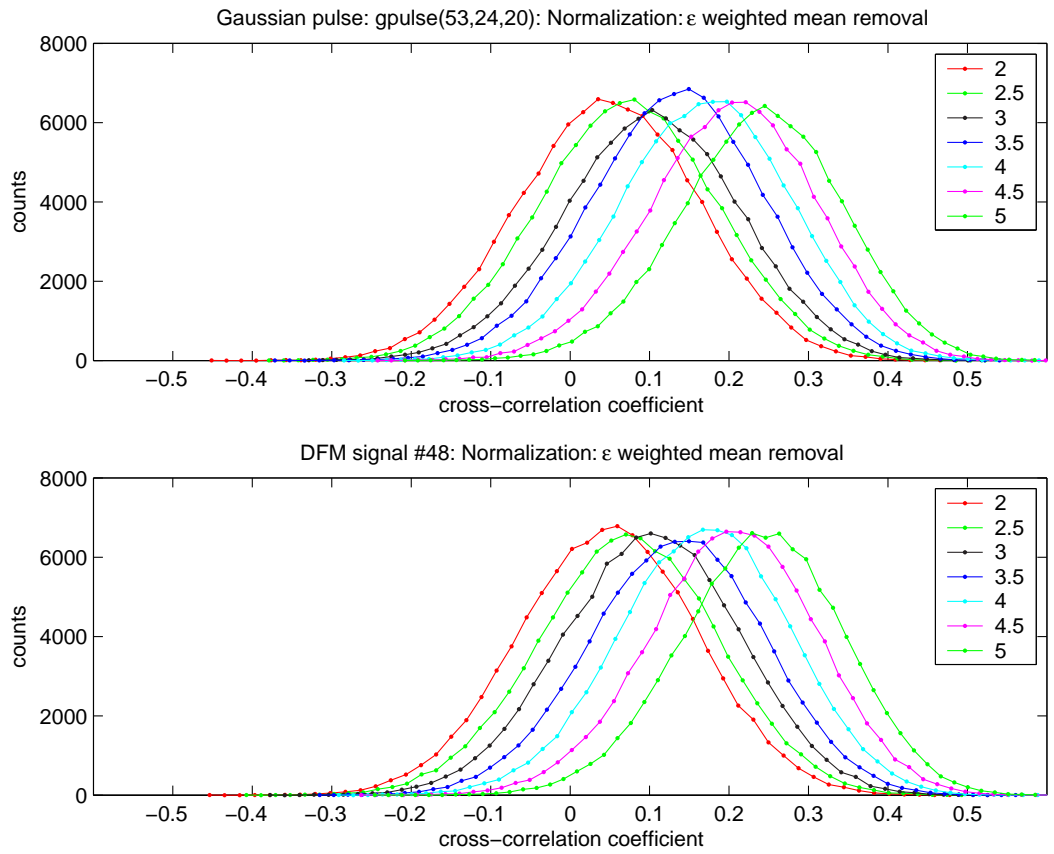


Figure 1: The probability density of  $r$  for different signal types as a function of  $\rho_r$ . The top panel is for a Gaussian pulse that is 50 msec wide. The bottom panel is for a signal (A4B4G5\_R) from the DFM catalog [2, 3]. The signals are shown in Fig. 2.

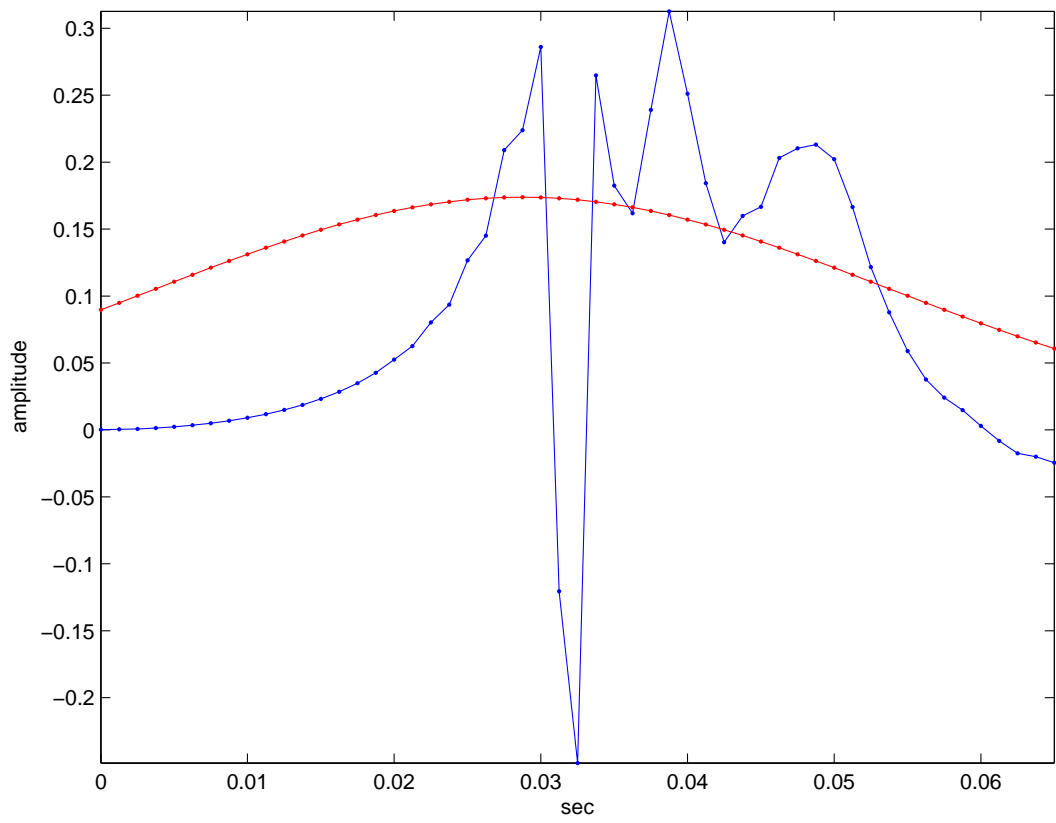


Figure 2: The signals used in the simulation (c.f. Fig. 1).fig2)