Model design of hemodynamic response functionwithin finite impulse responsebasis for functional magnetic resonance imaging.

Md. Roni Islam

Senior Lecturer, Department of Electrical and Electronic Engineering, KhwajaYunus Ali University, Enayetpur, Sirajgonj-6751, Bangladesh.

ABSTRACT: The MRI scanner doesn't measure the BOLD signal at such a high temporal resolution lack of required period for an individual fMRI measurement or short TR (Repetition time) is on the order of 1 to 2 seconds. However recent advances in parallel imaging and multiband excitation technologies are vastly shortening the required TR of fMRI. In this paper, we make an HRF model within FIR function basis that provides how the BOLD signal in a voxel will vary due to a short burst of neural activity.
Keyword: fMRI, BOLD Signal, FIR Basis function, HRF, TR, Voxel, Gamma Probability density function.

I. INTRODUCTION

Magnetic Resonance Imaging (MRI) is a process use to basically 'look inside' of ingredients in a non-invasive manner. The functional MRI is scanned the internal image of blood flow in human brain that consume fuel such as sugar and oxygen which is measured in form of BOLD signal. The BOLD signal mostly peaks 4 to 6 seconds after the beginning of neural activity, after which it decreases back toward baseline, even undershooting baseline amplitude around 8 to 12 seconds after onset [1]. If there is no addition neural activity the BOLD signal eventually returns to baseline levels, which is approximately 20 seconds [2]. The whole periodic portion of BOLD signal is referred to as Hemodynamic Response Function (HRF). In this paper, we estimate a model HRF to use in fMRI within FIR basis to show the brain activity in presence or absence hemoglobin in Human blood flow on brain tissue. The estimate model of HRF is a sum of two Gamma distributions [3]. One of the distributions models the initial peak of the BOLD signal, and another distribution which is inverted as previous distribution models the undershoot of BOLD signal

[4]. Finally, we will use the modeled HRF signal to represent the fMRI's image.

II. MATERIALS AND METHODS

Using functional magnetic resonance imaging, neuroscientists design experiments that present stimuli having particular features that are hypothesized to be encoded by neurons in a particular region of interest in the brain. We can perform this task three individual steps are described below:

1) Modeling the HRFs with the combine of two Gamma probability density functions which is characterizing the BOLD signal.
2) Modeling the HRFs with a set of Time-delayed Impulses as a series of weighted FIR basis functions.
3) Finally, selected HRF model is used to apply in voxels and producestimuli for fMRI

2.1 Step one: Modeling the HRFs with the combine of two Gamma probability density functions which is characterizing the BOLD signal in MATLAB.

Modeling the HRF combine of two gamma probability density functions [1st gampdf – 40% of 2nd gampdf]–

```
clc;
clear;
closeall;
t = 0:.1:20;
hrf1 = gampdf (t,4) + - .4* gampdf (t,8);
plot (t,hrf1,'r','linewidth',3);
holdon;
hrf2 = gampdf (t,6) + -.4*gampdf (t,10);
plot (t,hrf2,'b','linewidth',3);
hrf3 = gampdf (t,8) + -.4*gampdf (t,12);
plot (t,hrf3,'y','linewidth',3);
p = size (t);
q = zeros (p);
baseline = plot (t,q,'k--','linewidth',3);
```

```
xlabel ('Time for HRF activity onset(s)');
ylabel ('BOLD signal');
title (sprintf('Model of three deferent values HRF \n
[1st gampdf - 40 percent of 2nd gampdf]'));
legend ('hrf1','hrf2','hrf3','baseline');
holdoff;
```

Modeling the HRF combine of two gamma probability density functions [1^{st}gampdf – 50% of 2^{nd}gampdf]–

```
clc;
clear;
close all;
t = 0:.1:20;
hrf1 = gampdf (t,4) + - .5* gampdf (t,8);
plot (t,hrf1,'r','linewidth',3);
hold on;
hrf2 = gampdf (t,6) + -.5*gampdf (t,10);
plot (t,hrf2,'b','linewidth',3);
hrf3 = gampdf (t,8) + -.5*gampdf (t,12);
plot (t,hrf3,'y','linewidth',3);
p = size (t);
q = zeros (p);
baseline = plot (t,q,'k--','linewidth',3);
xlabel ('Time for HRF activity onset(s)');
ylabel ('BOLD signal');
title (sprintf('Model of three deferent values HRF
\n[1st gampdf - 50 percent of 2nd gampdf]'));
legend ('hrf1','hrf2','hrf3','baseline');
hold off;
```

Modeling the HRF combine of two gamma probability density functions [1^{st}gampdf – 60% of 2^{nd}gampdf]–

```
clc;
clear;
closeall;
t = 0:.1:20;
hrf1 = gampdf (t,4) + - .6* gampdf (t,8);
plot (t,hrf1,'r','linewidth',3);
holdon;
hrf2 = gampdf (t,6) + -.6*gampdf (t,10);
plot (t,hrf2,'b','linewidth',3);
hrf3 = gampdf (t,8) + -.6*gampdf (t,12);
plot (t,hrf3,'y','linewidth',3);
p = size (t);
q = zeros (p);
baseline = plot (t,q,'k--','linewidth',3);
xlabel ('Time for HRF activity onset(s)');
ylabel ('BOLD signal');
title (sprintf('Model of three deferent values HRF \n
[1st gampdf - 60 percent of 2nd gampdf]'));
legend ('hrf1','hrf2','hrf3','baseline');
holdoff;
```

2.2 Step two: Modeling the HRFs with a set of Time-delayed Impulses as a series of weighted FIR basis functions in MATLAB-

% selected HRF model as a series of weighted basis function.

```
clc;
clear;
closeall;
t = 0:1:20;
hrf3 = gampdf (t,8) + -.5*gampdf (t,12);
stem (t,hrf3,'y','linewidth',1.5);
holdon;
p = size (t);
q = zeros (p);
baseline = plot (t,q,'k--','linewidth',3);
xlabel ('Time for HRF activity onset(s)');
ylabel ('BOLD signal');
title (sprintf('Selected HRF model as a series of \n
weighted basis function'));
legend ('hrf3','baseline');
holdoff;
```

% HRF as weighted FIR Representation

```
figure;
holdon
cnt = 1;
map = jet (64);
cRange = linspace (min(hrf3), max(hrf3),64);
foriT = numel(hrf3):-2:1
firSignal = ones (size(hrf3));
firSignal (cnt) = 2;
[~,cIdx] = min(abs(cRange-hrf3(cnt)));
color = map (cIdx,:);
plot      (1:numel(hrf3),firSignal   +   2*(iT-
1),'color',color,'Linewidth',1)
cnt = cnt +1;
end
colormap(map);colorbar;caxis([min(hrf3)
max(hrf3)]);
axissquare;
ylabel ('FIR Basis Function')
xlabel ('Time (TR)')
set (gca,'YTick',0:2:39,'YTickLabel',20:-1:1)
title (sprintf('HRF as weighted FIR basis, \n Seting
20 FIR basis functions'));
```

2.3 Step three: Experiments have on verities types of voxels conducted by using selective HRF model. The related MATLAB code is described in following -

% An Experiment on a Voxels by the selected HRF model.

```
trPerStim =20;
nRepeat = 8;
nTRs = trPerStim * nRepeat + length (hrf3);
nCond = 3;
nVox = 3;
impulseTrain0 = zeros(1,nTRs);

% Random onset Times (TRs)
onsetIdx = randperm (nTRs - length (hrf3));

% Voxel Type one [Visual Stimulus]
impulseTrainLight = impulseTrain0;
impulseTrainLight (onsetIdx (1:nRepeat)) = 1;
onsetIdx (1:nRepeat) = [];

% Voxel Type two [Auditory Stimulus]
impulseTrainTone = impulseTrain0;
impulseTrainTone (onsetIdx(1:nRepeat)) = 1;
onsetIdx (1:nRepeat) = [];

% Voxel Type Three [somatosensory stimulus]
impulseTrainHeat = impulseTrain0;
impulseTrainHeat (onsetIdx(1:nRepeat)) = 1;

% Experiment design and stimulus sequence
D                                        =
[impulseTrainLight',impulseTrainTone',impulseTra
inHeat'];
X = conv2 (D,hrf3');
X = X (1:nTRs,:);

% Stimulate response of voxels with various
selectivity
visualTuning = [4 0 0];
auditoryTuning = [0 2 0];
somatoTuning = [0 0 3];
noTuning = [1 1 1];
```

```
beta = [ visualTuning', ...
auditoryTuning', ...
somatoTuning', ...
noTuning'];
y0 = X*beta;
SNR = 5;
noiseSTD = max (y0)/SNR;
noise          =          bsxfun          (@times,
randn(size(y0)),noiseSTD);
y = y0 + noise;

% Display four tpyes Voxel Timecourses
voxNames                                          =
{'Visual','Auditory','Somat','Unselective'};
cols = lines (4);
figure;
foriV = 1:4
subplot (4,1,iV)
    plot (y(:,iV), 'Color', cols(iV,:), 'Linewidth',2);
xlim ([0,nTRs]);
ylabel('BOLD Signal')
legend (sprintf('%s Voxel', voxNames{iV}))
end
xlabel('Time(TR)')
set (gcf,'position', [100,100,880,500]);
```

III. RESULTS

The simulation results mentioned above three steps are represented graphically and sequentially.In 1st step, we design nine HRF model with different values of various parameters, which are fitting in linear and cubic methods, are showing in the following table with their estimate error (residuals) –

HRF Model	Parameters	Residual's value	
		Linear	Cubic
Step1-40(hrf1)		0.82643	0.7094
Step1-40(hrf2)		0.68991	0.45557
Step1-40(hrf3)		0.63565	0.32138
Step1-50(hrf1)		0.86315	0.73686
Step1-50(hrf2)		0.70184	0.48314
Step1-50(hrf3)	**selected**	**0.63103**	**0.32963**
Step1-60(hrf1)		0.90383	0.76456

Table 1 : HRF model with their residual

|			
Step1-60(hrf2)		0.719 63	0.511 34
Step1-60(hrf3)		0.631 43	0.339 57

The result shows that a voxel located in visual cortex will be more selective for the light than for the tone or the heat stimulus. A voxel in auditory cortex will be more selective for the tone than for the other two stimuli. A voxel in the somatosensory cortex will likely be more selective for the heat than the visual or auditory stimuli.
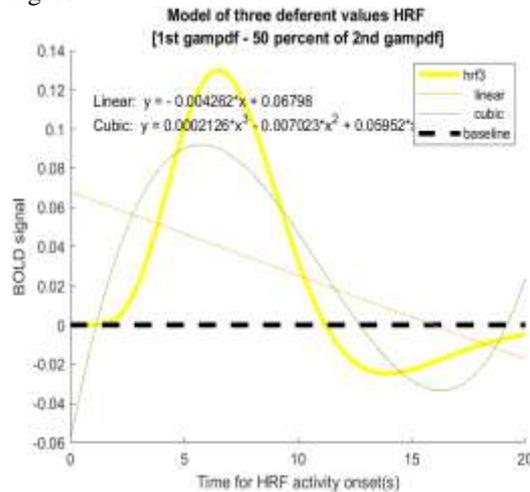
Figure 1:HRF models showing with their error estimation (residuals) in following nine figure -
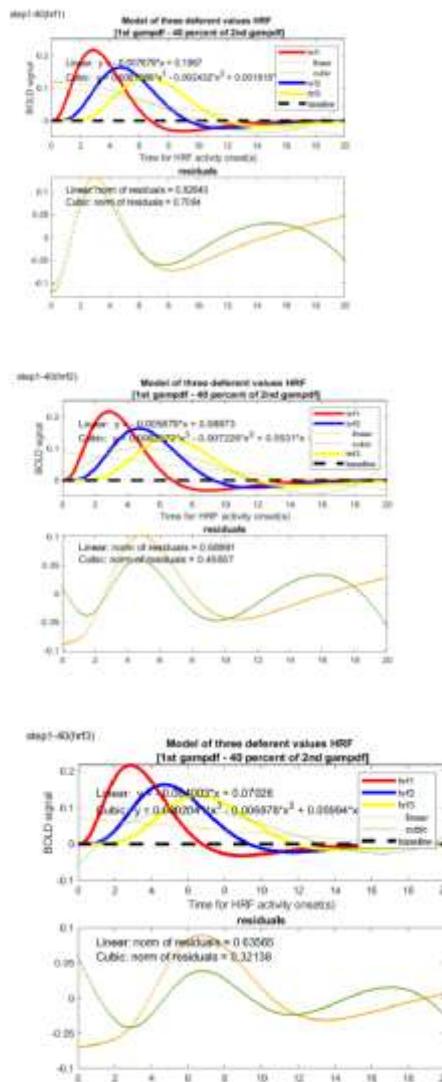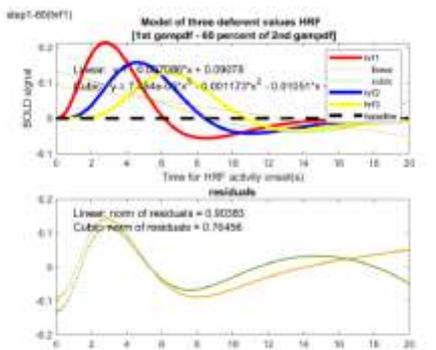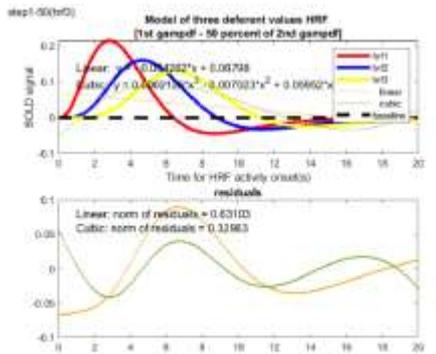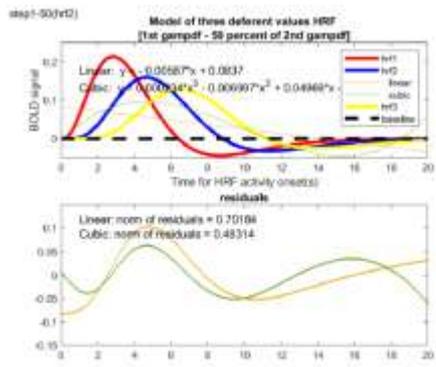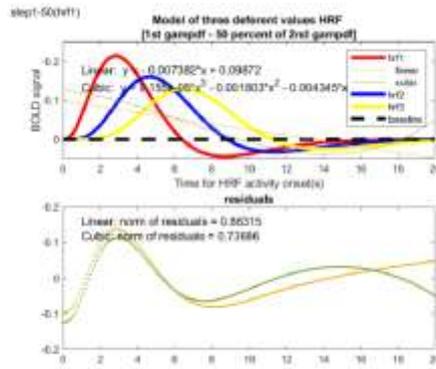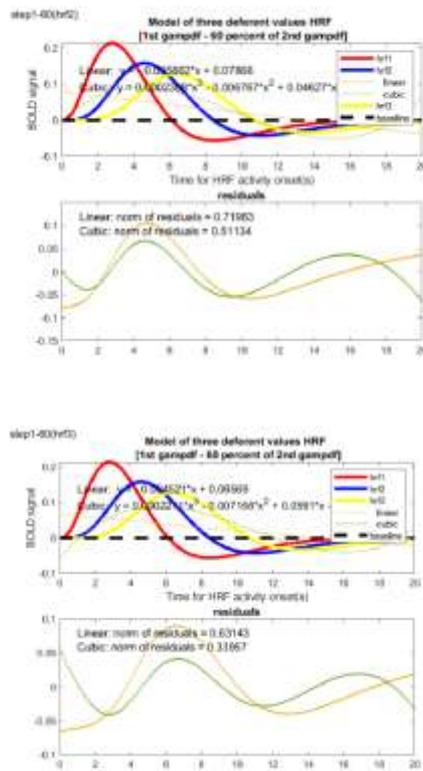
Figure 2: Selected HRF model of minimum residuals among the above nine model is showing in following figure -

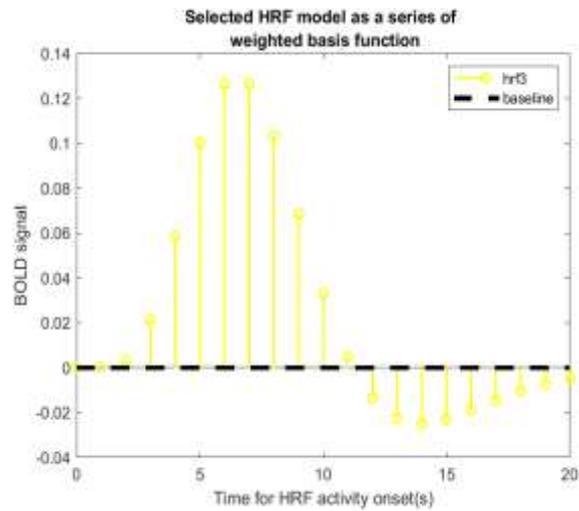**Figure 3**: Discrete signal of the HRF within FIR series.

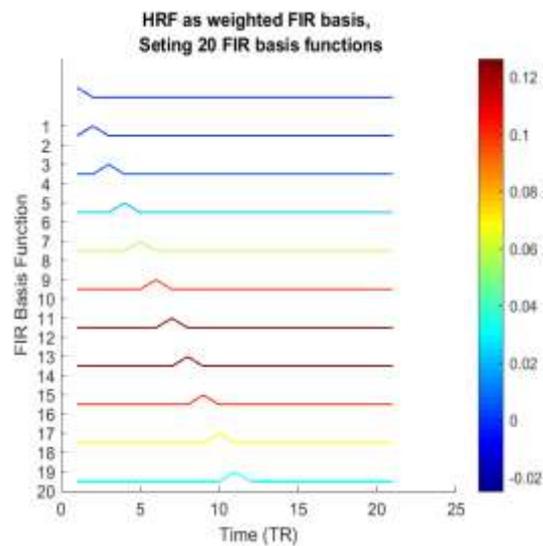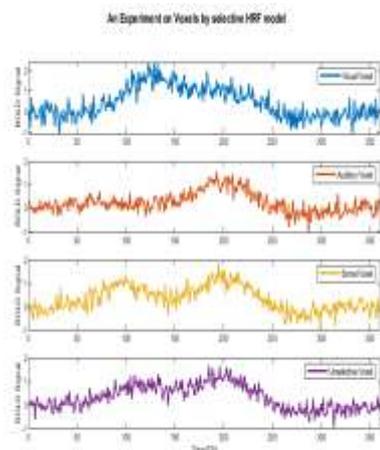**Figure 4: Selected** HRF as weighted FIR basis.

Figure 5: Various Stimuli regarding Voxels.

An Experiment on Voxels by selective HRF model

IV. DISCUSSION AND CONCLUSION:

The three steps methodology provides a valuable reduction in repetition time and makes it shorter than that of fMRI scanner's BOLD signal. The modeled hemodynamic response function within FIR 20 functions makes BOLD signal as a high temporal resolution. Given the evoked BOLD signal measured from a voxel during stimulus presentation, along with the HRF for the voxel, and the assumptions of FIR model framework, it is possible to calculate the degree to which the neurons in the voxel must be selective for each the stimulus features in order to produce the measured BOLD signal.

REFERENCES

[1]. David M. Afonso, Joao M. Sanches, and Martin H. Lauterbach (2007) "Neural physiological modeling towards a hemodynamic response function for fMRI'', Conference of the IEEE EMBS, Lyon, France.

[2]. F.Scarpa, S.Brigadoi, S.Cultini, P.Scantturin, M.Zorzi, R.Dell'Acqua, and G. Sparacino (2011) "A methodology to improve estimation of stimulus evoked hemodynamic response from fNIRS measurements", 33rd annual international conference of the IEEE EMBS, Boston, USA.

[3]. Dustinstansbury (2016) "Fmri in neuroscience: modeling the HRF with FIR basis functions", The OG clecer Machine.

[4] Daniel A. Handwerker, John M. Ollinger, and Mark D'Esposito, "Variation of BOLD hemodynamic response across subjects and brain regions and their effects on statistical analyses",NeoroImage,www.elsevier.com/lo cate/ynimg, NeuroImage 21 (2004) 1639-1651.

IJAEM