EVOLVING A SUPERCOMPUTING ARCHITECTURE FOR MODELLING THE CORTEX:

TOWARDS UNDERSTANDING COLOR INFORMATION ENCODING

(Summary of Work Progressed)

Submitted to:

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TIME-FREQUENCY GABOR ANALYSIS:

The TF analysis is a powerful tool employed extensively in digital and biological signal processing. While TF has been employed frequently in analyzing EEGs, this transformation has not been applied to analyze the spatio-temporal electrical activities of different layers across sensory pathways for varying input stimulus to study the neural encoding process. In particular this thesis, deals with application of the Gabor transformation to analyze the spatio-temporal electrical activities of different layers in the retinal pathway for color recognition. This is to evolve the encoding process within and along the different retinal layers in terms of the amplitude variations of dominant harmonics and to obtain the corresponding transfer function.

ANALYSIS OF DOMINANT HARMONIC COMPONENTS:

A harmonic that is dominant in a particular layer might either get lost in the subsequent layers or might remain as a dominant harmonic throughout or might undergo changes. In fact there could be several dominant harmonics existing in a particular layer for a set of input stimuli. All these set of dominant harmonics are analyzed, grouping them into different harmonic ranges.

STATISTICAL ANALYSIS:

As a part of this work the author has developed a MOdified Statistical Analyzer (MOSA) to investigate the output of the TF transform. The different units are shown in the figure 1. The mean is calculated by taking the range from the probabilistic value 0.5 of all the harmonics till the maximum probability of 1. The SDE is a part of the MOSA. The DHE extracts all the dominant harmonic having amplitudes higher than the mean + SD. The DHT traces the amplitude variations of particular dominant harmonics across layers.

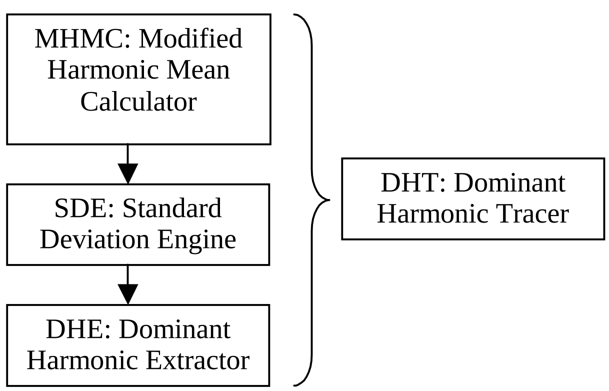

Figure 1: MOdified Statistical Analyzer- MOSA

SIMULATION METHODOLOGY:

The simulation methodology explained in the companion paper part I is provided as an algorithm here.

Algorithm 1 Simulation Methodology

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Input : Varying stimulus
Output: Polynomial function indicating variation in amplitude
of dominant harmonics

Algorithm :
Step1: Present the stimulus over the receptor cells.
Step2: Record the spiking activity from each layer.
Step3: Sample the spikes at discrete intervals.
Step4: Apply the time frequency Gabor transformation to the
       discretized values.
Step5: Feed the frequency components to MOSA
Step6: Dominant harmonic tracer gives the amplitudes of the
       particular dominant harmonic.
Step7: Plot the extracted dominant harmonic components to
       decipher the polynomial encoding.
Step8: Fit the curve to extract the polynomial function.
Step9: Apply Z transform to yield the transfer function.
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SIMULATION RESULTS AND INFERENCE

Simulations are carried out for different hue and saturation of different colors. The colors considered are red, green, blue and gray. With respect to red, simulations were carried out by varying the saturation. Simulation results are provided for 'within the layer' and 'across the different retinal layers'. Table 1 gives the list of figures showing the different simulation results.

Table 1 List of figures with description

Figs.	Description
2 a-h	Different Primary colors across layers†
3 a-f	Different Colors within layers
4 a-h	Different variations of Red across layers
5 a-f	Variations of Red within layers

† Horizontal, Bipolar & Ganglion,

The tables 2—5 provide the different polynomial functions. These functions give the amplitude variations of the dominant harmonic component corresponding to the spatio-temporal neural activities for different input stimulus.

Both for encoding within and across layers, we define an encoding format through set S_i which contains the order of the polynomial and the different coefficients. Let these sets be S_1, S_2, S_3, S_4. The set S_i contains the coefficients A, B, C, D & O (order of the corresponding polynomial).

The core observation is that the polynomial remains same across different colors (hues) across the layers (table 2). The dominant harmonic variations are reflected through the polynomial coefficients. Within the layers (table 3) also the encoding process remains the same. The order of the polynomial varies for within and across the layers.

For different shades (saturation) of red color, the neuronal code within the layers is given by the encoding format as above (Refer table 5). For encoding across the layers refer table 4.

Simulation Environment:
Platform: PIV
Tools employed: Matlab, Ret4, C/C++, Sigmaplot, Labfit
Neuronal Population size: 10,000 +

VERIFICATION OF SIMULATION RESULTS:

Inverse Gabor transformation of all the polynomial functions (which give the dominant harmonic variations with respect to the input stimulus) corresponding to individual layers and across the layers are taken. These sample values are to be correlated with the corresponding set of input samples with respect to variations in orientation, shape, & distances. Couple of initial verifications shows promising results.

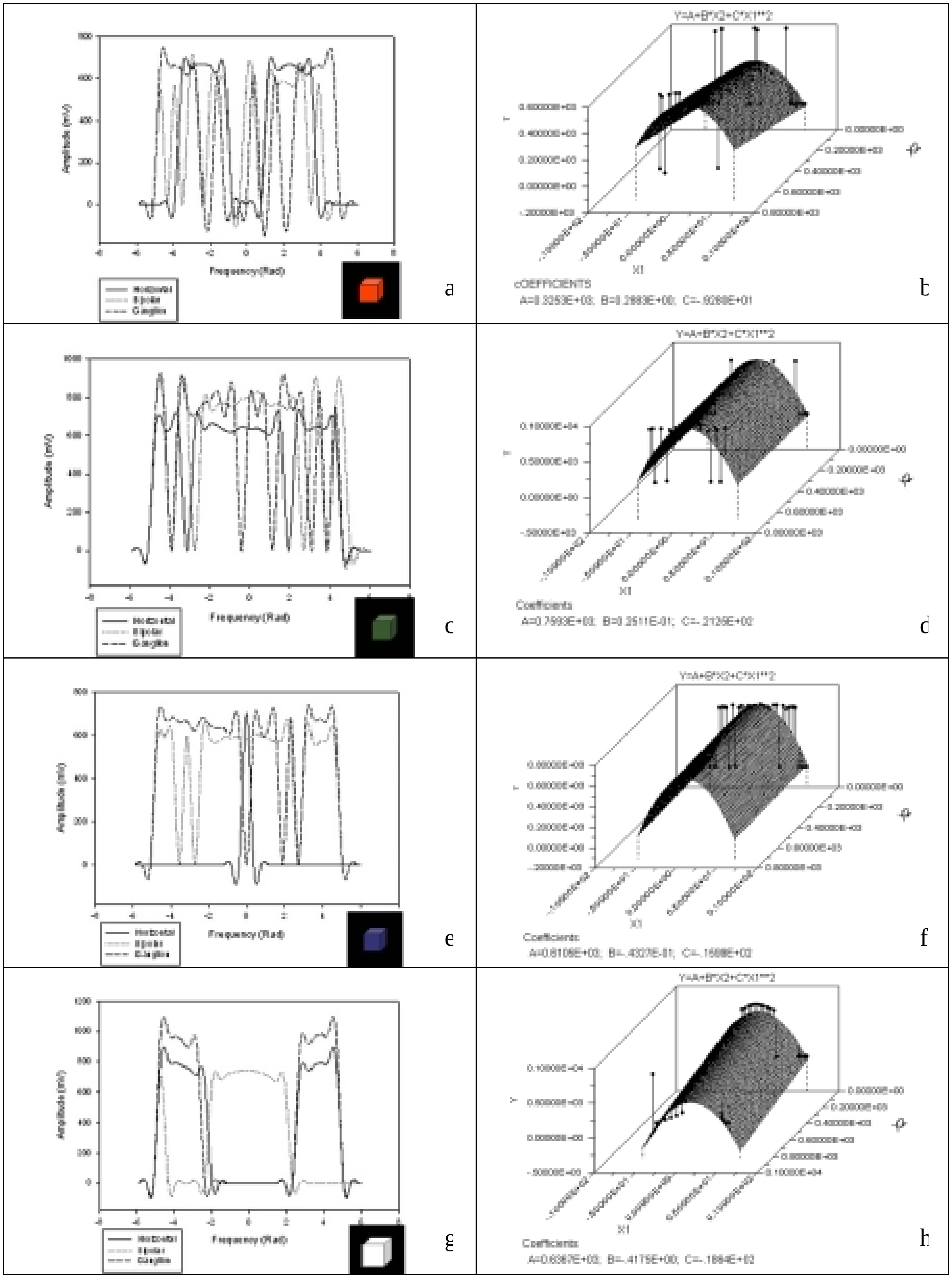

Figure 2 Simulation Results for primary color stimulus

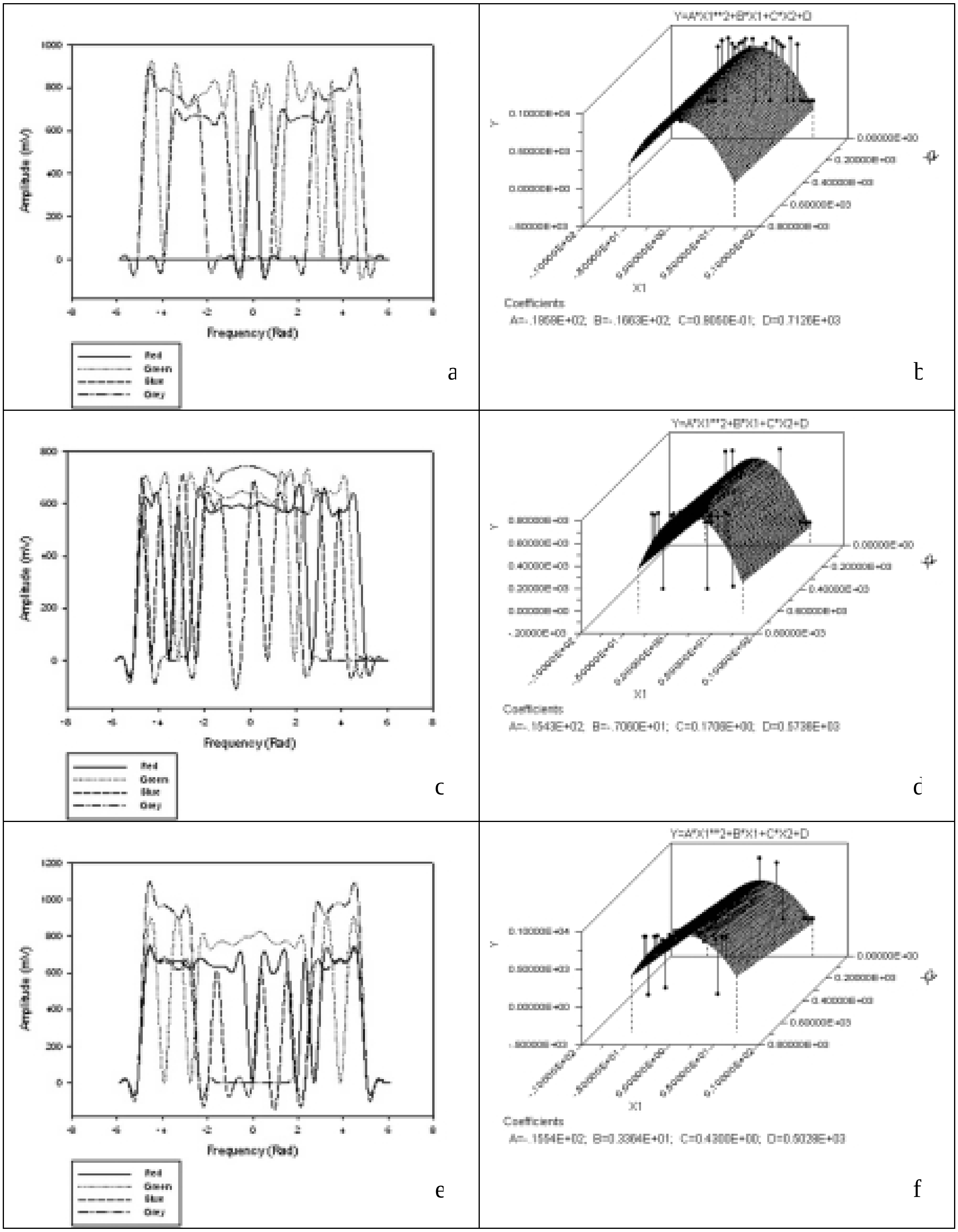

Figure 3 Responses of Horizontal, Bipolar and Ganglion for different color input stimulus

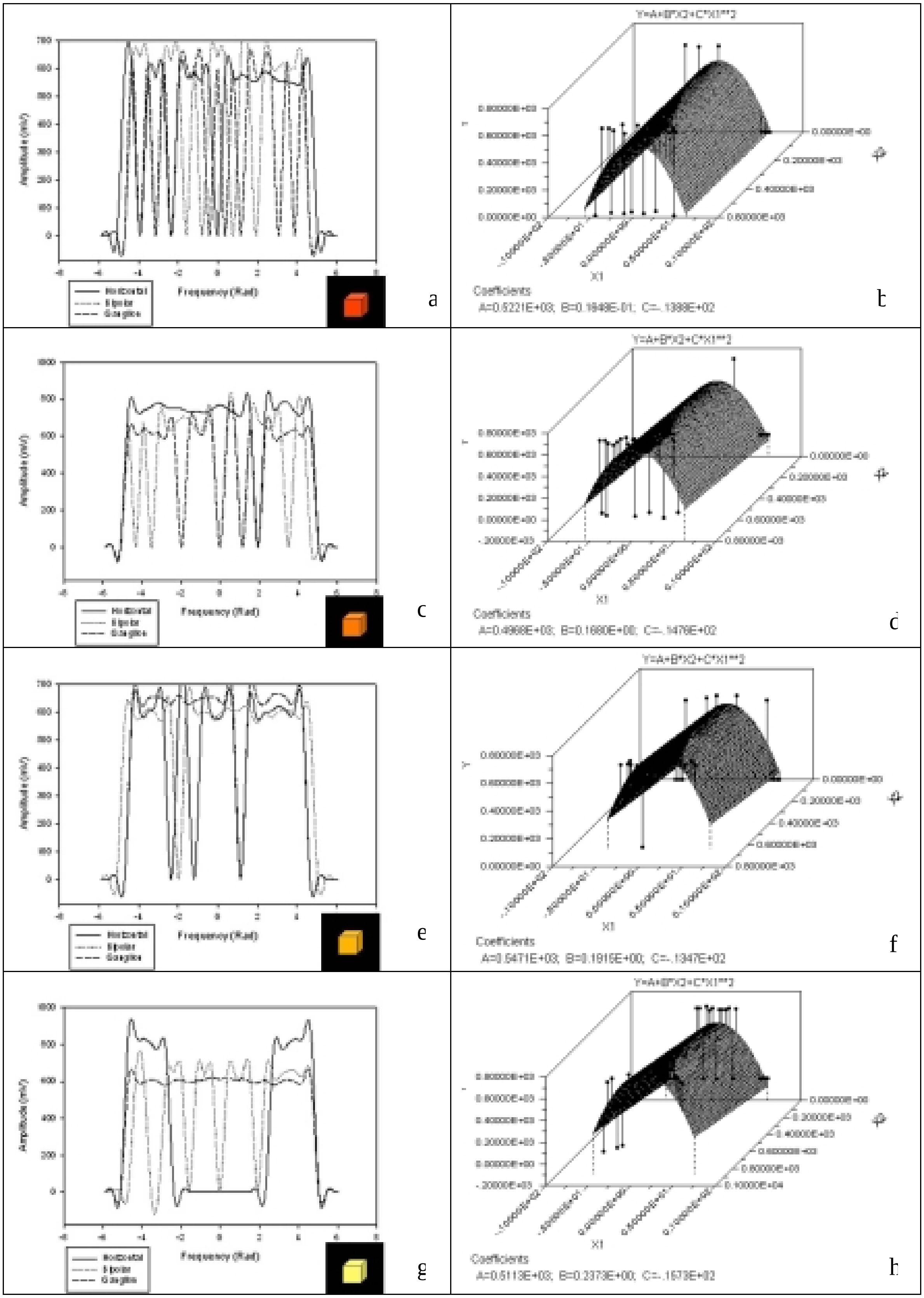

Figure 4 Simulation Results for different saturation of red color

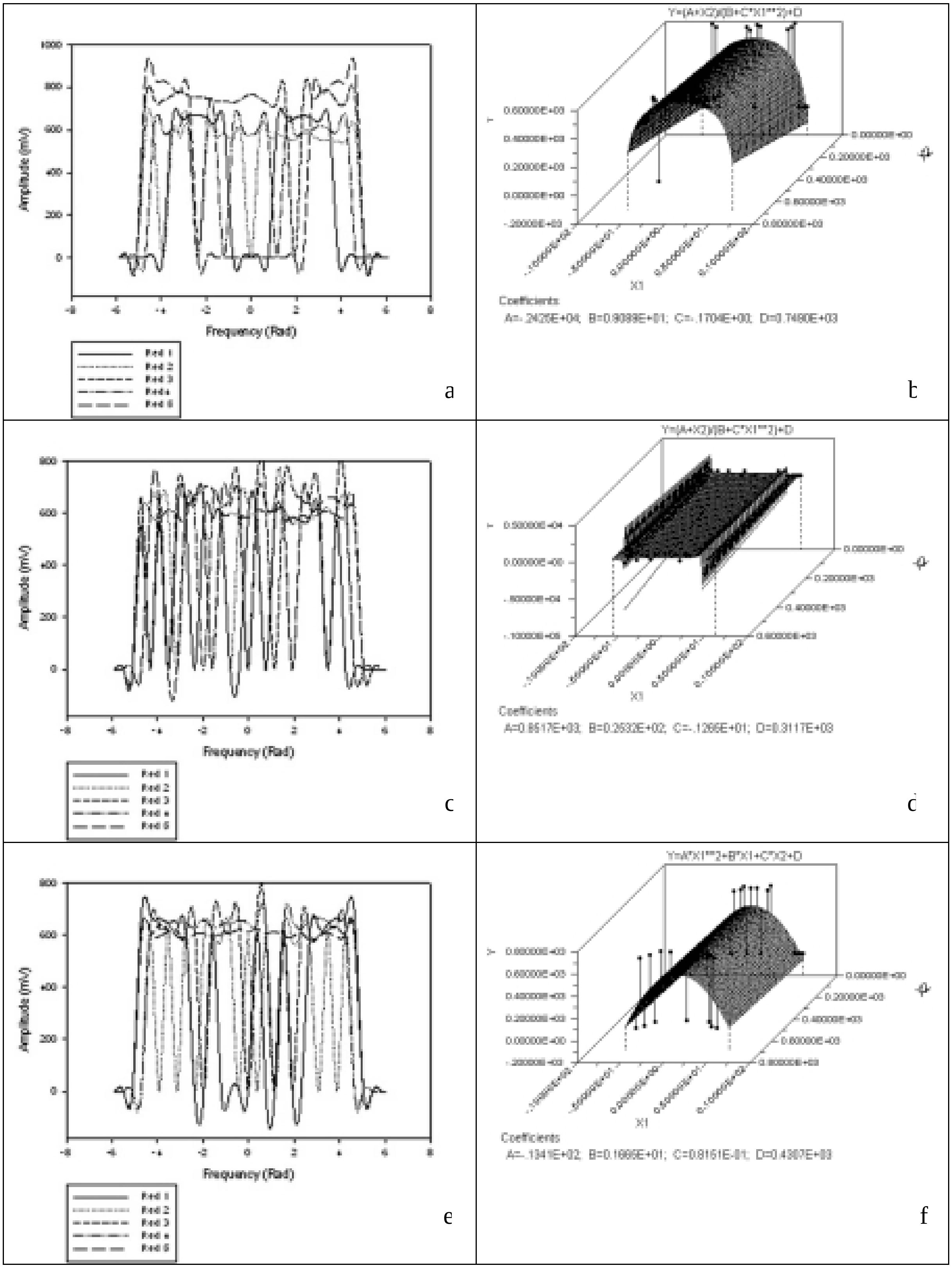

Figure 5 Responses of Horizontal, Bipolar and Ganglion for different saturation of red color

Table 2 Polynomial and Coefficients from figure 2

Stimulus	*Polynomial*	*A*	*B*	*C*
	A+B*X2+C*X1^2	0.3253E+03	0.2883E+00	-0.9280E+01
	A+B*X2+C*X1^2	0.7593E+03	0.2511E-01	-0.2125E+02
	A+B*X2+C*X1^2	0.6105E+03	-0.4327E-01	-0.1599E+02
	A+B*X2+C*X1^2	0.6367E+03	-0.4175E+00	-0.1864E+02

Table 3 Polynomial and Coefficients from figure 3

Layer	*Polynomial*	*A*	*B*	*C*	*D*
Horizontal	A*X1^2+B*X1+C*X2+D	0.1959E+02	-0.1663E+02	0.9050E-01	0.7126E+03
Bipolar	A*X1^2+B*X1+C*X2+D	-0.1543+E02	-0.7060E+01	0.1706E+00	0.5736E+03
Ganglion	A*X1^2+B*X1+C*X2+D	-0.1554E+02	0.3664E+01	0.4330E+00	0.5028E+03

Table 4 Polynomial and Coefficients from figure 4

Stimulus	*Polynomial*	*A*	*B*	*C*
	A+B*X2+C*X1^2	0.3253E+03	0.2883E+00	-0.9280E+01
	A+B*X2+C*X1^2	0.5221E+03	0.1648E-01	-0.1388E+02
	A+B*X2+C*X1^2	0.4968E+03	0.1680E+00	-0.1476E+02
	A+B*X2+C*X1^2	0.5471E+03	0.1915E+00	-0.1347E+02
	A+B*X2+C*X1^2	0.5113E+03	0.2373E+00	-0.1573E+02

Table 5 Polynomial and Coefficients from figure 5

Layer	*Polynomial*	*A*	*B*	*C*	*D*
Horizontal	(A+X2)/(B+C*X1^2)+D	-0.2425E+04	0.9089E+01	-0.1704E+00	0.7490E+03
Bipolar	(A+X2)/(B+C*X1^2)+D	0.8517E+03	0.2532E+02	-0.1265E+01	0.3117E+03
Ganglion	A*X1^2+B*X1+C*X2+D	-0.1341E+02	0.1665E+01	0.8151E-01	0.4307E+03