Indian Statistical Institute

Mid-Semestral Examination : 2013 – 2014

Master of Technology in Computer Science, Semester III

Functional Brain Signal Processing: EEG & fMRI

Date: 14 September 2013 Maximum Marks: 50 Duration: 2 hours

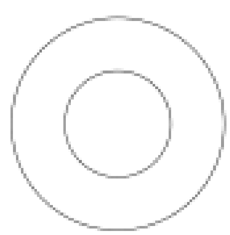
Attempt all the questions. Credit will be given for precise and brief answers.

1. Write short notes on each of the following EEG bands: (1) delta, (2) theta, (3) alpha, (4) beta and (5) gamma. 5 x 3 = 15

2. You are given 10 human scalp EEG signals recorded from different locations on the head of the same subject during a particular task execution pertaining to a single trial and you are asked to determine the ensemble cross-correlation across all the 10 signals. Describe an algorithm to accomplish this measure. You can describe the entire process in plain English (mathematical equations and derivations are not required) in numbered steps. 10

3. Define *Hilbert transformation*. Show that Hilbert transformation of $\sin(t)$ is $-\cos(t)$. Hint: $\int_{-\infty}^{\infty} \frac{\sin(x)}{x} dx = \pi$ and $\int_{-\infty}^{\infty} \frac{\cos(x)}{x} dx = 0$. Describe a wavelet based phase synchronization measure between a pair of EEG channels. Precisely, but concisely describe in numbered steps. 2 + 4 + 4 = 10

4. Consider the following configuration in a two dimensional space. If a neural network is designed to identify this configuration at the least how many hidden layers the neural network must have and why? 5



5. a) In Fisher's linear discriminant the expression $J(\mathbf{w}) = \frac{\mathbf{w}^T \mathbf{S}_B \mathbf{w}}{\mathbf{w}^T \mathbf{S}_\mathrm{w} \mathbf{w}}$ has to be maximized, where $\mathbf{w}$ is a vector, $\mathbf{S}_B$ and $\mathbf{S}_\mathrm{w}$ are nonsingular, square matrices of appropriate dimension. Show that when $J(\mathbf{w})$ is maximum, $\mathbf{S}_B \mathbf{w} = \lambda \mathbf{S}_\mathrm{w} \mathbf{w}$ will have to hold for some

scalar λ. Also show that for the optimally discriminating hyperplane $\mathbf{w}^T\mathbf{x} = c$, $\mathbf{w}$ is given by $\mathbf{w} = \mathbf{S}_{\mathbf{w}}^{-1}(\mathbf{m}_1 - \mathbf{m}_2)$ (assume that $\mathbf{S}_B$ is in the direction of $\mathbf{m}_1 - \mathbf{m}_2$, only the direction of $\mathbf{w}$ matters not the magnitude). $\mathbf{m}_1$ and $\mathbf{m}_2$ are mean of the two data sets respectively which will have to be optimally discriminated (separated) from each other by a hyperplane. 2.5 + 2.5 = 5

b) Write a short note on logistic regression and mention why logistic regression is more efficient than Fisher's discriminant. 5