# fMRI Visual Image Reconstruction Using Sparse Logistic Regression with a Tunable Regularization Parameter

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**Abstract.** fMRI has been a popular way for encoding and decoding human visual cortex activity. A previous research reconstructed binary image using a sparse logistic regression (SLR) with fMRI activity patterns as its input. In this article, based on SLR, we propose a new sparse logistic regression with a tunable regularization parameter (SLR-T), which includes the SLR and maximum likelihood regression (MLR) as two special cases. By choosing a proper regularization parameter in SLR-T, it may yield a better performance than both SLR and MLR. An fMRI visual image reconstruction experiment is carried out to verify the performance of SLR-T.

**Keywords::** fMRI · Visual image reconstruction · Sparse regression

## 1 Introduction

Functional magnetic resonance imaging (fMRI) is an effective means used by researchers to investigate brain activities to different kinds of tasks and stimuli noninvasively [1–8]. Many visual encoding and decoding experiments have been carried out. Kay showed that using the receptive field models, it's possible to identify images with fMRI signals [9]. Miyawaki reconstructed visual images directly using a sparse logistic regression (SLR) [10]. Each visual stimulus used in their experiment was made up of 10 by 10 square patches with each patch was either a gray patch or a flickering checkboard. SLR was applied to calculate the class label of voxel's fMRI signal patterns. The most significant feature of SLR is that it simultaneously performs feature (voxel) selection and training of the model parameters for classification [11], thus it may yield a very sparse classification model.

In this work, we propose a more general sparse logistic regression with a tunable regularization parameter (SLR-T). The SLR-T offers another point of view to explain the optimization equation derived from SLR, that is the optimization cost consists of a usual cost function and a regularization term. Thus, a more general regression model can be obtained by substituting a variable regularization coefficient for the constant value of

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0.5 in SLR. By setting this coefficient to 0 and 0.5, SLR-T reduces to a maximum likelihood regression (MLR) and SLR respectively. By choosing a proper regularization coefficient, SLR-T can achieve a better performance than both SLR and MLR.

# 2 Materials and Methods

## 2.1 fMRI Experiment

Three subjects participated in this fMRI experiment. All of them are males, with an average age of 23, and have normal or corrected-to-normal visual acuity. Informed written consents were obtained from all subjects.

Two types of stimuli were used in the experiment. One is random shape stimuli and another is regular shape stimuli.

In random shape stimuli, totally 198 different random patterns were used. Each stimulus pattern consisted of 12×12 patches (1.13°×1.13° each). There were two types of patch, a flickering checkboard and a neutral gray area. Each type of patch was randomly used with equal probability. Patterns, formed by different type of patches, were presented on a neutral gray background. A fixation spot was placed at the center of each stimulus to instruct subjects to fixate on it.

In regular shape stimuli, 10 kinds of stimulus patterns were used. Each kind of patterns consisted of specific shapes formed by the same types of patches as in random shape stimuli(“B”, “R”, “A”, “I”, “N”, “square”, “arrow”, “cross”, “frame” and “X”).

A 3.0-Tesla GE MR Scanner was used to collect functional MRI data at the First Affiliated Hospital of Xi’an Jiaotong University. A T1-Weighted, MP-RAGE sequence (TR: 2250ms; TE: 2.98ms; Tl: 900ms; Flip angle: 9°; FOV: 256 × 256mm; Voxel size: 1.0 × 1.0× 1.0mm), was firstly used to acquire high-resolution structure images. Then a T2*-weighted EPI sequence (TR: 4000ms; TE: 30ms; Flip angle: 80°; FOV: 192× 192mm; Voxel size: 1.875 × 1.875 × 3mm; Slice gap: 0mm; Number of slices: 48) was used to collect functional images covering the whole brain.

## 2.2 MRI Data Preprocessing

The first 3 volumes of each run were discarded in order to avoid the noise caused by MRI scanner’s instability. SPM 12 was used to preprocess the MRI data.

The general linear model was used to model the BOLD signal and predict the amplitude of BOLD response of each voxel. For each voxel, we calculated the correlation between its BOLD time-series signal and stimuli time-series. Finally, we chose 998 voxels in V1 area that show high correlation.

## 2.3 Classification Algorithm

We first introduce the SLR algorithm proposed by Yamashita et al[11].

In a discriminant classification model, there is a discriminant function for each class:

$$f_c(x;\theta^{(c)}) = \sum_{d=1}^{D} \theta_d^{(c)} x_d + \theta_0^{(c)} \quad c = 1,\ldots,C \tag{1}$$

where $x = (x_1,\ldots,x_D)^t \in \mathbb{R}^D$ is an input feature vector in $D$ dimensional space (here it's a voxel response pattern vector) and $\theta^{(c)} = (\theta_0^{(c)}, \theta_1^{(c)} \ldots, \theta_D^{(c)})^t$ is a weight vector including a bias term for $x$ belonging to class $c$.

Then the probability of a new input $x$ belonging to the class $c$ can be calculated using the softmax function:

$$\mathrm{P}(\mathrm{S}_c \mid x) = \frac{\exp(f_c(x;\theta^{(c)}))}{\sum_{k=1}^{C} \exp(f_k(x;\theta^{(c)}))} \quad c = 1,\ldots,C \tag{2}$$

One can estimate the free parameter $\theta$ by maximizing the following likelihood function,

$$\mathrm{P}(y_1,\ldots,y_N \mid x_1,\ldots,x_N;\theta) = \prod_{n=1}^{N} \prod_{c=1}^{C} p_n^{(c)\,\mathrm{y}_n^{(c)}} \tag{3}$$

SMLR assumes a prior Gaussian distribution for the parameters $\theta$:

$$\mathrm{P}(\theta_d \mid \alpha_d) = \mathrm{N}(0, \alpha_d^{-1}) \quad d = 1,\ldots,D \tag{4}$$

where $\alpha$ is a hyper-parameter representing the inverse of the variance of the weight value of the $i$'th feature and class $d$. Furthermore, a prior distribution is assumed for the hyper-parameter:

$$\mathrm{P}(\alpha_d) = \alpha_d^{-1} \quad d = 1,\ldots,D \tag{5}$$

With the above two prior distributions, SLR can obtain a sparse weight vector with most of the components being zeros.

Since it's difficult to calculate the posterior probability of $\theta$ directly, a variational Bayesian method is applied to get an approximation solution. After a few steps of derivations, the problem can be transformed into an optimization problem which aims to maximize the following cost function:

$$E(\theta) = \sum_{n=1}^{N} \left[ \sum_{c=1}^{C} y_n^{(c)} x_n^t \theta^{(c)} - \log\left\{ \sum_{c=1}^{C} \exp\left( x_n^t \theta^{(c)} \right) \right\} \right] - \frac{1}{2} \sum_{c=1}^{C} \theta^{(c)\mathrm{t}} \overline{A}^{(c)} \theta^{(c)} \tag{6}$$

where $\overline{A}^{(c)}$ is a diagonal matrix with each element on the diagonal being the expectation of $\alpha^{(c)}$. This optimization problem can be solved using Newton method.

Now we explain Eq. (6) from another point of view. The first term of Eq. (6) is a log function of Eq. (3), which is the log-likelihood function. It can be regarded as a usual cost function. The second term is a penalty term in that it is the sum of the $L_2$-norm of each weight value weighted by the inverse of their variances. Thus, we propose here to a free coefficient $\lambda$ to the penalty term:

$$E(\theta)=\sum_{n=1}^{N}\left[\sum_{c=1}^{C} y_n^{(c)} x_n^t \theta^{(c)} - \log\left\{\sum_{c=1}^{C}\exp\left(x_n^t \theta^{(c)}\right)\right\}\right] - \lambda\sum_{c=1}^{C}\theta^{(c)\mathrm{t}}\overline{A}^{(c)}\theta^{(c)} \tag{7}$$

By modifying the constant 0.5 in Eq. (6) to a variable $\lambda$, a trade-off between the fitness performance and the generalization capability can be obtained by adjusting $\lambda$. A small $\lambda$ gives a high classification performance on the training data, but the generalization capability cannot be guaranteed. Meanwhile, the proposed model is a more general model, and it will reduce to MLR and SLR when $\lambda$ is set to 0 and 0.5 respectively.

To reconstruct the center 8 by 8 patches (the outer patches are not concerned to eliminate the edge effects) of the stimuli, 64 local classifiers described above are used with each classifier classifying its corresponding patch's contrast (either 1 with flickering checkboard or 0 with a gray patch). All the local classifiers are trained on the training data separately, and $\lambda$ is chosen from a predetermined set {1, 0.5, 0.5e-2, 0.5e-4, 0.5e-6, 0.5e-8, 0}.

# 3 Results

## 3.1 Performances of SLR-T

Classifiers trained with different $\lambda$ values have different test performances. In Fig. 1, three patch classifiers' performances are shown. Each of them is trained with different $\lambda$ chosen from the $\lambda$ sets described in the above. Note that with $\lambda$ set index being set to 2 and 7, SLR-T becomes SLR and MLR respectively. One can see that with a proper $\lambda$, a better test accuracy can be obtained by SLR-T.

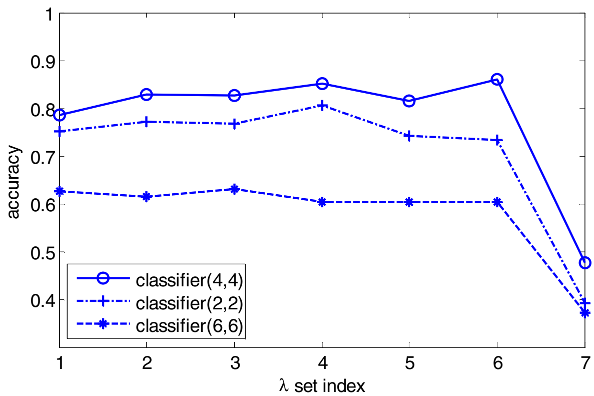


**Fig. 1.** Performances of 3 SLR-T classifiers trained with different $\lambda$

### 3.2 Image Reconstruction

Fig. 2 shows the accuracy of 30 classifiers trained using SLR-T method, SLR method and MLR method respectively. The mean accuracy of SLR and MLR is 0.6875 and 0.5005, while it is 0.7188 for SLR-T classifiers. The reconstructed results are shown in Fig. 3.

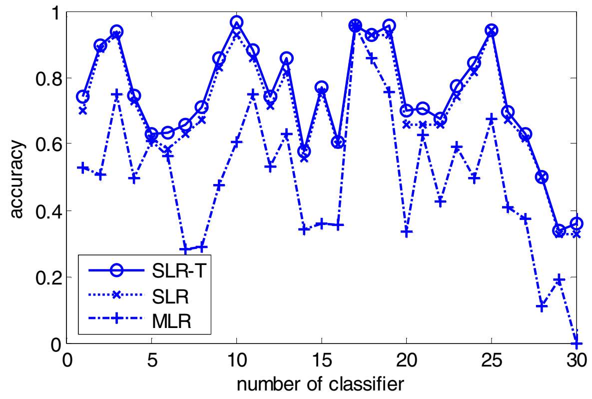


**Fig. 2.** Performance of 30 classifiers trained by SLR-T, SLR and MLR

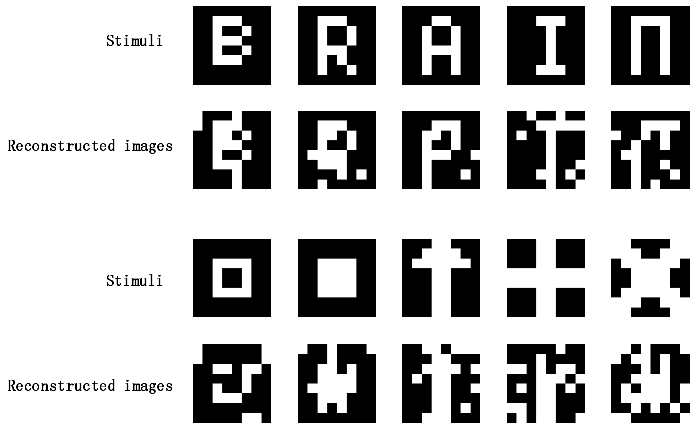


**Fig. 3.** Reconstructed images

## 4 Conclusion

A new sparse logistic regression model called SLR-T is proposed in this paper. The maximum likelihood regression and SLR are two special cases of SLR-T with the regularization coefficient being set to 0 and 0.5 respectively. An fMRI visual reconstruction experiment is carried out to verify the performance of SLR-T. The results show that, by choosing a proper regularization coefficient, the SLR-T may achieve a better performance than MLR and SLR on the test data set.

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