DeepBinaryMask: Learning a Binary Mask for Video Compressive Sensing

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Abstract—In this paper, we propose a novel encoder-decoder neural network model called DeepBinaryMask for video compressive sensing. The proposed framework is an end-to-end model where the sensing matrix is trained along with the video reconstruction. The encoder learns the binary elements of the sensing matrix and the decoder is trained to reconstruct the video sequence. The reconstruction performance is found to improve when using the trained sensing mask from the network across a wide variety of compressive sensing reconstruction algorithms. Finally, our analysis and discussion offers insights into understanding the characteristics of the trained mask designs that lead to the improved reconstruction quality.

Index Terms—Computer Society, IEEE, IEEETran, journal, \LaTeX, paper, template.

1 INTRODUCTION

In signal processing, a popular problem refers to Compressive Sensing (CS) which has been incorporated in various applications [1], [2]. In principle, CS theory suggests that a signal can be perfectly reconstructed using a small number of random incoherent linear projections by finding solutions to underdetermined linear systems. The underdetermined linear system in CS is defined by,

\[ y = \Phi x, \]

where \( \Phi \) is the \( M_f \times N_f \) measurement matrix with \( M_f \ll N_f \). We denote the vectorized versions of the unknown signal and the compressive measurements as \( x : N_f \times 1 \) and \( y : M_f \times 1 \), respectively. Thus, having more unknowns than equations, to guarantee a single solution in system (1) sparsity on the signal is enforced. Many signals, such as natural images, are sparse in well-known bases (e.g., Wavelet). Therefore, most reconstruction approaches employ a regularization term \( F(\cdot) \) which promotes sparsity of the unknown signal \( x \) on some chosen transform domain. Thus, the following minimization problem is sought after,

\[ \hat{a} = \arg\min_a F(a) \quad \text{s.t.} \quad y = \Phi Da, \]

where \( D \) is a chosen sparse representation transform resulting in a sparse \( a \), such that \( x = Da \). For example, in case \( F = ||a||_0 \), the problem in Eq. (2) is translated to a \( \ell_0 \) minimization problem. \( \ell_0 \) minimization can be solved with standard numerical methods such as Orthogonal Matching Pursuit (OMP) and Basis Pursuit (BP).

Multiple algorithms have been proposed for reconstructing still images using CS by solving the problem in (2). In video compressive sensing (VCS) the problem refers to the recovery of an unknown spatio-temporal volume from the limited compressive measurements. There are two different approaches in VCS, the spatial and temporal. Spatial VCS architectures perform spatial multiplexing per measurement based on the well-known single-pixel-camera [3] and enable video recovery by expediting the capturing process. In temporal VCS multiplexing occurs across the time dimension. Figure 1 demonstrates this process, where the modulation of \( t \) binary random masks with a spatio-temporal signal of size \( W_f \times H_f \times t = N_f \) during the exposure time of a single capture produces a coded frame of size \( W_f \times H_f = M_f \).

The acquisition model in (1) applies for the temporal VCS, however, the construction of \( \Phi \) is different in this case. In temporal VCS the sensing matrix is binary and sparse and is given by,

\[ \Phi = [\text{diag}(\phi_1), \ldots, \text{diag}(\phi_t)]: M_f \times N_f, \]

where each vectorized sampling mask is expressed as \( \phi_1, \ldots, \phi_t \) and \( \text{diag}(\cdot) \) creates a diagonal matrix from its vector argument.

Performance guarantees for sparse reconstruction methods, i.e., OMP, indicate that matrix \( \Phi \) must be an incoherent unit norm tight frame [4]. Incoherence is a property that characterizes the degree of similarity between the columns of \( \Phi \) (or \( \Phi D \)). Therefore, the choice of matrix \( \Phi \) is crucial in the reconstructed image and video quality irrespectively of the choice of \( F(\cdot) \). For signals that can be represented sparsely in some basis various popular matrices in the literature are known to perform particularly well (e.g.,
Gaussian). However, in CS the design of \( \Phi \) in the acquisition hardware (e.g., camera) is a significant issue. For practical implementations, binary random matrices (e.g., Bernoulli) are considered more applicable while they perform favorable to Gaussian random matrices [5]. As mentioned earlier, particularly in temporal video CS, the sensing matrix \( \Phi \) as given by Eq. (3) consists of binary values and is sparse.

The problem of optimizing the \( \Phi \) matrix has been analyzed by several researchers [4], [6], [7], [8]. Unfortunately, optimization approaches usually rely on minimizing coherence between the sampling matrix and the sparsifying basis \( (\Phi D) \), which mostly applies to spatial compressive sensing for images where dense matrices are used. Instead, the masks used for temporal video compressive sensing systems, as the one described herein, result in a sparse binary matrix with entries across diagonals, as presented by Eq. (3).

In this work, we optimize and transform the projection matrix \( \Phi \) for temporal VCS into a form that is more suitable for reconstruction using deep neural networks. The proposed neural network architecture, which we call Deep-BinaryMask, consists of two components that act as a pair of an encoder and a decoder. The encoder maps a video block to compressive measurements by learning binary weights (which correspond to the sensing mask). The decoder maps the measurements back to a video block utilizing real-valued weights. Both networks are trained jointly. We show that the mask trained from data using neural networks provides significantly improved recovery performance than a non-trained sensing matrix.

1.1 Contributions

- **Binary weights**: We propose a novel encoder-decoder neural network for temporal VCS where the encoder learns binary weights that belong to the sensing mask and the decoder learns to reconstruct the video sequence given the encoded measurements.
- **Learning a generic mask**: We show that the reconstruction performance is improved when using the optimized trained mask over the initial random one. Performance improvements are reported not only when the reconstruction method is the neural network decoder but also when other reconstruction methods are employed (e.g., \( \ell_1 \)).
- **Mask analysis**: We present reconstruction performance of the trained sensing matrix for different mask initial parameters (e.g., initial number of nonzero elements).

2 Motivation and Related Work

Recent advances in Deep Neural Networks (DNN) [9] have demonstrated state-of-the-art performance in several computer vision and image processing tasks, such as image recognition [10] and object detection [11]. In this section we briefly discuss previous works in designing optimal masks for VCS and then we survey recent studies in image restoration problems using DNN. Finally, we describe advances in DNN utilizing binary weights, a key ingredient of our proposed method.

Designing optimal masks. Most of the previous proposed optimized mask patterns for temporal VCS rely on some heuristic constraints and trial-and-error patterns. A thresholded Gaussian matrix was employed in [12], [13] and [14] as it was assumed that it results in a sensing matrix that most closely resembles a dense Gaussian matrix. A normalized mask such that the total amount of light collected at each pixel is constrained to be constant was proposed by [15]. It was found by [16] that these normalized patterns produce improved reconstruction performance. In [16] a hybrid normalized and Gaussian thresholded mask was utilized which was found to outperform the masks proposed in [15] and [13].

Different from these works our proposed approach does not rely on any mask constraint and it allows to produce mask patterns that are learnt from data. To the best of our knowledge this is the first study that investigates the construction of an optimized CS mask through DNN.

DNN for image restoration. The capabilities of deep architectures have been investigated in image restoration problems such as deconvolution [17], [18], [19], denoising [20], [21], [22], inpainting [23], and super-resolution [24], [25], [26], [27]. In CS for still images deep architectures have also been proposed. In [28], stacked denoising auto-encoders (SDA) were employed to learn a mapping between the CS measurements and image blocks. Similar approach was also utilized in [29] but instead of SDA, convolutional neural networks (CNN) were used.

A closely related work is the [30] which focuses on learning to map directly temporal VCS measurements to video frames using deep fully-connected networks. The authors showed that the deep learning framework enables the recovery of video frames from temporal compressive measurements in a few seconds at significantly improved reconstruction quality.

Binary neural networks. Recently, several approaches have been proposed using neural networks with binary weights [31], [32], [33], [34]. The main objective of such studies is to simplify computations in neural networks and making them more efficient. Efficiency is performed by approximating the standard real-valued DNN with binary weights. In BinaryConnect [32] the authors proposed to binarize the weights for all layers during the forward and backward propagations and keeping the real-valued weights during the parameter update. The real-valued updates was found to be necessary for the stochastic gradient descent (SGD) to work. Performance on various classifications tasks showed that binary neural networks compare favorable with the real-valued weight networks. In [34], the authors introduced a weight binarization scheme where both binary filter and a scaling factor are estimated. Such scheme was proven more effective over the BinaryConnect.

Motivated by the success in CS using DNN and binary DNN, we wanted to investigate the problem of learning an optimized binary sensing matrix using DNN for temporal VCS.
Our work is different from the studies in image restoration using DNN and from the binary neural networks. First, this work is different from [30] since our focus is on learning an optimized projection mask along with the video reconstruction. In [30] the scope is to recover video frames directly from the temporal measurements (e.g., mask is predefined). Furthermore, our objective is to learn binary masks that will encode video frames on VCS cameras for video reconstruction. Thus, the scope of this paper is different than the scope of binary neural network studies (e.g., efficiency).

3 DeepBinaryMask

In this work, we propose a novel neural network architecture that learns to encode a video block to compressive measurements by learning the binary weights of \( \Phi \) and to decode the measurements back to a video block, as illustrated in Figure 2. Let us now describe in details the encoder and decoder.

3.1 Encoder

In order our learning approach to be practical reconstruction has to be performed on video blocks [29], [30]. Thus, each video block must be sampled with a block-based measurement matrix which should be the same for all blocks. Furthermore, such a measurement matrix should be realizable in hardware. We follow the pattern in [30] and we consider \( \Phi_p \) of size \( w_p \times h_p \times t = N_p \). An implementation of such a matrix on existing systems employing DMDs, SLMs or LCoS [12], [14], [15], [35], [36] can be easily performed. At the same time a repeated mask can be printed and shifted appropriately to produce the same effect in systems utilizing translating masks [13], [16].

Let consider a set of \( N \) training video blocks denoted by \( X = [x_1, \ldots, x_N] \) where \( x_i, i \in \mathbb{N} \) is of size \( w_p \times h_p \times t \). The encoder is defined as the mapping \( g(\cdot) \) that transforms \( x_i \) to measurements \( y_i \) of size \( w_p \times h_p = M_p \) followed by a non-linearity given as,

\[
g(x_i; \theta_e) = \sigma_e(\Phi_p x_i), \tag{4}
\]

where \( \theta_e = \{\Phi_p\} \) is the parameter set and function \( \sigma_e(\cdot) \) is the non-linearity.

The formulation in (4) would have been ideal if matrix \( \Phi_p \) was dense and consisting of real-values. However, as mentioned earlier in case of temporal VCS, matrix \( \Phi \) should be binary and sparse following the structure defined in (3).
In order to realize such a structure in a neural network and be able to train it we transform the encoder into a network that involves two steps:

1) The first step will be consisting of \( M_p \) binary parallel layers given as,  
\[
e(x_{i,j}) = B_j x_{i,j} \quad \text{for} \quad j = 1, \ldots, M_p,  
\]
where \( x_{i,j} \) is the \( j^{th} \) pixel of the video block with \( t \times 1 \) dimensions and \( B_j \) is a binary weight vector of \( 1 \times t \) dimensions.

2) The second step consists of a concatenation layer which concatenates the outputs of the parallel layers in order to construct a single measurement vector,  
\[
g(x_i; \theta_e) = \text{concat}(e(x_{i,1}), \ldots, e(x_{i,M_p})), \tag{5}  
\]
with a parameter set \( \theta_e = \{B_1-M_p\} \) where the block-based binary matrix \( B \) is of size \( M_p \times t = w_p \times h_p \times t \). Note, that a non-linearity such as the rectified linear unit (ReLU) [37] defined as, \( \sigma(y) = \max(0,y) \), is implicitly applied here after the concatenation since the output is always positive. This is due to the fact that the weights are binary with values 0 and 1 and the video inputs are positive values.

The above two steps follow the same modulation operations as presented in Figure 1 but translated to a neural network and the set \( \theta_e \) consists of the elements of the trained projection matrix. The two steps of the encoder are also illustrated in bottom part of Figure 2.

**Overlapping blocks and weight sharing.** The \( w_p \times h_p \times t \) block-based projection matrix \( B \) we have considered so far corresponds to non-overlapping video patches. In order to realize overlapping patches which can usually aid at improving reconstruction quality we can utilize repeating blocks of dimensions \( \frac{w_p}{4} \times \frac{h_p}{4} \times t \), which we call sub-blocks as shown in Figure 2. Thus, for the final trained matrix \( \Phi \) each \( \frac{w_p}{4} \times \frac{h_p}{4} \times t \) block is the same allowing reconstruction for overlapping blocks of size \( w_p \times h_p \times t \) with spatial overlap of \( \frac{w_p}{4} \times \frac{h_p}{4} = w_s \times h_s \), as presented in Figure 3. In such a case the parameter set \( \theta_e \) is also different. Instead of learning \( M_p \) binary weight vectors we learn \( M_p/4 \) where each weight vector is *shared* four times for each of the corresponding pixel positions of the input. For example, in case where \( w_p \times h_p = 8 \times 8 \) there will be four identical \( 4 \times 4 \) block projection matrices. Thus, we only need to estimate 16 binary weight vectors and each one is shared for four different inputs. For instance for the input pixels \( 1, 5, 33, 37 \) we calculate \( e(x_{i,1}), e(x_{i,5}), e(x_{i,33}), e(x_{i,37}) \) using the weights of \( B_1 \) (assuming column-wise vectorization of the input).

**Binary weights.** Let us now proceed on describing how to estimate the binary weights. We follow the BinaryConnect method [32] to constraint the weights of the encoder to either 0 or 1 during propagation. The binarization scheme to transform the real-valued weights to two binary values is based on the sign function,
\[
b_b = \begin{cases} 1 & \text{if } b_r \geq 0, \\ 0 & \text{otherwise} \end{cases} \tag{6}  
\]
where \( b_b \) and \( b_r \) are the binarized and real-valued weights of \( B_p \) respectively. Following the training process in [32] we binarize the weights of the encoder only during the forward and backward propagations. The update of the parameters is performed by using the high-precision real-valued weights. As explained in [32] keeping the real-valued weights during the updates is necessary for training the networks using SGD. In addition, we enforced the real-valued weights to lie within the \([-1,1]\) interval in each training iteration. The weight clipping was chosen since otherwise the weights may become infinitely large and have no impact during the binarization.

**Weight initialization.** The weight initialization of the encoder corresponds in our case to the mask initialization. Typically, in VCS the mask is generated randomly. Similarly here, we start with a random mask generated by a Bernoulli distribution. However, since real-valued weights are also required by the network to perform the updates we consider the following initialization scheme,
\[
b_b \sim \text{Bern}(p), \quad b_r = \begin{cases} \sim \text{Unif}(0,1/\sqrt{t}) & \text{if } b_b = 1, \\ \sim \text{Unif}(-1/\sqrt{t},0) & \text{otherwise,} \end{cases} \tag{7}  
\]
where Bern(\( \cdot \)) and Unif(\( \cdot \)) are Bernoulli and Uniform distributions respectively and \( p \) is the probability of the weight to be initialized with 1. Such initialization scheme allows us to fully understand the benefits of learning vs. non-learning the mask along with video reconstruction. This is due to the fact that in case of choosing the non-learnable mode we only have to keep fixed the initial \( b_b \) weights drawn from the Bernoulli distribution.

### 3.2 Decoder

The resulting hidden measurement \( y_i \) produced by the encoder is then mapped back to a reconstructed \( w_p \times h_p \times t \) dimensional video block through the decoder \( f(y_i; \theta) \), as illustrated in upper part of Figure 2. Thus, the decoder of the proposed method is another network which is trained to reconstruct the video output sequence given \( y_i \). We consider an MLP architecture to learn a nonlinear function \( f(\cdot) \) that maps a measured frame patch \( y_i \) via several hidden layers to a video block \( x_i \) as in [30].
Each hidden layer $L_k$, $k = 1, \ldots, K$ is defined as,

$$h_k(y_i) = \sigma_d(W_ky_i + b_k),$$

where $W_k$ is the output weight matrix containing linear filters, and $b_k \in \mathbb{R}^{N_p}$ is the bias vector. $W_1 \in \mathbb{R}^{N_p \times M_p}$ connects $y_i$ from the encoder to the first hidden layer of the decoder, while for the remaining hidden layers, $W_{2-k} \in \mathbb{R}^{N_p \times N_p}$. The last hidden layer is connected to the output layer via $b_o \in \mathbb{R}^{N_p}$ and $W_o \in \mathbb{R}^{N_p \times N_p}$ without nonlinearity. The non-linear function $\sigma_d(\cdot)$ is the ReLU and the weights of each layer are initialized to random values uniformly distributed in $(-1/\sqrt{N_p}, 1/\sqrt{N_p})$ [38].

There are few reasons why the MLP architecture for the decoder is a reasonable choice for the temporal video compressive sensing problem which have been explained in [30]. Besides, our focus is to investigate the performance of the trained vs. non-trained sensing matrix without giving too much emphasis on obtaining the best reconstruction quality.

### 3.3 Training the encoder-decoder network

The two components of the proposed MLP encoder-decoder are jointly trained by learning all the weights and biases of the model. The set of parameters is denoted as $\theta = \{B_{1-M_p/4}, W_{1-K}, W_o, b_{1-K}, b_o\}$ and is updated by the backpropagation algorithm [39] minimizing the quadratic error between the set of the encoded mapped measurements $f(y_i; \theta)$ and the corresponding video blocks $x_i$. The loss function is the mean squared error (MSE) which is given by,

$$L(\theta) = \frac{1}{N} \sum_{i=1}^{N} \|f(y_i; \theta) - x_i\|_2^2.$$  

The MSE was used in this work since our goal is to optimize the PSNR which is directly related to the MSE.

**Training procedure.** The overall training procedure can be summarized in the following steps:

1. Forward propagation is performed by using weights $B$ after binarization in the encoder and real-valued weights $W$ in the decoder.
2. Then, backpropagation is performed to compute the gradients with respect to layer’s activation knowing $B$ and $W$.
3. Parameter update is computed using the real-valued weights from both encoder and decoder.

Note that one other difference between our work and [32] is that our encoder-decoder neural network does not utilize binary weights in all layers, instead it utilizes binary weights at the encoder and standard real-valued weights at the decoder.

**Implementation details.** Our encoder-decoder neural network is trained for 480 epochs using a mini-batch size of 200. We used SGD with a momentum set to 0.9. We further used $\ell_2$ norm gradient clipping to keep the gradients in a certain range. Gradient clipping is a widely used technique in recurrent neural networks to avoid exploding gradients [40]. The threshold of gradient clipping was set to 0.1.

One hyper-parameter that was found to affect the performance in our approach is the learning rate. We decided to choose a starting learning rate for the encoder that was 10 times larger than the decoder’s learning rate. This was found to be important as we wanted the weights of the encoder to have their sign changed during the training iterations. In addition, the learning rate was divided by 2 in every 10 epochs in the encoder and by 10 after 400 epochs in the decoder.

All hyper-parameters were selected after cross-validation using a validation test set.

**Test inference.** Once the encoder-decoder neural network is trained we use the trained projection matrix $B \rightarrow \Phi$ to calculate the compressive measurements $y$. Then, given $y$ we can use any VCS algorithm or the decoder network to reconstruct the video blocks.

### 4 EXPERIMENTAL RESULTS

In this section we present quantitatively and qualitatively reconstruction results to show the effect of the proposed projection mask in temporal VCS. The performance of our trainable masks is investigated under using different reconstruction algorithms and initial mask parameters. Our analysis offers insights into understanding how the different initial parameters of the mask affect reconstruction performance. The metrics used for reconstruction evaluation were the PSNR and SSIM.

#### 4.1 Training Data Collection and Test set

In order to train our encoder-decoder we collected a diverse set of training samples using 400 high-definition videos from Youtube, depicting natural scenes. The video sequences contain more than $10^5$ frames which were converted to grayscale. All videos are unrelated to the test set. We randomly extracted 1 million video blocks of size $w_p \times h_p \times t$ to train our encoder-decoder neural network while keeping the amount of blocks extracted per video proportional to its duration.

Our test set consists of 14 video sequences that were used in [15], provided by the authors. We also included in the test set the “Basketball” video sequence used by [41]. All video sequences are unrelated to the training set.

#### 4.2 Mask Patterns

Our experimental investigation is motivated by the following two questions: 1) “How does performance of trained and non-trained masks compare using different reconstruction algorithms?” and 2) “Does training produce the optimal sensing matrix $\Phi$ irrespectively of its initialization parameters?”

In order to answer the two questions we simulated noiseless compressive video measurements by realizing four different $\frac{w_p}{12} \times \frac{h_p}{12} \times t$ mask patterns. We denote as “RandomMask-$p$” the mask that is initialized with Bern($p$) and is not learnable (e.g., elements of the encoder are fixed). We also denote as “DeepMask-$p$” the learnable mask trained by our proposed encoder-decoder network described in
section 3 and is initialized with Bern \( p \). Thus, we consider the following four mask patterns:

- RandomMask-20 and DeepMask-20, with \( p = 20 \).
- RandomMask-40 and DeepMask-40, with \( p = 40 \).
- RandomMask-60 and DeepMask-60, with \( p = 60 \).
- RandomMask-80 and DeepMask-80, with \( p = 80 \).

In the remainder of this paper, we select a block of size \( w_p \times h_p \times t = 8 \times 8 \times 16 \), such that \( N_p = 1024 \) and \( M_p = 64 \). Therefore, the compression ratio is 1/16. In addition, for each of the eight \( \Phi \) mask types above, each \( \frac{w_p}{2} \times \frac{h_p}{2} \times t = 4 \times 4 \times 16 \) block is the same allowing reconstruction for overlapping blocks of size \( 8 \times 8 \times 16 \) with spatial overlap of \( 4 \times 4 \). Note that the same random seed was utilized for all patterns.

In the following section we present the reconstruction algorithms used to test the eight mask types.

### 4.3 Reconstruction Algorithms

Since our main goal is to compare the performance between a trained sensing mask over a non-trained one in an implementation agnostic to mask patterns, we tested a number of different reconstruction algorithms. Candidate reconstruction algorithms were selected for their utility in solving the underdetermined system in the VCS setting. We evaluated the following optimization algorithms as potential solvers:

1) **DICT-L1**: In (1), we have assumed that data are noise-free. However, very often in VCS real data are noisy and dealing with small dense noise is required. In order to deal with such noise we transform the problem in (2) into the LASSO (Least-Absolute Shrinkage and Selection Operator) problem for \( F = \lambda \|a\|_1 \) given as,

\[
\hat{a} = \underset{a}{\text{argmin}} \|y - \Phi Da\|_2^2 + \lambda \|a\|_1,
\]

where \( \lambda = 0.005 \) is a regularization parameter related to noise tolerance. For this problem we chose to use an overcomplete dictionary \( D \) as a sparsifying basis. The dictionary consists of 10,000 atoms trained on video data in [15] and reconstruction is performed block-wise on overlapping sets of \( 7 \times 7 \) patches of pixels.

2) **TV-MIN**: A popular CS reconstruction method is when \( F(\cdot) \) is the total variation (TV) norm defined as,

\[
TV(x) = \sum_n \sum_{i,j} \left( \left( x(i+1,j,n) - x(i,j,n) \right)^2 + \left( x(i,j+1,n) - x(i,j,n) \right)^2 \right)^{1/2}.
\]

Thus, the TV minimization problem is given as,

\[
\hat{x} = \underset{x}{\text{argmin}} \|y - \Phi x\|_2^2 + \lambda TV(x).
\]
where $\lambda = 0.01$. In order to solve (12) we used the two-step iterative shrinkage/thresholding (TwIST) algorithm [42].

3) **GMM-TP**: Another reconstruction algorithm we considered in our experiments is the GMM-TP, a Gaussian mixture model (GMM)-based algorithm [43]. We followed the settings proposed by the authors and used our training data (randomly selecting 20,000 samples) to train the underlying GMM parameters. In our experiments we refer to this method by GMM-4 and GMM-1 to denote reconstruction of overlapping blocks with spatial overlap of $4 \times 4$ and $1 \times 1$ pixels respectively.

4) **FC4-1M**: Finally, a potential reconstruction method is the the decoder neural network introduced in subsection 3.2. The decoder is a $K = 4$ MLP trained on 1 million samples similar to [30]. In this case, a collection of overlapping patches of size $w_p \times h_p$ is extracted by each coded measurement of size $W_f \times H_f$ and subsequently reconstructed into video blocks of size $w_p \times h_p \times t$. Overlapping areas of the recovered video blocks are then averaged to obtain the final video reconstruction results. The step of the overlapping patches was set to $\frac{w_p}{2} \times \frac{h_p}{2}$ due to the special construction of the utilized measurement matrix, as discussed in subsection 3.1.

For each algorithm, $\lambda$ values were determined based on the best performance among different settings. All code implementations are publicly available provided by the authors.

### 4.4 Reconstruction Results

For each reconstruction algorithm described above, we tested the eight mask types presented in subsection 4.2.

**Quantitative results.** Figure 4 shows average reconstruction quality for each mask and algorithm combination, using the PSNR and SSIM metric. The presented metrics refer to average performance for the reconstruction of the first 32 frames of each test video sequence, using 2 consecutive captured coded frames using each of the eight masks for every algorithm. First, we note that the DeepMasks perform consistently better compared to the RandomMasks across all reconstruction algorithms and initial percentage of nonzeros. In particular, we observe an improvement around 1-2 dB, in terms of PSNR between the trained and non-trained masks across all initial percentages and algorithms. Furthermore, we observe that the decoder FC4-1M demonstrates the highest PSNR and SSIM values among all the algorithms.

Figure 5 compares the PSNR for all the frames of 2 video sequences using our FC4-1M algorithm and the previous methods GMM-4 [43] and DICT-L1 [15] between the RandomMasks and DeepMasks. The varying PSNR performance across the frames of a 16 frame block is consistent for both algorithms and is reminiscent of the reconstruction
tendency observed in other video CS papers in the literature [13], [16], [41], [43].

4.5 Training analysis

We start our analysis by examining the real-valued weight histogram of the encoder (DeepMask-40) upon convergence in Figure 6. First, we observe that negative values are more frequent than positive, which suggests that zero elements of the mask are more important than the nonzero. More importantly, we observe that many weights are around zero, hesitating between being negative or positive, a phenomenon that was also reported in [32].

Average test MSE per epoch calculated on a validation test set for DeepMask-40 and RandomMask-40 is demonstrated in Figure 7. It is shown that the test error curve of the RandomMask-40 is smooth while the DeepMask-40 is noisy. Perhaps, this is due to the fact that many real-valued elements of the encoder stay around zero. Thus, during the binarization process some of the encoder’s binary weights change from zero to one and vice versa even with very small learning rates. This effect causes the curve to be noisy, however, as the encoder’s learning rate gets really small the curve becomes smooth. A better optimized learning rate decay schedule of the encoder would have probably provided smoother curve and perhaps higher performance. We leave this as a task for future work as further investigation into this may be needed. Furthermore, as showed in reconstruction results, DeepMask performs consistently better than RandomMask which also explains the lower test MSE produced by the former during training.

Lastly, in Figure 8 we demonstrate the number of binary weights that change from zero to one and vice versa per epoch. We observe that a large number of weights change at the first few epochs and the number gets decreasing as the number of epochs increase.

5 DISCUSSION

Having obtained better reconstruction performance using the DeepMasks across a wide variety of reconstruction algorithms our next step is to analyze the masks produced by the networks and highlight few crucial points. We start our analysis by posing the following question.

Does DeepMask produce the optimal sensing Φ? To answer this question we examine the differences between the produced DeepMasks with respect to their percentage of nonzero elements and to their support.

First, in Figure 9 we demonstrate the percentage of nonzero binary weights per epoch for the different DeepMasks. This figure allows us to examine optimality with respect to the percentage of nonzero elements produced by each DeepMask. We observe that the masks with \( p = 40 \), \( p = 60 \) and \( p = 80 \) converge to a close percentage around 40\%. The \( p = 20 \) mask though, converges to a bit lower percentage (around 38\% nonzero binary elements).

Next, in Figure 10 we present the support similarity between any two DeepMasks given by,

\[
P = 1 - \frac{1}{N_p} ||M_1 - M_2||_1,
\]

where \( M_1 \) and \( M_2 \) denote the two examined masks. This similarity metric is important as we can evaluate optimality...
with respect to their support. For completeness we present also the support similarity between any two RandomMasks. From the similarity metric between the DeepMasks we do not observe any strong correlation. This suggests that most of the masks produced by the network converge to the same nonzero percentage, however, their support is different.

Finally, Figure 11 demonstrates the four mask patterns produced in this work. The first row illustrates the RandomMasks and the second row presents the four DeepMasks produced by the proposed encoder-decoder neural network. All $4 \times 4 \times 16$ masks are reshaped to $16 \times 16$ for better visualization. From the visualization we deduce two important findings:

- First, it is apparent that regardless the initial realization (shown in RandomMasks), the trained DeepMasks produce a similar amount of nonzero elements which confirms our findings discussed earlier.
- Second, an important observation from Figure 9 is that DeepMasks are smoother than the RandomMasks as we notice continuous patterns. For example in many rows the binary weights seem to be sequential, meaning that there is a bunch of ones followed by a bunch of zeros etc. instead of having ones and zeros interchangeable in each pixel. In other words, the networks tend to produce masks that are smooth and such smoothness provides higher reconstruction performance.

Overall, our findings above suggest that an optimized mask design $\Phi$ for temporal VCS incorporates the following two characteristics: 1) smoothness as explained above and 2) a percentage of nonzero elements around 40%.

6 Conclusions

In this paper, we proposed a new encoder-decoder neural network architecture for video compressive sensing that is able to learn an optimized binary sensing matrix. We evaluated the proposed model on several video sequences and we documented the superiority of the trained sensing matrices over the random ones both quantitatively and qualitatively. Our qualitative analysis of the trained model shows that the optimized sensing masks converge to a similar amount of nonzero elements regardless their initial parameters and that they incorporate a smoothness property. The proposed architecture has large potential for further analysis. Our next step is to examine the reconstruction performance in real video sequences acquired by a temporal compressive sensing camera.

References

Aggelos K. Katsaggelos Biography text here.