Deep Residual Neural Networks for Image in Speech Steganography

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Steganography is the art of hiding a secret message inside a publicly visible carrier message. Ideally, it is done without modifying the carrier, and with minimal loss of information in the secret message. Recently, various deep learning based approaches to steganography have been applied to different message types. We propose a deep learning based technique to hide a source RGB image message inside finite length speech segments without perceptual loss. To achieve this, we train three neural networks; an encoding network to hide the message in the carrier, a decoding network to reconstruct the message from the carrier and an additional image enhancer network to further improve the reconstructed message. We also discuss future improvements to the algorithm proposed.

Additional Key Words and Phrases: Deep Learning, Neural Networks, Steganography, Information hiding

1 INTRODUCTION

In Steganography, the main goal is secret communication. The sender encodes an image in an audio sample such that the receiver can decode the secret message but, an uninformed listener should not be able to detect the presence of the hidden image.

We introduce a method for image-in-speech steganography using a trainable end-to-end neural network. An encoder network receives a cover speech segment and a secret image and outputs an embedded speech segment. The decoder network attempts to reconstruct the hidden image from the embedded speech segment. A separate network is used to enhance the reconstructed image quality.

Classical steganography methods usually use heuristics to decide how much to modify each pixel. For example, some algorithms change the least significant bits of some selected parts of the cover[20]. Whereas, some change the mid-frequency components in the frequency domain [21]. These heuristics are usually not robust to variation in the environment. While, Deep Neural Networks are trained to achieve the objective of interest thereby providing much better steganography quality. Recently, Deep Learning methods have been successfully applied to image-in-image steganography[1] and audio-in-audio steganography[2]. In this work we present a method for image-in-audio steganography using deep residual neural networks for encoding, decoding and enhancing the secret image.

2 RELATED WORK

A large number of steganography methods have been proposed over the years. Most of these are applied on Images[15] or Audio[19]. The most common approach is to manipulate the Least Significant Bits of the cover to embed the secret information. This can be done by simply replacing the LSBs of the cover uniformly or adaptively[16] with the secret data. Simple statistical analysis of the embedded carrier reveals presence of a hidden messages. More complex approaches such as HUGO[17] provide better steganography by preserving the input statistics. Another example is WOW (Wavelet Obtained Weights)[18] that penalizes distortion of predictable regions of the input data using a bank of directional filters.

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Recently, neural networks have been applied to Steganography and Steganalysis. Neural networks provide much better results compared to the traditional techniques because of their ability to model the entire hiding and revealing process. Additionally, neural nets can be trained end-end further reducing cumulative errors caused while using individual modules. S. Baluja[1] proposed an encoder-decoder architecture for image-in-image steganography using end-to-end neural networks. A similar technique was proposed by F. Kruek et al[2] for audio-in-audio steganography. However, these techniques have been applied to same message types, either image-in-image or audio-in-audio only. In this work we present a method to hide images in finite length speech segments.

3 PROBLEM FORMULATION

In this section we define the notation we contrive for the task of image in audio steganography and define the notation for the rest of the paper. We denote the set of fixed length acoustic feature vectors $X \in \mathbb{R}^{m \times n}$ and the set of all fixed resolution images as $Y \in \mathbb{R}^{m \times n}$. The goal of this model is to conceal an image message in a fixed length speech segment. The steganography model gets the input carrier spectrogram denoted by $C$ such that $C \in X$ and the input message as $M$ such that all $M \in Y$. The model outputs the embedded carrier spectrogram denoted as $\hat{C} \in X$ and the reconstructed image denoted as $\hat{M} \in Y$. $\hat{C}$ and $\hat{M}$ should satisfy the following conditions:

1. $\hat{C}$ and $\hat{M}$ should be similar to $C$ and and $M$ respectively.
2. $\hat{M}$ should be reconstructible from $\hat{C}$ without any perceptual loss.
3. An uninformed human listener must not be able to detect the presence of a hidden message in $\hat{C}$.

4 MODEL ARCHITECTURE

In this section we present the the model architecture for the problem in hand. Our model consists of two parts:

4.1 Main Model

The main architecture is composed of 2 blocks; the Hiding Block(H), the Reveal Block(R). The Hiding Block takes in both $C$ (input speech segment) and $M$ (the input image). Precisely, the $C$ is carrier spectrogram and $M$ is a single channel of the image to be hidden. $C$ is passed through stack of gated convolutions [5] and $M$ is passed through a stack of vanilla convolutional layers with a receptive field of 3x3. The convolution stride is fixed to 1 pixel. The two outputs are concatenated and passed through downsampling encoder followed by a upsampling decoder. There are also residual connections between the downsampling and upsampling block at the same scales. This block outputs $\hat{C}$ (the embedded carrier).

$\hat{C}$ (the embedded carrier spectrogram) generated by H (Hiding block) is passed as an input to R (Reveal block). We use an encoder-decoder network similar to the Hidding Block, H. In this block the reconstructed message, $\hat{M}$ is obtained from the embedded carrier, $\hat{C}$. All layers in the reveal block is attached with ReLU activation[10] and sigmoid activation[12] function for for the last layer. Lastly, the appropriate parameters are found by minimizing the Mean Squared Error(MSE) between the carrier spectrogram and the embedded carrier spectrogram and between the input image and the reconstructed image. In addition, we add a small component of the Structured Similarity(SSIM)[7]. SSIM is a useful metric for evaluating the quality of the predictions. The SSIM for two signals $x$ and $y$ is defined as:

$$SSIM = \frac{(2\mu_x \mu_y + c_1)(2\sigma_{xy} + c_2)}{\mu_x^2 + \mu_y^2 + c_1)(\sigma_x + \sigma_y + c_2)}$$
Where $\mu$ and $\sigma$ are the local mean and variance of $x$ and $y$. $c_1 = (k_1 L^2)$ and $c_2 = (k_2 L^2)$ are two sizable variables to stabilize the division with weak denominator and $L$ is the dynamic range of signal values. We use the default values of $k_1 = 0.01$ and $k_2 = 0.03$ as in the original paper[7]. Since SSIM is upperbounded to 1 we need to maximise it. Instead we minimise:

$$L_{SSIM}(x, y) = [1 - SSIM(x, y)]$$

The final loss function is given by the equations:

$$L_C = \lambda_{C_1} (C - H(C, M))^2 + \lambda_{C_2} (L_{SSIM}(C, \hat{C}))$$

$$L_M = \lambda_{M_1} (M - R(\hat{C}))^2 + \lambda_{M_2} (L_{SSIM}(M, \hat{M}))$$

$$L = \lambda_M L_M + \lambda_C L_C$$

### 4.2 Message Enhancer

We also trained a fully convolutional image enhancer network. This module removed small noises from the reconstructed images on the receiver side. We use a U-net architecture with skip connections from the encoder and decoder blocks at the same scale with downsampling while encoding and upsampling while decoding and ReLU activation function.

### 5 EXPERIMENTAL SETUP

In this section, we present our experimental results. First, we describe our experimental setup. Then we evaluate our model. Lastly, we show visual analysis of the images and spectrograms. We have implemented our code with tensorflow [3]. Codes for this experiment can be found [here](#).

#### 5.1 Experimental setup:

We evaluated our approach on TIMIT[6] for audio segments and Pascal Voc dataset for images. Each audio sample was sampled at 16 kHz and represented as a power spectrum by taking the Short Term Fourier Transform(STFT) according to the parameters shown in Table 2. These parameters were obtained to achieve an STFT of size 512*513 and whose inverse can be obtained. The magnitude of STFT is passed as input to the model. The model produces the magnitude spectrogram of the embedded carrier. We use the same phase for estimating the time domain audio sample by
calculating the Inverse STFT. Each image was resized to 512*513 from the Pascal Voc dateset. The model was trained using the Adam optimizer[4] for 203K steps for TIMIT. The losses were balanced according to Table 1.

The model is trained with single greyscale images. For color images, individual Red, Green and Blue channels are separately passed to the model and the corresponding audio samples are concatenated to form the carrier. RGB images are generated with this mechanism from the message decoder network. These images are used to train the image enhancer network that removes small noises in the reconstructed images on the receiver side.

| $\lambda_{C_1}$ | $\lambda_{C_2}$ | $\lambda_{M_1}$ | $\lambda_{M_2}$ | $\lambda_{C}$ | $\lambda_{M}$ |
|-----------------|-----------------|-----------------|-----------------|----------------|----------------|
| 0.995           | 0.005           | 0.85            | 0.15            | 0.69           | 1              |

Table 2. STFT Parameters

| Duration of audio | FFT Length | Frame Step | Frame Length |
|-------------------|------------|------------|--------------|
| 1 second          | 1024       | 31         | 1024         |

5.2 Analysis:

To evaluate the results obtained we compute the Mean Absolute Error:

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} \mod (x_i - x'_i)$$
Where \( x_i \) and the \( x'_i \) are the true and the predicted values respectively. For the carrier we evaluate the Pearson correlation coefficient.

\[
r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{n \sum x^2 - (\sum x)^2}[n \sum y^2 - (\sum y)^2]}
\]

Where \( x \) and \( y \) are the two sets of data and \( n \) is the number of samples. We also evaluate the MAE for each audio sample. Experimental results are tabulated in table III.

### Table 3. Results obtained

| Parameter                  | Model+SSIM+Image Enhancer | Model + SSIM | Base Model |
|----------------------------|---------------------------|--------------|------------|
| MAE(Image)                 | 8.1673                    | 7.3529       | 13.3901    |
| SSIM(Image)                | 0.9486                    | 0.9246       | 0.8666     |
| MAE(Spectrogram)           | 0.0715                    | 0.0715       | 0.0633     |
| SSIM(Spectrogram)          | 0.99878                   | 0.99878      | 0.9987     |
| Pearson Correlation Coefficient | 0.4943                  | 0.4943       | 0.4999     |

### 6 DISCUSSIONS AND FUTURE WORK

We have shown that deep learning steganography techniques using encoder-decoder setup can be used for steganography where the carrier and source message data types are different. More sophisticated methods of hyperparameter search can probably be used to further improve the results shown above. Future work could also involve better techniques to train networks with losses that compete with one another.

The output images were best when coupled with the image enhancer. This ends up slightly altering the color palette of some images, even though the outputs would fool most people when judged on their own. In the future, we could experiment with more sophisticated autoregressive decoders which might eliminate the need for a denoiser. We can also boost the audio quality by using vocoder architectures to account for losses while converting from spectrogram to time domain audio. Finally, hiding multiple images in short audio clips can definitely be studied in the future to increase its effectiveness.
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REFERENCES

[1] Shumeet Baluja, "Hiding Images in Plain Sight: Deep Steganography," Advances in Neural Information Processing Systems. NIPS 2017.

[2] Felix Kreuk, Yossi Adi, Bhiksha Raj, Rita Singh, Joseph Keshet, "Hide and Speak: Deep Neural Networks for Speech Steganography", arXiv preprint arXiv:1902.03083v1 Feb 7 2019.

[3] Mart América Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Rafal Jozefowicz, Yangqing Jia, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dan ManÁEl, Mike Schuster, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda ViÁElgas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng, "TensorFlow: Large-scale machine learning on heterogeneous systems", 2015. Software available from tensorflow.org.

[4] Diederik P. Kingma, Jimmy Ba, "Adam: A Method for Stochastic Optimization", arXiv:1412.6980 [cs.LG] 30 Jan 2017.

[5] Dauphin, Y. N., Fan, A., Auli, M., and Grangier, D. "Language modeling with gated convolutional networks". In Proceedings of the 34th International Conference on Machine Learning-Volume 70, pp. 933âĂŞ941. JMLR. org 2017.

[6] Garofolo, J. S., Lamel, L. F., Fisher, W. M., Fiscus, J. G., and Pallett, D. S. "Darpa timit acoustic-phonetic continuous Hide and Speak: Deep Neural Networks for Speech Steganography speech corpus cd-rom. nist speech disc 1-1.1" NASA STI/Recon technical report n. 93, 1993.

[7] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli. "Image quality assessment: from error visibility to structural-similarity". Transacions on Image Processing, 2004.

[8] H. Zhao, O. Gallo, I. Frosio, and J. Kautz."Loss functions forneural networks for image processing". IEEE Transactions onComputational Imaging(TCI), 2017.

[9] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. "U-Net: Convolutional Networks for BiomedicalImage Segmentation". arXiv:1505.04597v1 [cs.CV] 18 May 2015.

[10] Abien Fred M. Agarap. "Deep Learning using Rectified Linear Units (ReLU)". arXiv:1803.08375v2 [cs.NE] 7 Feb 2019.

[11] Everingham, M., Eslami, S. M. A., Van Gool, L., Williams, C. K. I., Winn, J. and Zisserman, A."The PASCAL Visual Object Classes Challenge: A Retrospective ". International Journal of Computer Vision, 111(1), 98-136, 2015.

[12] Chigozie Enynma Nwankpa, Winifred Ijomah, Anthony Gachagan, and Stephen Marshall "Activation Functions: Comparison of Trends in Practice and Research for Deep Learning". arXiv:1811.03378v1 [cs.LG]. 8 Nov 2018

[13] Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks". Advances in Neural Information Processing Systems 25 Advances in Neural Information Processing Systems 25 (NIPS 2012).

[14] Jont B. Allen (June 1977). "Short Time Spectral Analysis, Synthesis, and Modification by Discrete Fourier Transform". IEEE Transactions on Acoustics, Speech, and Signal Processing. ASSP-25 (3): 235âĂŞ238.

[15] Morkel, T., Eloff, J. H., and Olivier, M. S. "An overview of image steganography." ISSA, pp. 1âĂŞ11, 2005.

[16] Tamimi, A. A., Abdalla, A. M., and Al-Allaf, O. "Hiding an image inside another image using variable-rate" steganography. International Journal of Advanced Computer Science and Applications (IJACSA), 4(10), 2013.

[17] Pevny, T., Filler, T., and Bas, P. "Using high-dimensional image models to perform highly undetectable steganography." In International Workshop on Information Hiding, pp. 161âĂŞ177. Springer, 2010.

[18] Holub, V. and Fridrich, J. "Designing steganographic distortion using directional filters." In 2012 IEEE International workshop on information forensics and security (WIFS), pp. 234âĂŞ239. IEEE, 2012.

[19] Fatih Djebar, Baghdad Ayad, Karim Abed Meraim and Habib Hamam. "Comparative study of digital audio steganography techniques." EURASIP Journal on Audio, Speech, and Music Processing volume 2012.

[20] Pevná, T., Filler, T., Bas, P. "Using High-Dimensional Image Models to Perform Highly Undetectable Steganography." Springer Berlin Heidelberg, Berlin, Heidelberg (2010) 161âĂŞ177

[21] Bi, N., Sun, Q., Huang, D., Yang, Z., Huang, J. "Robust image watermarking based on multiband wavelets and empirical mode decomposition." IEEE Transactions on Image Processing (2007)