RF PIX2PIX Unsupervised Wi-Fi to Video Translation

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With the proliferation of Wi-Fi devices in the environment, our surroundings are increasingly illuminated with low level RF scatter. This scatter illuminates objects in the environment much like radar or LIDAR. We show that a novel unsupervised network, based on the PIX2PIX GAN architecture [2], can recover and visually reconstruct scene information solely from Wi-Fi background energy; in contrast to a significantly less accurate approach by Kefayati (et. al) [1] which requires careful object labeling to recover object location from a scene. This is accomplished by learning a more robust mapping function between the channel state information (CSI) from Wi-Fi packets and Video image sample distributions.

1 Introduction

Within the visible spectrum, light sources emit electromagnetic (EM) radiation that scatters across objects in the scene eventually reaching our eye where its reconstructed as images. Similarly, EM radiation from sources outside the visible spectrum, like Wi-Fi access points (WAP) scatters across objects in the environment. Until recently reconstructing images from this scattered energy was intractable due to complexities and ambiguities in the information received. We present a novel unsupervised approach to developing a robust mapping between the visible and invisible electromagnetic spectrum.

Intersection over Union (IoU) is a common method for evaluating the quality of bounding boxes. It is a ratio of the overlap between a bounding box and ground truth divided by the union of both boxes. A ratio of .50 for this metric (IoU-50) is often used as minimum threshold to determine the accuracy of a bounding box [1]. With one person in the scene we calculate an average precision intersection over union threshold (AP IoU-50) score of 92%. This is an 18% improvement over the accuracy we were able to obtain with a supervised approach on the same input data.

\[ IoU = \frac{\text{Overlap}}{\text{Union}} \]

2 Setup

We positioned a Wireless AP and a laptop 28’ apart. Using 2 Ettus N210 recievers, synced in MIMO mode, and GNURadio software we captured Wi-Fi packets from the WAP, filtering on media access control address (MAC) address. Video frames from the laptops webcam were captured synchronously with the reception of Wi-Fi packets.

2.1 CSI Calculation

The channel state information (CSI) indicates the change that the signal experiences while traversing
2.2 Normalization

The task of converting CSI to video can be summarized as functional mapping between two domains [5]. In the unsupervised case we would like to enforce a consistent mapping. Where for any 2 time pairs t0 and t1 the set

\[ CSI_{t0}, G(CSI_{t0}) \]

and

\[ CSI_{t1}, Video_{t1} \]

are indistinguishable by a discriminator function D. This is expressed by the GAN objective [6]. To satisfy this objective the function G must find a true mapping between CSI and video given to it by the environment. This technique has shown state of the art results transforming images in other domains [3][2].

Results from the training procedure are illustrated in Appendix B.

\[ Video = G(CSI) \] (5)

\[ L_{GAN} (G, D) = \mathbb{E}_{x,y} [\log D(x, y)] + \mathbb{E}_{x,z} [\log(1 - D(x, G(x, z)))] \] (6)

Figure 3: Image-to-Image Translation with Conditional Adversarial Networks

4.1 PatchGAN Discriminator Modification

In the original PatchGAN [2] paper the discriminator can classify whether 70×70 overlapping patches are real or fake [4]. Each patch consists of 6 input channels, RGB for the input image x and RGB for the output image y, which focus on a corresponding sub region of each pair. This allows for a smaller discriminator network with simpler training and a better focus on image detail.

In the case of CSI to video translation the original PatchGAN discriminator must be modified for successful training. One issue is that the input CSI data’s shape [4,1,56] did not match the output image y resolution shape of [3,160,120]. Additionally, we recognized that each pixel in the output image space depends on all the input CSI information. This is a result of each object in the scene contributing to the multipath wireless environment. To better match this characteristic of the data we designed a new PatchGAN that still used...
4.2 Unsupervised Training Results

In order to compare the results of the unsupervised training model vs that of the supervised, we devised a method for calculating an AP IoU-50 score for the CSI output images. Just like we did for the supervised case we used Torchvision’s pre-trained RCNN ResNet50 model to label objects within the image captures from the webcam. For the images created from the CSI data we hand annotated the labels. This was done because the CSI generated images could be missing some of the finer details the RCNN model uses to classify people. The bounding boxes are then compared in the standard AP IoU-50 fashion resulting in a score of 92%.

Electromagnetic radiation from visible light sources or Wi-Fi access points, interact similarly with the environment, scattering and refracting off objects on the way to a receiver. We showed that mapping input data from the invisible Wi-Fi domain to the visible domain captured by webcams can be accomplished in an unsupervised way. We developed a novel modification to a state of the art domain transfer unsupervised generative model Pix2Pix [2]. This methodology results in a more robust mapping with a measured 18% improvement in accuracy vs previously used supervised methods.

4.3 Results Summary

The results we show in the this paper show excellent performance in reconstructing video in a simple environment. In our scene we only had one person as an object of interest with consistent motion. We did have other motion outside of the vision of the webcam that, encouragingly, showed little effect on the quality of the mapping. We also experimented with 2 people in the scene with positive results. More work needs to be done evaluating this performance before publication.

4.4 Next Steps

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Appendix A  Supervised Training Results
Figure 7: Bounding Boxes Using Wi-Fi Input

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Appendix B  Unsupervised Training Results
Unsupervised Training Results

Figure 8: Unsupervised CSI to Video Translation
Unsupervised Training Results

(a) Capture11

(b) Capture12

[Images of webcam and Wi-Fi feeds]

(c) Capture13

(d) Capture14

(e) Capture15

(f) Capture16

(g) Capture17

(h) Capture18

(i) Capture19

(j) Capture20

Figure 9: Unsupervised CSI to Video Translation