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In this issue

Technology Developed in GICE

An Effective Via-Based Frequency Adjustment and Minimization Methodology for Single-Layered Frequency-Selective Surfaces

from Electromagnetics Group

INTRODUCTION

Frequency Selective Surfaces (FSSs) are microwave components formed by repetitive arrangement of unit cells, such as periodic arrays of a patch, dipole, loop, or one of their complementary structures. By properly designing the structures of unit cells, the FSSs can be controlled as spatial filters that perform selectively with respect to incident electromagnetic waves of different frequencies, as indicated in Fig. 1. FSSs are used for a wide variety of applications including antenna radomes, electromagnetic shielding, and absorbers.

Typically during the designing and analyzing steps of FSSs, the periodic arrays are in infinite arrangement. Nevertheless, this requirement can no longer be fulfilled in practical applications so designing miniaturized elements, which increases the number of unit cell in a fixed area, is of great importance. In contrast to the previous solutions, the proposed methodology suggests adding well-designed vias to a single-layered FSS for its further element minimization and frequency tuning. This via-based methodology has two major advantages. First, designers can easily adjust the resonant frequency of an FSS to meet design specifications without having to redesign the original element pattern. Second, no any bulk component is required in the proposed methodology.

Miniaturization Methodology

The frequency responses of most FSSs can be modeled as a series or a parallel LC equivalent circuit. Therefore, the resonant frequency is determined using the formula $1/(2\pi\sqrt{LC})$, where L and C represent the equivalent

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GICE Honors

Prof. Hung-yi Lee

The Chinese institute of Electrical Engineering 「2018 Excellent Young Engineering Award」

Prof. Liang-Hung Lu

Micron Teacher Award

Message from the Director

Hsuan-Jung Su

Professor & GICE Director

Congratulations to Prof. Hung-yi Lee for receiving the "2018 Excellent Young Engineering Award" from the Chinese institute of Electrical Engineering (CIEE), and Prof. Liang-Hung Lu for receiving the Micron Teacher Award! They well deserve these highly competitive awards. We would also like to congratulate Prof. Yu-Chiang Frank Wang's Vision & Learning Lab for winning the 2nd Prize at the International Conference on Computer Vision and Pattern Recognition (CVPR) Workshop. Well done!

In this issue, we invite Prof. Tzong-Lin Wu to share his research results on Frequency Selective Surface (FSS) and Prof. Yu-Chiang Frank Wang to share the results on a deep learning framework of Cross-Domain Representation Disentangler (CDRD). Please grab a coffee or tea and enjoy reading their research works.

Technology *(Continued from page 1)*

capacitance and inductance. Conceptually, a miniaturized-element FSS can be created by directly increasing either the equivalent capacitance or inductance to lower its resonant frequency while maintaining a fixed element size. Line meandering is frequently adopted for increasing the inductance.
End loading in the Jerusalem Cross (JC) is widely used for enlarging the capacitance. Although the discussed reactance-enhancing approaches are widely used for designing miniaturized-element FSSs, the two-dimensional planar structures (indicated as the horizontal X–Y plane here) restrict the enhancement. This study proposes that another dimension (the vertical Z-direction) can be considered as well to further enhance the miniaturization.

Adding vertical vias into a planar FSS element can be an effective methodology for increasing the equivalent capacitance and inductance. All vias possess their own inductance, which is determined by their diameter and length. A high mutual capacitance may result from two proximal and parallel vias at the neighboring elements. Such capacitance depends on the via length and the distance between vias. Furthermore, the inductance and capacitance can be controlled by the number and arrangement of vias in an element. The geometry of vias is simple. Hence, both the inductance and capacitance can be calculated through closed-form equations based on previous research results.

To demonstrate the performance of the proposed methodology, the classic JC FSS is considered as an example. As shown in Fig. 2(a) and (b), the element comprises a single metallic layer on a thin substrate, and combined with 8 and 24 vias, respectively. These two numbers of vias are used to represent two extreme cases, in which the vias are sparsely and densely distributed. The JC FSS with vias can be easily fabricated using a single-layered printed circuit board (PCB), with a dielectric constant 4.4 and loss tangent 0.02.

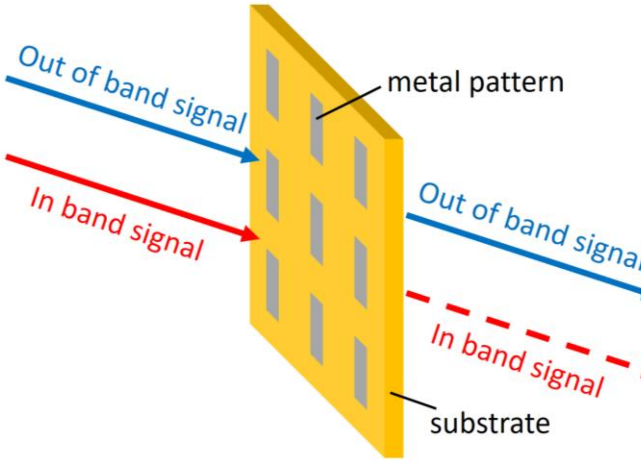

Fig 1. Illustration of the concept of FSS as a spatial filter.

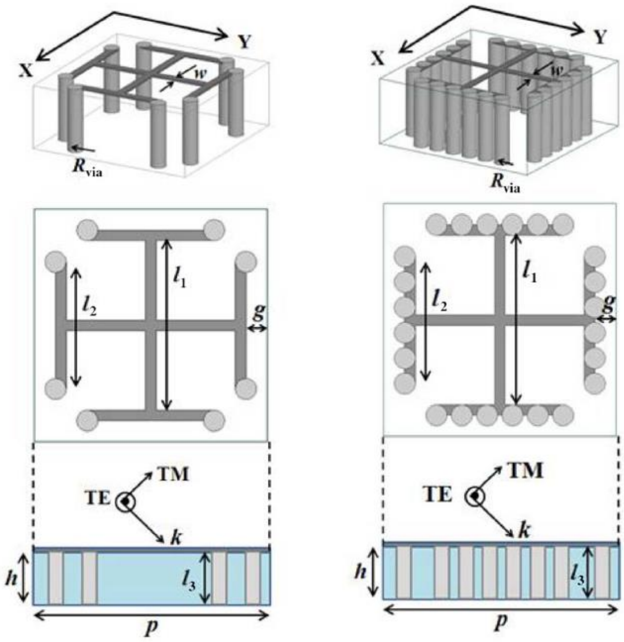

Fig 2. (a) Geometry of the JC element with 8 vias. (b) Geometry of the JC element with 24 vias.

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Simulation Result and Experimental Validation
Utilizing full-wave simulators, Fig. 3 shows the minimization performance resulting from via additions. Compared with the original JC FSS without vias, the resonant frequency is considerably shifted from 18.66 to 6.52 GHz and 5.60 GHz for the FSS with 8 and 24 vias in each element, respectively. Especially for the case of 24 vias, the size of the element is only $0.062\lambda_0 \times 0.062\lambda_0$, demonstrating a remarkable minimization, where λ_0 represents the wavelength in free space at the resonant frequency. Furthermore, the high frequency difference between the JC FSS without and with vias indicates that a wide frequency range for tuning could be established by properly adding the vias.

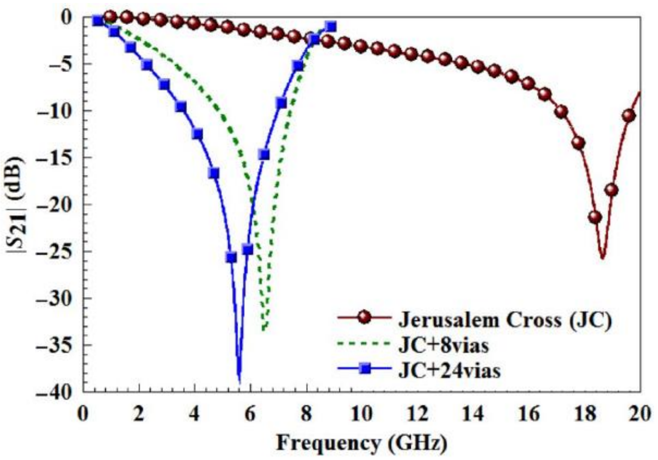

Fig. 3. Transmittance of the original JC FSS, JC FSS with 8 vias, and JC FSS with 24 vias.

To demonstrate again the validity of the proposed equivalent circuit model, a prototype of the JC FSS with eight vias at every element was fabricated and examined in a fully anechoic chamber. As shown in Fig. 4, the measurement setup comprises two high gain antennas and an Agilent 8722ES vector network analyzer (VNA). The FSS prototype or the devices under test (DUT) were fabricated using a single-layered FR-4 substrate and PCB technology. The FSS prototype is 660mm × 660mm in size and includes 200 × 200 elements.

In an attempt to calibrate the VNA used in measuring the transmittance (S21), a measurement must be performed initially in the absence of the DUT. Fig. 5 shows the FSS transmittance for normal incidence. Obviously, the measured results are consistent with those obtained using the full-wave simulation.

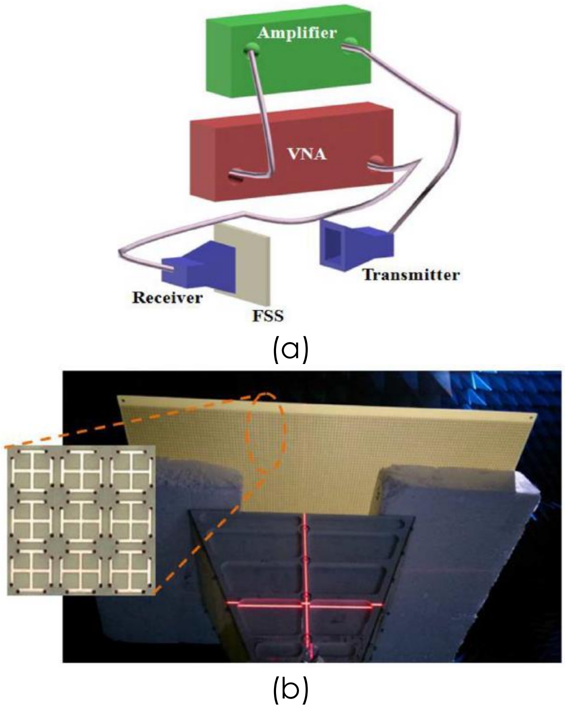

Fig. 4. (a) Setup of measurement. (b) Photo of the fabricated FSS prototype.

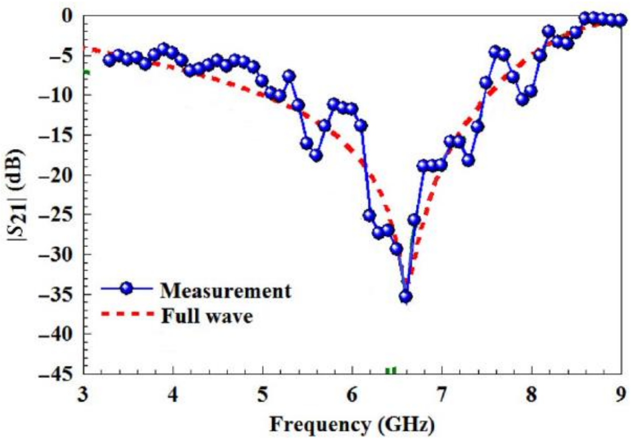

Fig. 5. Comparison between the measurement and the full-wave simulation.

Conclusion
This research proposes an effective via-based methodology for element minimization and frequency tuning of a single-layered FSS. This methodology suggests using additional vertical vias in FSS designs. Designers can easily create a via-based FSS with a wide operating frequency tuning range by implanting different numbers of vias with different lengths into a published FSS element. These desirable characteristics greatly broaden the applicability of FSS.

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Technology

Decomposing Deep Neural Networks for Visual Analysis – Learning Interpretable Disentangled Representation for Visual Classification and Manipulation*

from Data Science and Smart Networking Group

INTRODUCTION

The development of deep neural networks benefits a variety of areas such as computer vision, machine learning, and natural language processing, which results in promising progresses in realizing artificial intelligence environments. However, it is fundamental and desirable for understanding the observed information around us. To be more precise, the above goal is achieved by identifying and disentangling the underlying explanatory factors hidden in the observed data and the derived learning models. Therefore, the challenge of representation learning is to have the learned latent element explanatory and disentangled from the derived abstract representation.

With the goal of discovering the underlying factors of data representation associated with particular attributes of interest, representation disentanglement is the learning task which aims at deriving a latent feature space that decomposes the derived representation so that the aforementioned attributes (e.g., face identity/pose, image style, etc.) can be identified and described. Several works have been proposed to tackle this task in unsupervised, semi-supervised, or fully supervised settings. Once attribute of interest properly disentangled, one can produce the output images with particular attribute accordingly. However, like most machine learning algorithms, representation disentanglement is not able to achieve satisfactory performances if the data to be described/manipulated are very different from the training ones. This is known as the problem of domain shift (or domain/dataset bias), and requires the advance of transfer learning or domain adaptation techniques to address this challenging yet practical problem. Similarly, learning of deep neural networks for interpretable and disentangled representation generally requires a large number of annotated data, and also suffers from the above problem of domain shift.

We propose a novel deep neural networks architecture based on generative adversarial networks (GAN) [1]. As depicted in Figure 1, our proposed network observes cross-domain data with partial supervision, and performs representation learning and disentanglement in the resulting shared latent space. It is worth noting that, this can be viewed as a novel learning task of joint representation disentanglement and domain adaptation in an unsupervised setting, since only unlabeled data is available in the target domain during the training stage. Later in the experiments, we will further show that the derived feature representation can be applied to describe data from both source and target domains, and classification of target-domain data can be achieved with very promising performances.

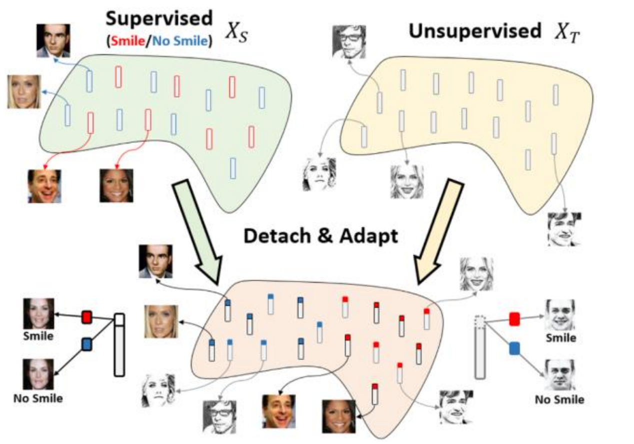

Fig.1 : Illustration of cross-domain representation disentanglement. With attributes observed only in the source domain, we are able to disentangle, adapt, and manipulate the data across domains with particular attributes of interest.

Cross-Domain Representation Disentangler (CDRD)

Since both AC-GAN [2] and InfoGAN [3] are known to learn interpretable feature representation using deep neural networks (in supervised and unsupervised settings, respectively), it is necessary to briefly review their architecture before introducing ours. Based on the recent success of GAN [1], both AC-GAN and InfoGAN take noise and additional class/condition as the inputs to the generator, while the label prediction is additionally performed at the discriminator for the purpose of learning disentangled features. As noted above, since both AC-GAN and InfoGAN are not designed to learn/disentangle representation for data across different domains, they cannot be directly apply for cross-domain representation disentanglement.

To address this problem, we propose a novel network architecture of cross-domain representation disentangler (CDRD). As depicted in Figure 2, our CDRD model consists of two major components: Generators {G_S,G_T,G_S}, and Discriminators {D_S,D_T,D_C}. Similar to AC-GAN and InfoGAN, we have an auxiliary classifier attached at the end of the network, which shares all the convolutional layers with the discriminator D_C, followed by a fully connected layer to predict the label/attribute outputs. Thus, we regard our discriminator as a multi-task learning model, which not only distinguishes between synthesized and real images

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but also recognizes the associated image attributes.

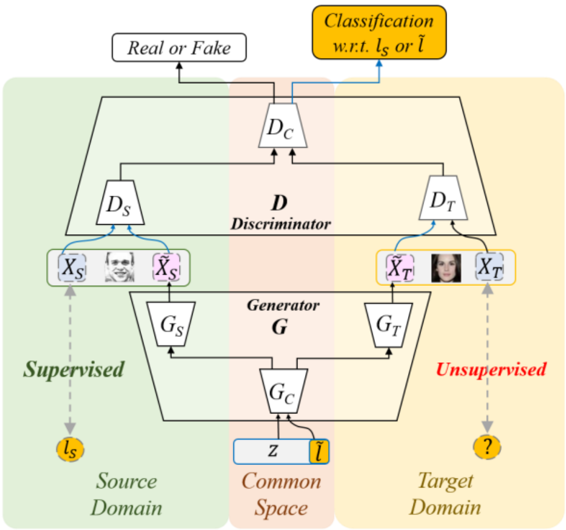

Fig.2 The network architecture of Cross-Domain Representation Disentangler (CDRD). Note that while source and target domain data are presented during training, only attribute supervision is available in the source domain, and no cross-domain data pair is needed.

To handle cross-domain data with only supervision from the source domain, we choose to share weights in higher layers in G and D, aiming at bridging the gap between high/coarse-level representations of cross-domain data. To be more precise, we split G and D in CDRD into multiple sub-networks specialized for describing data in the source domain $\{\mathrm{G_S}, \mathrm{D_S}\}$, target domain $\{\mathrm{G_T}, \mathrm{D_T}\}$, and the common latent space $\{\mathrm{G_C}, \mathrm{D_C}\}$ (see the green, yellow, and red-shaded colors in Figure 2, respectively).

Let $\mathrm{I_S}$ be the ground truth label in source domain. Following the challenging setting of unsupervised domain adaptation, each input image $\mathrm{X_S}$ in the source domain is associated with a ground truth label $\mathrm{I_S}$, while unsupervised learning is performed in the target domain. Thus, the common latent representation z in the input of CDRD together with a randomly assigned attribute I would be the inputs for the generator. For the synthesized images $\tilde{X}_S$ and $\tilde{X}_T$, we have:

$$\tilde{X}_S \sim \mathrm{G_S}\left(\mathrm{G_C}(\mathrm{z}, \tilde{I})\right), \tilde{X}_T \sim \mathrm{G_T}\left(\mathrm{G_C}(\mathrm{z}, \tilde{I})\right). \quad (1)$$

The objective functions for adversarial learning in source and target domain are now defined as follows:

$$\mathcal{L}_{adv}^{S} = \mathbb{E}\left[\log\left(\mathrm{D_C}(\mathrm{D_S}(\mathrm{X_S}))\right)\right] + \mathbb{E}\left[\log\left(1 - \mathrm{D_C}\left(\mathrm{D_S}((\tilde{X}_S))\right)\right)\right]$$

$$\mathcal{L}_{adv}^{T} = \mathbb{E}\left[\log\left(\mathrm{D_C}(\mathrm{D_T}(\mathrm{X_T}))\right)\right] + \mathbb{E}\left[\log\left(1 - \mathrm{D_C}\left(\mathrm{D_T}((\tilde{X}_T))\right)\right)\right]$$

$$\mathcal{L}_{adv} = \mathcal{L}_{adv}^{S} + \mathcal{L}_{adv}^{T}. \quad (2)$$

Let $\mathrm{P(I|X)}$ be a probability distribution over labels/attributes I calculated by the discriminator in CDRD. The objective functions for cross-domain representation disentanglement are defined below:

$$\mathcal{L}_{dis}^{S} = \mathbb{E}[\log \mathrm{P}(\mathrm{I} = \tilde{I}|\tilde{X}_S)] + \mathbb{E}[\log \mathrm{P}(\mathrm{I} = I_S|\mathrm{X_S})]$$

$$\mathcal{L}_{dis}^{T} = \mathbb{E}[\log \mathrm{P}(\mathrm{I} = \tilde{I}|\tilde{X}_T)]$$

$$\mathcal{L}_{dis} = \mathcal{L}_{dis}^{S} + \mathcal{L}_{dis}^{T}. \quad (3)$$

With the above loss terms determined, we learn our CDRD by alternatively updating Generator and Discriminator with the following gradients:

$$\theta_G \overset{+}{\leftarrow} -\Delta_{\theta_G}(-\mathcal{L}_{adv} + \lambda\, \mathcal{L}_{dis})$$

$$\theta_D \overset{+}{\leftarrow} -\Delta_{\theta_D}(\mathcal{L}_{adv} + \lambda\, \mathcal{L}_{dis}). \quad (4)$$

We note that the hyperparameter λ is used to control the disentanglement ability. We will show its effect on the resulting performances in the experiments.

Similar to the concept in InfoGAN, the auxiliary classifier in $\mathrm{D_C}$ is to maximize the mutual information between the assigned label $\tilde{I}$ and the synthesized images in the source and target domains (i.e., $\mathrm{G_S}\left(\mathrm{G_C}(\mathrm{z}, \tilde{I})\right)$ and $\mathrm{G_T}\left(\mathrm{G_C}(\mathrm{z}, \tilde{I})\right)$). With network weights in high-level layers shared between source and target domains in both G and D, the disentanglement ability is introduced to the target domain by updating the parameters in $\mathrm{G_T}$ according to $\mathcal{L}_{adv}^{T}$ during the training process.

Results: Cross-Domain Representation Disentanglement and Translation

We apply our CDRD to perform cross-domain representation disentanglement, in which a single source domain and multiple target domains are of use. From the results shown in Figures 3 and 4, we see that our CDRD can be successfully applied for this challenging task even with only attribute supervision from the single source-domain data. This confirms our design of high-level sharing weights in CDRD.

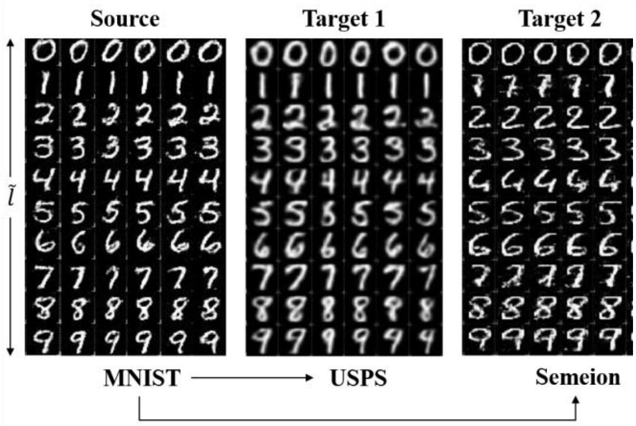

Fig.3. Cross-domain conditional image synthesis from a single source to multiple target domains: MNIST to USPS and Semeion with labels as digits.

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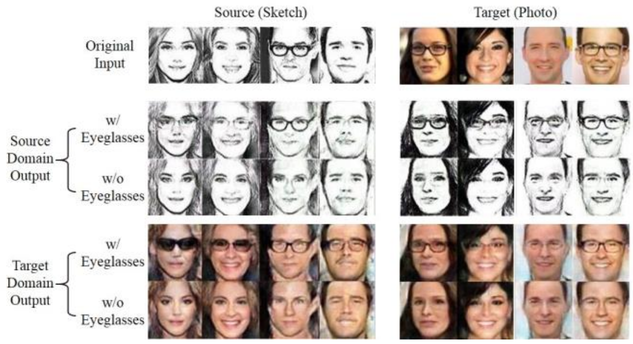

Fig. 4. Cross-domain conditional image translation for facial images (sketch to photo) with labels as glasses.

Results: Unsupervised Domain Adaptation

For UDA with digit images, we consider MNIST to USPS and USPS to MNIST, and we evaluate the classification accuracy for target-domain images. Table 1 lists and compares the performances of recent UDA methods. We can see that a significant improvement was achieved by our CDRD. It is worth noting that, while UNIT reported 0.9597 for M to U and 0.9358 for U to M, UPDAG achieved 0.9590 for M to U, they considered much larger datasets (UNIT required 60000/7291 images for MNIST/USPS, and UPDAG required 50000/6562 for MNIST/USPS).

Table 1 UDA accuracy (%) for recognizing target-domain images with the attribute of digits (0-9). Take M to U as example, we set MNIST and USPS as source and target domains, respectively.

	GFK [8]	JDA [22]	SA [4]	TJM [23]	SCA [6]	JGSA [33]	DC [30]	GR [5]	CoGAN [20]	ADDA [31]	DRCN [7]	ADGAN [28]	CD
M → U	67.22	67.28	67.78	63.28	65.11	80.44	79.10	77.10	91.20	89.40	91.80	92.50	95.
U → M	46.45	59.65	48.80	52.25	48.00	68.15	66.50	73.00	89.10	90.10	73.67	90.80	94.
Average	56.84	63.47	58.29	57.77	56.55	74.30	72.80	75.05	90.15	89.75	82.74	91.65	94.

Conclusions

We presented a deep learning framework of Cross-Domain Representation Disentangler (CDRD). Our model is able to perform joint representation disentanglement and adaption of cross-domain images, while only attribute supervision is available in the source domain. We successfully verified that our models can be applied to conditional cross-domain image synthesis, translation, and the task of unsupervised domain adaptation.

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*Work published at International Conference on Computer Vision and Pattern Recognition (CVPR 2018)

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Activity

The 2018 2nd Semiannual Report of Taiwan Electromagnetic Industry-Academia Consortium: 5G Antenna and RF Frontend Key Technical Challenges and Trends Symposium

The fifth-generation(5G) mobile communication system, since 3GPP released the first international 5G standard on June 13, 2018, many countries are dedicated to the development of related technologies and commercial applications. The 5G blueprint proposed by the ITU is: eMBB (enhanced Mobile Broadband), URLLC (Ultra Reliable Low Latency Communications), mMTC (massive Machine Type Communications). In Taiwan, we expect to be a leader in 5G industries, but we have to face many challenges. This time, many active researchers and engineers were gathered in the 2018 5G antenna and RF front-end key technical challenges and trends symposium on 5th of October, 2018 at the Barry Lam Hall, National Taiwan University (NTU) in Taipei, Taiwan to discuss the challenges currently we face and the possible future directions. The symposium was organized by Taiwan Electromagnetic Industry-Academia Consortium, and co-organized by the Department of Electronic and Computer Engineering, NTUST, the Department of Electrical Engineering, NTU, Graduate Institute of Communication Engineering, NTU, 5G Industrial Technology Consortium, Wireless Communication and Electromagnetic Compatibility Research Center, NTUST, Industry Liaison Office, NTU, High-Speed RF and mm-Wave Technology Center, NTU Department of Electrical Engineering, and IEEE Council of EMC Taipei Chapter.

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Activity (Continued from page 6)

In this event, the organizers invited Professor Hsi-Tseng Chou, Professor Hsuan-Jung Su and Professor Tzong-Lin Wu from National Taiwan University, Professor J.H. Tarng from National Ciao Tung University, Fu Yi-Kang, Manager of MediaTek, Zhou Rui-Hong, Technical Director of Auden Technology to share their research and experience for the 5G antenna and RF front-end techniques. They discussed these issues on views of systems, circuits and industry. The topics include millimeter wave antenna design, engineering challenges, measurement requirements and practical applications. It is really exciting.

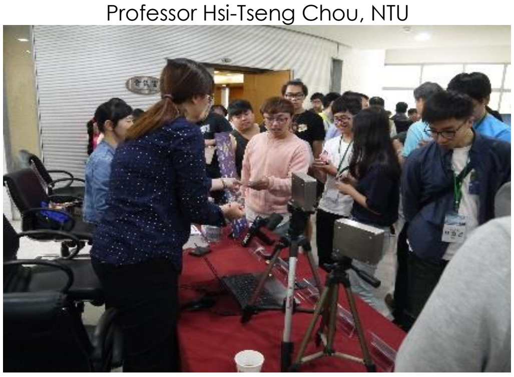
Professor Tzong-Lin Wu, NTU

Dr. Yi-Kang Fu, MTK

Professor Ruey-Beei Wu from National Taiwan University shared two news related to 5G with us: First, the Executive Yuan will complete the first phase of the 5G spectrum market in 2020 in Taiwan. What did we gain from Taiwan's telecom industry since the development of 4G in 2013? The second is that Morris Chang proposed an issue at APEC. In the era of digital economy in the world, what role does Taiwan play? The era of 5G has arrived, and many technologies have developed in various ways, which can roughly conclude five important applications: three high and two low, respectively high capacity: High amounts of connected devices, high spectrum efficiency, low latency and low power consumption.
The following topics include development and application of Massive MIMO and Smart Antenna Technology, 5G communication technology of industry 4.0, 5G system design to commercialization, Technology and Challenge of 5G Millimeter Wave Antenna Module, Technology Development and Application of Millimeter Wave Phase Array, Application of millimeter wave RF front-end circuit and shielding technology in 5G communication. They follow the specification of 5G, trying to develop their application in the future. Our goal is that through the exchange of 5G development trends, discussing about current situation and future prospects, Taiwan can be well-developed for the next generation. The technology of millimeter-wave design now appears to be everywhere in our daily life.

Professor Ruey-Beei Wu, NTU

Professor Hsi-Tseng Chou, NTU



Corner of student news

Vision & Learning Lab winning the 2nd Prize at the CVPR Workshop

The International Conference on Computer Vision and Pattern Recognition (CVPR) is known as the flagship and top-tier international conference on computer vision and machine learning for researchers in the above fields. This year, CVPR is held at Salt Lake City, Utah, USA (June 18-22, 2018). With more than 3,300 submissions to the main conference, only 979 papers are accepted with a 29% acceptance rate. Moreover, the total number of registration is 6,128. Not only people from academia, a very large number of participants come from industries. This again shows and explains why CVPR is recognized as the major event to share the latest research outputs with high impacts, and to identify high-quality researchers and engineers in these research areas.

Under the supervision of Prof. Yu-Chiang Frank Wang, Vision and Learning Lab of the Graduate Institute of Communication Engineering from National Taiwan University has two papers accepted for the main conference. The titles of the two papers are "Detach and Adapt: Learning Cross-Domain Disentangled Deep Representation" and "Multi-Label Zero-Shot Learning with Structured Knowledge Graphs" (poster presentation", respectively. The former addresses the challenging task of representation disentanglement, which decomposes the deep learning models and derives interpretable feature representation, with the goal of explaining the remarkable capability of the deep neural networks in perform image classification and synthesis tasks. This work is accepted as spotlight presentation, and the co-authors of this papers (both are members of GICE) deliver excellent talks to the audience. As for the latter work, we address the practical challenge of multi-label zero-shot image classification. By utilizing visual and semantics information, this work can be successfully applied to predict multiple seen and unseen labels from a single input image, which would be very beneficial for visual analysis tasks.

In addition to the main conference, our lab members also attend two challenges. One is Visual Understanding of Humans in Crowd Scene and Look Into Person Challenge, and the other is DeepGlobe: A Challenge for Parsing the Earth through Satellite Images. With both works accepted at this workshop, our team is awarded the 2nd Prize for the challenge of DeepGlobe, beating outstanding teams like MIT and University of Maryland.

Finally, with an increasing number of participants, our lab members also hold the event of CVPR Taiwan Night (with the support by the AI office of the Ministry of Science and Technology). About 100 Taiwanese researchers, students, and engineers who either are based in Taiwan or overseas attend this social event, exchanging their statuses and recent progresses with each other. This great event not only brings all Taiwanese in the above fields together, it also promotes our visibility and connects the networks of Taiwanese AI community.

Member of Vision & Learning Lab winning the 2nd Prize at the CVPR Workshop DeepGlobe Challenge, under the supervision of Prof. Yu-Chiang Frank Wang (second from the right).

Vision and Learning Lab member Yu-Ying Yeh and Yen-Cheng Liu perform spotlight presentation at CVPR main conference during the oral session.

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