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# MMTC Communications – Review

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# Message from the Review Board Directors

Welcome to the August 2022 issue of the IEEE ComSoc MMTC Communications – Review.

This issue comprises four reviews that cover multiple facets of multimedia communication research including image enhancement, mobile edge computing, machine learning, and vehicular networks. These reviews are briefly introduced below.

The first paper, published in IEEE Transactions on Multimedia and edited by Dr. Qin Wang, proposes a new method of utilizing the just-noticeable-difference (JND) transform to achieve joint contrast enhancement and noise reduction based on human visual perception.

The second paper, edited by Dr. Ye Liu, was published in IEEE Journal on Selected Areas in Communications. This paper investigates service provisioning for unmanned aerial vehicle (UAV)-enabled mobile edge computing (MEC) for the first time with involving service placement, task scheduling, trajectory, and computation resources for optimal energy consumption of the IoT end devices under required latency demand and resource constraints.

The third paper, edited by Dr. Shengjie Xu, was published in IEEE Wireless Communications. The authors resort to machine learning (ML) models to empower underwater acoustic communications (UAC) with intelligence capabilities.

The fourth paper, to be published in IEEE Transactions on Vehicular Technology, and edited by Dr. Qichao Xu. The paper proposes a novel trust management mechanism to integrates active detection and blockchain techniques.

All the authors, reviewers, editors, and others who contribute to the release of this issue deserve appreciation with thanks.

IEEE ComSoc MMTC Communications – Review Directors

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## Joint Contrast Enhancement and Noise Reduction of Low Light Images

*A short review for "Joint Contrast Enhancement and Noise Reduction of Low Light Images Via JND Transform"*

Edited by Qin Wang

*H. Su, L. Yu and C. Jung, "Joint Contrast Enhancement and Noise Reduction of Low Light Images Via JND Transform," in IEEE Transactions on Multimedia, vol. 24, pp. 17-32, 2022.*

Low light image has problems such as color distortion, low contrast, high noise, and blurred details, which make it difficult to extract target feature information and affect the subsequent image processing tasks. [1] Low light image enhancement technology refers to restoring the low light image to the normal level through a series of mathematical methods. It can greatly improve the quality of visual perception and the accuracy of subsequent image processing tasks. Therefore, the enhancement of low light images has become an important topic in the field of visual image processing and analysis.

Low light image enhancement methods can be classified into two categories: traditional and deep learning-based. Among them, the traditional methods include Retinex theory-based methods [2], histogram equalization-based methods [3], and dark channel defogging-based methods [4]. The traditional methods do have some effect on illumination adjustment and small noise elimination. But the parameters in the model need to be set manually, which cannot adapt to the diversity of the processed images. The image processing effect for higher noise is poor, and there are local details such as underexposure or overexposure. Although deep learning-based methods can compensate for the shortcomings of traditional methods to a certain extent and achieve better enhancement for a certain type of image set. However, most deep learning-based methods heavily rely on the quality of the dataset and do not consider the distribution of noise in different illumination regions. There are deviations between a priori knowledge and real images, and it is difficult to obtain a completely realistic image dataset. These problems caused that existing deep learning models cannot suppress the real image noise effectively, and visual quality can hardly be satisfying.

Through the study of traditional and deep learning-based methods, there are two main challenging problems in enhancing low light images, one is the illumination variability problem, and the other is the non-uniform noise problem. The spatial feature distribution of real low light images is complex, resulting in strong illumination variability in image space. The existing methods are not ideal for enhancing the overall image visibility and underexposed areas. For the non-uniform noise features introduced in the image acquisition, the traditional methods cannot solve them well, and the deep learning-based methods cannot achieve the desired effect by simple cascade noise reduction. Denoising before image enhancement will lose part of the image details and make it difficult to reconstruct the high noise pixel information, while denoising after enhancement will easily lead to blurred images. Therefore, how to effectively suppress the noise and recover the information hidden in the dark is a challenge in current low light image enhancement models.

Since the human visual system is the ultimate receiver of the majority of processed images and videos, it is very advantageous to incorporate HVS into image processing. In this paper, the authors propose a new method of utilizing the just-noticeable-difference (JND) transform to achieve joint contrast enhancement and noise reduction based on human visual perception. The proposed method consists of six steps, including (a) JND transform, (b) contrast enhancement, (c) refining the JND map, (d) JND inverse transform, and (e) chroma denoising. Here, the step (a) and (c) are core mechanisms, and the details are presented as follows.

Authors transform the image details into the JND domain, namely JND transform. This is different from traditional layer decomposition methods in the way that the proposed method quantizes the luminance difference between foreground and background based on luminance adaptation. The JND transform perceptually adjusts detail enhancement based on JND without noise amplification after image enhancement. Authors use luminance adaptation as JND threshold to constrain the enhancement of each gray level, thus avoiding the under-enhancement and over-enhancement. Moreover, the JND transform alleviates the halo artifacts and noise amplification caused by detail enhancement.

The JND transform alleviates noise amplification and preserves main structure after image enhancement. However, it leads to blur artifacts with some noise because the details are attenuated after image enhancement. Considering the non-uniform noise problem, authors utilize visual masking to assess the texture of the JND map and consider the local characteristics. For smooth regions, human eyes are more sensitive to noise, thus need to weaken detail enhancement to avoid noise amplification. Inversely, in textural regions, human eyes have high visual masking effect, and thus need to enhance details. Authors refine the JND map using Weber's law, luminance adaptation, and visual masking. Weber's law enhances the JND map based on the luminance variation after contrast enhancement. Luminance adaptation suppresses noise for smooth regions, while visual masking enforces detail enhancement for textural regions.

After the inverse JDN transformation, authors conduct chroma denoising by transferring texture information of the enhanced luma channel to the chroma channels with guided filtering.

Authors analyze the performance of the proposed method in comparison with some state-of-the-art ones for low light image contrast enhancement and denoising. Thanks to the JND transform, the proposed method produces image enhancement results with less halo artifacts and prevents under- and over-enhancement. It is because the proposed method perceptually allocates a dynamic range based on the visual sensitivity to background luminance. Moreover, authors use visual masking and luminance adaptation to extract textural regions and enforce detail enhancement with noise reduction. For low light images with little noise, main textures and structures are successfully enhanced compared to others. Concerning low light images with serious noise, main structures are preserved with the least noise amplification. Thus, it leads to a proper allocation of the dynamic range with good noise reduction and structure preservation.

In summary, authors adopt the JND transform to achieve both contrast enhancement and noise reduction with detail preservation. The proposed method successfully preserves main structures without noise amplification after image enhancement and outperform state-of-the-art ones in terms of visual quality and quantitative measurements.

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## Service Provisioning for Crowd Aerial Mobile Edge Computing

*A short review for "Service Provisioning for UAV-Enabled Mobile Edge Computing"*

Edited by Ye Liu

*Y. Qu, H. Dai, H. Wang, C. Dong, F. Wu, S. Guo, and Q. Wu, "Service Provisioning for UAV-Enabled Mobile Edge Computing," in IEEE Journal on Selected Areas in Communications, vol. 39, no. 11, pp. 3287-3305, Nov. 2021.*

Mobile edge computing (MEC) [1] has emerged as a powerful paradigm for the Internet of Things [2] (IoT), since it can act as a bridge between cloud platforms and massive IoT devices. The MEC can not only meet the requirements of low latency and heavy computation capability for mobile applications but also release the burden on cloud and end IoT devices. In recent years, academia and industry have put significant efforts [3, 4] to it in terms of techniques, applications, and standardization.

However, current MEC usually relies on mobile infrastructures (e.g., 4G/5G micro stations), which has several limitations regarding deployment cost, service coverage, burden traffic, and so on. To mitigate these limitations, the concept of unmanned aerial vehicle (UAV)-enabled MEC has been proposed in recent days, in which crowd UAVs are serviced as edge computing servers for target IoT devices. This concept has many advantages, such as convenient deployment, flexible coverage, line-of-sight communication, and on-demand service.

Before achieving the blueprint of UAV-enabled MEC, several fundamental problems must be addressed. Among them, service provisioning is of particular concern, namely, how to optimally deploy the services in these UAVs with diverse application requirements. Previous research efforts have mainly focused either on UAV-enabled wireless communication networks or service provisioning in fixed MEC architectures. However, no research has been paid to joint consideration of UAV-enabled MEC and service provisioning.
To fill the above gap, this paper investigates service provisioning for UAV-enabled MEC for the first time. Specifically, this work comprehensively involves service placement, task scheduling, trajectory, and computation resources for optimal energy consumption of the IoT end devices under required latency demand and resource constraints. First, the network model is introduced. Then, the problem of minimizing the total energy consumption is mathematically formulated in detail. After that, an alternating optimization-based solution is proposed, along with an improved low complexity approach. The performances of the proposed two algorithms are evaluated extensively, and the results show their outperformance.

In the network model, the scenario consists of multiple rotary-wing UAVs and multiple IoT end devices. The mission period is divided into many time slots, and a computation-intensive task is generated in every time slot for each IoT device. In terms of the service placement model, the various services are video streams, games, virtual reality, and navigation information, presenting different storage resource requirements in terms of storage space and storage capacity. Moreover, a 3D Cartesian coordinate system is considered for the movement trajectory of UAVs. In terms of the latency model, a binary variable is introduced to indicate the status of remote execution. A triple representation is used to describe tasks about service type, data size, and required processing periods. In terms of the energy consumption model, local computation power, communication time, transmission distance, and data rate are considered to calculate the energy consumption of IoT devices.

The object is to minimize the total consumed energy of all the IoT devices. Therefore, the problem formulation jointly considers the service placement, UAV movement trajectory, task scheduling, and computation resource allocation. This formulated problem is new because the shape totally changes due to the service placement. Furthermore, the formulation is a non-convex mixed integer nonlinear programming problem, making it hard to obtain an optimal solution.

The aforementioned problem is split into three subproblems, namely, joint service placement and task scheduling subproblem, UAV trajectory subproblem as well as computation resource allocation subproblem. First, the Branch and Bound (BnB) is introduced to solve the first subproblem. Second, a continuous slack variable is introduced to translate the second subproblem from a non-convex to a convex problem, which is then solved through the successive convex approximation (SCA). Third, a closed-form optimal solution is proposed to solve the last subproblem.

One limitation of the proposed solution is high computation complexity. Thus, an improved version, an alternating optimization-based solution with low complexity, is further proposed. It includes a randomized rounding algorithm, a conversion algorithm for feasible service placement and task scheduling, and a low-complexity alternating optimization-based algorithm.

In the performance evaluation, extensive numerical simulations are conducted to compare the proposed algorithms with benchmark solutions (i.e., random, greedy, and local). It analyzes the convergence, optimized UAV trajectory, effect of UAV's storage capacity, the impact of UAV's communication access ability, the impact of UE's computation workload, and execution time comparison.

In summary, this paper presents a novel application and solid theoretical contributions for service provisioning in UAV-enabled mobile edge computing.

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## Machine learning techniques to empower UAC with intelligence capabilities

*A short review for "Machine Learning for Underwater Acoustic Communications"*

Edited by Shengjie Xu

*L. Huang, Y. Wang, Q. Zhang, J. Han, W. Tan and Z. Tian, "Machine Learning for Underwater Acoustic Communications," in IEEE Wireless Communications, vol. 29, no. 3, pp. 102-108, June 2022.*

Energy-efficient and link-reliable underwater acoustic communication (UAC) systems are of vital importance to both marine scientific research and oceanic resource exploration. Because of the nature of the unique characteristics of marine environments, underwater acoustic (UWA) propagation experiences arguably the harshest wireless channels in nature. In this setting, the traditional model-based approaches to communication system design and implementation may no longer be effective or reliable for UAC systems.

In this article, the authors resort to machine learning (ML) models to empower UAC with intelligence capabilities, which capitalize on the potential of ML in progressively improving system performance through task-oriented learning from data. The literature of both UAC and ML is discussed first. Then, some promising ML-based solutions for UAC are presented and the authors highlight one specific niche application of adaptive modulation and coding (AMC). Lastly, other key open issues and research opportunities layer-by-layer are discussed, with focus on providing a concise taxonomy of ML algorithms relevant to UAC networks.

Recently, ML has received much attention as a key enabler for the evolution of terrestrial wireless communications. For instance, deep learning (DL) has been advocated for demodulation in OFDM systems [1]. For 5G wireless systems, an efficient online channel state information (CSI) prediction scheme has been designed, which learns from the historical data via deep neural networks (DNN) [2]. These successes illuminate the feasibility and potential benefits of exploring ML for wireless communication systems.

Typical ML algorithms can be generally classified into four categories depending on the nature of the dataset for learning as well as the feedback mechanism available to the learning system. They are supervised learning (SL), unsupervised learning (UL), semi-supervised learning (SSL), and RL, where supervised, unsupervised or semi-supervised learning indicates whether the available data samples are labeled, unlabeled or a mix of both, and a reinforcement scheme provides feedback in terms of rewards or regret to navigate the learning process.

Due to the lack of accurate and usable models for the complex channel characteristics and adverse node features in harsh UWA environments, there are critical issues to be addressed at each of these layers, beyond the capability of existing model-based wireless solutions. ML technology presents a great potential, thanks to its capability to effectively extract the underlying relationship among key parameters of UAC systems from data, even in the absence of any predefined models or prior knowledge. ML is expected to offer major performance enhancement to UAC systems, which will in turn facilitate better exploration and protection of the precious marine resources.

The relevant principles in employing ML techniques for UACs are discussed in five aspects. The first principle is about problem modeling. It is essential to fully understand the target problem before applying ML (i.e., define the input and the corresponding output), and then build a proper ML model for training.

The second principle is about data gathering. For ML-based UACs, it is vital to collect a sufficiently large training dataset of good quality. Unfortunately, either real data collection from field experiments or synthetic data generation via simulations is highly challenging in UWA scenarios. It is of foremost importance to construct a rich training set by gathering and sharing a large volume of data from field experiments and/or even generating realistic data from a generative adversarial network that is informed by both real and synthetic data.

The third principle is about data preprocessing. Both the quality and quantity of the initially constructed training set need to be enhanced continuously. The critical components include denoising, feature scaling, and complexity reduction [3].

The fourth principle is about model parameter tuning. The model prediction ability shall be refined through iterative adjustments of model parameters, until reaching desired performance. By now, the trained ML model is ready for deployment in practice.

The fifth principle is about learning on the fly. During the online deployment stage, semi-supervised learning can be used to keep learning from the operating scenarios to update the ML model, so as to continually enhance the performance in terms of model accuracy and scalability. Training ML models takes practice. For those who are new to ML or want to get results quickly, it is advised to extract some key features based on domain knowledge and experience to represent the original data, and train the model using simple ML algorithms. These two strategies help to obtain usable outcomes while greatly reducing the demand for computing resources and training time. When further improvement of model intelligence is desired, one can turn to a DL-aided AMC framework that utilizes the data itself for intelligent feature extraction and sustainable performance improvement.

The authors also offered an outlook on ample research opportunities and open issues across multiple layers. For UWANs, their unique node characteristics give rise to adverse impacts on the link quality. First, the water current causes unavoidable node mobility, resulting in nontrivial Doppler effects and high dynamics in the topology of UAC systems. Second, the noise sources consist of not only the ambient noise but also the echoed self-noise, both of which are quite complex. Third, marine nodes are usually powered by batteries that are expensive to recharge or replace in underwater conditions, and hence the network lifetime is a limiting factor in design and implementation

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In this paper, the authors contribute to analyzing major challenges in UAC and laying out potential solutions from an ML perspective. Relevant ML techniques are categorized, and promising applications of ML in UWANs are outlined and discussed in a layer-by-layer manner.

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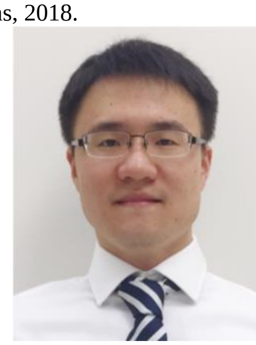

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# ATM: An Active-Detection Trust Mechanism for VANETs Based on Blockchain

*A short review for "ATM: An Active-Detection Trust Mechanism for VANETs Based on Blockchain"*

Edited by Qichao Xu

*F. Li, Z. Guo, C. Zhang, W. Li and Y. Wang, "ATM: An Active-Detection Trust Mechanism for VANETs Based on Blockchain," in IEEE Transactions on Vehicular Technology, doi: 10.1109/TVT.2021.3050007.*

VANETs are vulnerable to many types of malicious attacks from both internally or externally [1]. For example, malicious vehicles existing in VANETs [2] can bring disastrous consequences in emergency message delivery scenario [3]. Thus providing VANETs with an adequate level of security is essential [4]. The trust management mechanism (TMM) is a powerful tool for building trust and ensuring real-time communication between nodes in VANETs. Compared to centralized trust management mechanisms (CTMM), distributed trust management mechanisms (DTMM) do not require nodes to request trust data from the server and calculate trust values locally based on criteria and recommendations, which achieves shorter processing times and greater applicability [5].

However, due to the lack of a global management policy in DTMM, nodes can only maintain their locally calculated or accepted trust values. And since it requires some time for a node to propagate its calculated trust values to other nodes, malicious nodes that have been detected can move to a new region to masquerade as normal nodes. Most existing works on trust management mechanisms do not consider active collaboration as a mode of attack, where malicious nodes collude to increase their trust values or deliberately decrease the trust values of normal nodes.

To solve to above problems, a novel trust management mechanism called ATM (Active detection Trust Management) is proposed to integrates active detection and blockchain techniques. VANET area is divided into multiple regions, with each region assigned one or more primary servers to compensate for the limited transmission distance of a single server. To avoid clusters instability, the servers' location in each region is fixed. A node actively broadcasts probe packets to its surrounding nodes, asking them to forward the packets to a nearby road side unit (RSU). The node calculates the direct trust between them based on the feedback received from the RSU and uses it to determine whether the detected node has abnormal behaviors. Then, the node requests the reference trust values from its neighbors with normal behaviors and select a node with highest reference trust value to transmit data based on median absolute deviation (MAD). Finally, blockchain technology is utilized to ensure the consistency of trust value information across different regions and to prevent tampering with trust values effectively.

To avoid error replies caused by multiple copies of the same packet, which can cause the incorrect calculations of trust values, each type of packet will be processed only at its first arrival. Encounter records (ER) including success encounter record (SER) and failure encounter record (FER) are used to record interactions between nodes.

Each block contains a block head and a block body. The head encapsulates the information such as previous block address and timestamp, etc. The body mainly records detailed transaction information such as the ID, the trust value, and the node type. When primary servers receive the updated trust values of nodes, they update these trust values based on the history values stored in the blockchain. The updated values of all nodes will be judged with the trust threshold value. If it is less than the trust threshold value, the type of certain nodes will be set to malicious and the Blockchain Reset Mechanism (BRM) will be triggered. And the blacklist will be updated and broadcasted to all normal nodes by RSUs. BRM is used to eliminate the cumulative number of failures between normal nodes over a long period, and the high success factor between malicious nodes. Malicious nodes disguise themselves as normal nodes in the early stage to accumulate trust values. After having enough trust value, they start to commit malicious behaviors, which can lead to disastrous consequences. The high historical trust value and expectation can keep them from being recognized for a long time. Through BRM, periodically restore the corresponding parameters, making ATM more likely to detect each malicious behavior successfully.

Extensive simulations have evaluated the performance of the proposed scheme. The simulation results show that the proposed ATM scheme perform well in the detection accuracy, delivery ratio, and trust value compared with other trust management schemes.

In summary, this paper designed an efficient active-detection trust management mechanism named ATM to provide adequate levels of security. The active detection is utilized to proactively detect possible malicious nodes in the surrounding area to improve the ability of filtering malicious nodes without the assistance of central servers. And MAD is used to eliminate outliers in the neighbor reference trust values. Moreover, blockchain is used to record trust value information to ensure the consistency of trust information across different regions.

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MMTC examines systems, applications, services and techniques in which two or more media are used in the same session. These media include, but are not restricted to, voice, video, image, music, data, and executable code. The scope of the committee includes conversational, presentational, and transactional applications and the underlying networking systems to support them.