IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal
SPECIAL SECTION ON URBAN COMPUTING AND INTELLIGENCE

Received August 14, 2019, accepted September 5, 2019, date of publication September 19, 2019, date of current version October 3, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2942391

Energy-Efficient Joint Resource Allocation Algorithms for MEC-Enabled Emotional Computing in Urban Communities

ZIYAN YANG[1], YAO DU[2], CHANG CHE[2], WENYONG WANG[1], HAIBO MEI[2], DONGDAI ZHOU[1], AND KUN YANG[3], (Senior Member, IEEE)
[1]School of Information Science and Technology, Northeast Normal University, Changchun, China
[2]School of Information and Communication Engineering, University of Electronic Science and Technology of China, Chengdu 611731, China
[3]School of Computer Science and Electronic Engineering, University of Essex, Colchester CO4 3SQ, U.K.

Corresponding author: Haibo Mei (haibo.mei@uestc.edu.cn)

This work was supported in part by the Natural Science Foundation of China under Grant 61572389 and Grant 61620106011, and in part by the Zhongshan City Team Project under Grant 180809162197874.

ABSTRACT This paper considers a mobile edge computing (MEC) system, where the MEC server first collects data from emotion sensors and then computes the emotion of each user. We give the formula of the emotional prediction accuracy. In order to improve the energy efficiency of the system, we propose resources allocation algorithms. We aim to minimize the total energy consumption of the MEC server and sensors by jointly optimizing the computing resources allocation and the data transmitting time. The formulated problem is a non-convex problem, which is very difficult to solve in general. However, we transform it into convex problems and apply convex optimization techniques to address it. The optimal solution is given in closed form. Simulation results show that the total energy consumption of our system can be effectively reduced by the proposed scheme compared with the benchmark.

INDEX TERMS Internet of Things, emotional computing, mobile edge computing (MEC), resources allocation.

I. INTRODUCTION

With the change of time, a great leap in human society is the emergence of cities. In the modernization, the city is not only a two-dimensional static plan but also a more systematic, dynamic and comprehensive social network. A certain number and quality of artisans and merchants from all walks of life who live in cities are separated from agriculture and engaged in some commercial or industrial activities, forming urban communities.

People live in this huge network, interwoven and harmonious. As a new computing technology, artificial intelligence algorithm is rising. And digitization, networking and informatization are also increasingly integrated into people's life, which fundamentally change the living state of human beings [1]. In the network, big data, Internet of things, and the support of technologies such as artificial intelligence develop rapidly, as far as possible to meet the diverse needs of people, enhance and improve people's living conditions. For example, unmanned aerial vehicle (UAV) is a kind of intelligent product [2]. It will be used in big data analysis, mobile Internet, sensor technology to meet the needs of people. And there are many other application scenarios such as smart homes, smart grid, wearable devices and traffic monitoring equipment, etc.

With intelligence entering into every aspect of life, people put forward higher requirements for it, hoping to gain the ability to perceive and calculate human emotions. For example, the elderly are one of the focuses of modern society. Shall we design some emotional products to take care of the elderly under modern technology [3]? Can the computer understand the emotions of the elderly as they interact with the computer? In the ubiquitous computing environment, computing will be introduced into people's daily life and people can access computing and information services at any time. Pervasive computing emphasizes user-centered computing theory. Computing should meet people's habits and actively interact with users so that users can concentrate on completing tasks [4].

Under the demand of this era, emotional computing comes into being. It is aimed to study human interaction and the emotional interaction process between human and computer.

The associate editor coordinating the review of this manuscript and approving it for publication was Lu Liu.

In the calculation, emotional perception sensors and other tools are used to collect some physiological indicators of human, such as human expression, behavior and electroencephalogram (EEG) signals. Inter-personal human communication includes verbal as well as non-verbal cues such as hand gestures, facial expressions and verbal tones that express emotions. The autonomous recognition of emotions can potentially enhance the human-computer interface. The growing interest in this field has led to the development of emotional computation, which is a branch of artificial intelligence that designs computer systems that recognize, interpret and process human emotions [5]. These indicators are transmitted to the mobile edge computing (MEC) server through communication technology, where physiological data are classified and recognized, and emotional calculation is carried out by adopting emotional analysis method based on deep learning, so as to judge and obtain users' emotional state.

MEC is a cloud-based technology that combines mobile computing, cloud computing and wireless network to provide rich computing resources for mobile users. The Multi-Layer Perception (MLP) is an effective deep learning method to collect and analyze film reviews from the Internet Movie Database (IMDB) [6]. There are altogether 25,000 pieces of IMDB film review data. After reading the data, one need to do some processing on the data. For emotional analysis, the program adopts python language, Keras as the deep learning framework and TensorFlow as the back-end, and runs on a GPU server.

The collected data is transmitted over a wireless channel to a MEC server, where the data is used for emotional computing. The relationship between the computational complexity of emotion analysis and prediction accuracy is fitted. Fitting is to find a simple and reasonable function approximate expression to fit the given data from a given set of data. In this paper, we adopt the linear fitting method to fit the relationship between the computational complexity of emotion analysis and prediction accuracy. Computational complexity is calculated by computational iteration time. The more data collected, the more accurate the calculation is, but the energy consumption will be greater and the transmission time will be longer. Compared with traditional network protocols such as TCP/IP to transmit data over network media, this model has the advantages of maximum energy saving, integrated communication and computing, and minimizes the total energy consumption and total latency of MEC servers and sensors by jointly optimizing computing resource allocation and data transmission time.

As illustrated in Fig. 1, in this paper, we investigate the MEC-enabled emotional computing. There is one MEC server and multiple emotion sensors, which are installed on the Internet of things devices (IoTDs) and can collect emotional data from users. We study how the MEC server can optimally allocate its computing resources. According to the emotional prediction accuracy requirement, we provide the optimal transmission scheduling scheme for the proposed system.

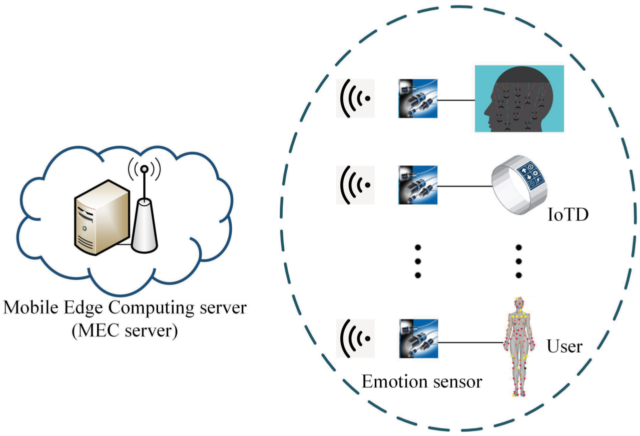

FIGURE 1. The MEC-enabled emotional computing.

Our optimization goal is to minimize computational and communication energy consumption while processing all emotional computational data. Our contributions are summarized as follows:

- Deep learning method is used to collect and analyze IMDB movie reviews, and then the collected data are transmitted to the MEC server through wireless channels;
- Emotional calculation is carried out in MEC server to fit the relationship between computational complexity of emotional analysis and prediction accuracy. Computational complexity is selected as computational iteration time. The longer the computing time, the more accurate the calculation will be.
- We formulate the emotional computing problem as a non-convex problem which is further converted into convex problems. Using convex optimization techniques such as interior point method and Lagrangian dual method, the proposed algorithm performs better than the benchmark, and the simulation results show that it is very energy-efficient.

The rest of this article is organized as follows. Section II introduces the related work of emotion perception and prediction. In Section III, the system model and optimization problem are constructed. We also study the emotional sensing and prediction in Section IV. Also, we give the formula of the emotional prediction accuracy. In Section V, resources allocation algorithms are proposed to solve the problem. Section VI gives the simulation results. Finally, the paper is summarized in Section VII.

II. RELATED WORKS

Emotion, as a subjective cognitive concept in the traditional sense of human society [7], gradually shows its unity, versatility and importance in cyberspace and human society with the rapid development of Internet technology [8]. The psychology was applied to the research of emotional computing in the

19th century, and much progress has been made in the field of emotions sensing and processing in the last decades [9]. Researchers promote the related research from the subjective experiment of psychology to the emotional computing of cyberspace big data [10]. The core problem of emotional computing is to add elements of subjective cognition to classical logic computing, which requires understanding the cognitive behavioral mechanisms of humans [11].

According to the types of data that need to be processed, the emotional computing can be divided into four types: text-based emotional analysis, audio-based emotional analysis, image-based emotional analysis and video-based emotional analysis. Acoustic features for speech emotion recognition include acoustic features (e.g., tone, timbre, length) and sentence features (e.g., speech speed, frequency, spectral energy). Moreover, most of the face emotion recognition is based on low-level features (e.g., color, texture, shape). The image content including the picture of face and skin is called high-level features. In the field of emotional computing, a large number of literatures have made different contributions. The current emotional computing research differs in theory, algorithm and application environment, etc.

An image sentiment calculation model based on PMJ model is proposed in the literature [11]. The cognitive process is summarized as perception, memory and judgment, corresponding to the analysis, modeling and decision-making of the calculation process. A three-stage and multi-path processing framework combining cognition and computation is clarified.

As for the algorithms, each sample can be represented by its nearest k neighbors in the method of k-nearest-neighbor (KNN) [12]. If a sample has a majority of the k nearest neighbors in the feature space belonging to a certain category, the sample is also classified into this category. Therefore, the selected neighbors are all objects that have been correctly classified in KNN. Linear Discriminant Classifiers (LDC) makes classification based on the value obtained from the linear grouping of the feature values [13]. Support vector machine (SVM) constructs the optimal hyperplane as the decision surface to maximize the separation margin between the two classes in the data [14]. SVM can be divided into two major categories, linear and nonlinear. It is aimed to find a hyperplane in space that can slap all data samples, and to make the distance of all data in the set to this hyperplane the shortest. Artificial neural networks (ANN) are a kind of computational models [15]. The learning of neural networks, also known as training, adjusts the free parameters of neural networks (such as connection weights) through the stimulation of the environment in which the neural network is located, so that the neural network reacts to the external environment in a new way. The Back Propagation (BP) is a famous algorithm of ANN. It is composed of two processes: forward propagation of the signal and back propagation of the error. The process of weight adjustment of each layer of signal forward propagation and error backpropagation is repeated and the process of constant adjustment of weights is the learning and training process of the network. When it comes to the future of ANN, some algorithms will be applied, in which convolutional neural networks and deep learning are the most potential way to be widely applied [16], [17].

In the supervised learning algorithm of machine learning, our goal is to get a stable model that performs well in all aspects, but the actual situation is often not so ideal and sometimes we can only get multiple models with preferences. The ensemble learning [18] is to combine multiple weak monitoring models here in order to get a better and more comprehensive strong monitoring model. For example, Derakhshani and Lovelace created an ensemble way to sort startle eyeblink out from video records shot in a high speed [19].

As for the accuracy of different models in scientific research [20], Kahou et al. got an accuracy of 47.67% by proposing two different models for audio and video [21]. Jiang et al. achieved an accuracy of 66.54% by using a triple-stream Deep Belief Network (DBN) model to recognize the extracted speech features and image features [22]. Kim et al. got an accuracy around 70.46% to 73.78% by proposing an expression recognition system with DBN [23]. Hossain et al. achieved an accuracy of 84% by proposing a Multi-Directional Regression (MDR) and an SVM-based bimodal emotion classification system [24]. An accuracy of 83.06% was achieved in his another work in which MDR was used to extract speech features and the ridgelet transform was used to extract image features [25]. Zhang et al. achieved 85.97% by using a pretrained 2D CNN model for speech and a pretrained 3D CNN model for visual images [26].

As the combination of artificial intelligence and emotional computing, JIBO [27] is one of the major applications developed by MIT Lab of Robotics. With the help of emotional computing, it could response to the users according to their emotions. It could do what other voice assistants do and behave like a cartoon character.

In recent years, the era of the Internet of Everything has brought new demands for data transmission bandwidth, delay, and service performance and reliability. It is estimated that in the near future, tens of billions of edge devices will be deployed, and their processor speed will also increase exponentially according to Moore's Law [28]. By integrating these large amounts of free computing power and storage space distributed at the edge of the network to provide computing and storage support for mobile devices seamlessly, a new computing pattern, Mobile Edge Computing (MEC), was proposed.

With MEC technology, mobile users have richer computational resources to finish their tasks. What deserves our attention is that mobile computing, cloud computing and wireless networks are no longer separated. It really does good to end devices because they will have lower power consumption and better performance. With MEC technology, it is no longer necessary to perform emotional analysis calculation on a large computer as before [29].

A very important area of research in edge computing is how to coordinate the computing resources of edge nodes [30].

To ensure that all users who wish to use MEC resources are able to get ubiquitous services, MEC servers and compute/storage resources should be distributed throughout the edge network. Therefore, MEC servers should be complemented in a hierarchical manner in the placement of physical locations, which will enable efficient use of computing resources and storage resources, while greatly meeting the requirements of user quality of service (QoS) and quality of experience (QoE). In this context, an important challenge is to find the best way to physically place an edge computing server based on expected user needs, while considering operational costs.

According to [31], the offloading design and resource allocation are very critical to the energy consumption control of MEC systems. Researchers in [32] designed different resources allocation schemes for computational resource and radio resource in edge networks. For the minimization of energy consumption, [33] assumed that the communication is at a fixed rate in order to make a feasible computation offloading decision. However, the transfer rate is not constant actually. An optimal binary computation offloading decision was proposed in [34], where power-rate function was given to settle the problem. But it cannot be applied to dynamic systems due to the random changes in the wireless communication.

The design of energy-efficient MEC requires the joint allocation of communication and computation resources [35]. To minimize the delay in a single-user MEC system, [36] worked on optimal offload control and resource allocation for multiple tasks. [37] worked similarly to minimize the energy consumption but for a single task. [38] proposed a multi-user system and worked on optimal task splitting and resource allocation to minimize the mobile energy consumption.

Now we creatively apply the emotional calculations we talked about to towns. However, in terms of resource allocation, the above-mentioned literatures have only considered the resources of calculation and have not considered the resources of communication. And most of them are for single users rather than multiple users [39].

This paper will propose a joint community consideration of computing and communication resources, multi-user, urban community emotional computing scheme using MEC technology.

III. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a MEC-enabled emotional computing system, as illustrated in Fig. 2. Without loss of generality, a two-dimensional (2D) Euclidean coordinate is adopted. We define O as the geometric center of all the sensors. The location of each i-th sensor is given as (x_i, y_i), $i \in \mathcal{N} = \{1, 2, \ldots, N\}$. Also, we assume that the location of the MEC server is fixed at (X, Y). Each sensor uploads its data and waits for the executions from the MEC server. In our proposed system, sensors transmit their data simultaneously by using FDD technique. Once received the data, the MEC server performs the computing task.

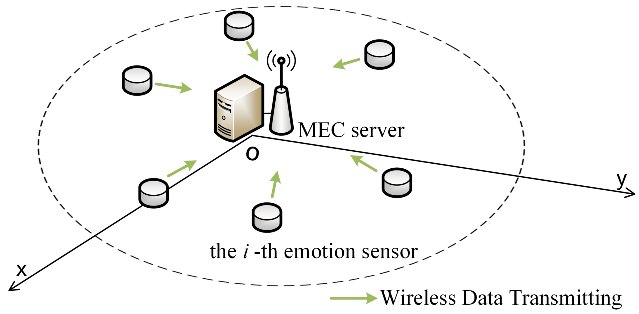

FIGURE 2. The proposed MEC-enabled emotional computing system.

A. TASK MODEL

We define D_i as the amount of the transmitted data from each i-th sensor to the MEC server and F_i is the total number of the CPU cycles that the MEC server costs to process the data. Thus, one can express the task from each i-th sensor as (D_i, F_i, t_i^{qos}), $\forall i \in \mathcal{N}$, where $F_i = \phi D_i$. The parameter ϕ can be obtained by using the approaches provided in [40].

We assume all the uploading and computing process for each sensor have to be completed in t_i^{qos}, then one has

$$t_i^c + t_i^u \leq t_i^{qos}, \quad \forall i \in \mathcal{N} \tag{1}$$

The time used to send the data from each i-th sensor to the MEC server is

$$t_i^u = \frac{D_i}{r_i}, \quad \forall i \in \mathcal{N} \tag{2}$$

We define $\frac{B}{N}$ as the channel bandwidth of each i-th sensor and p_i as the transmitting power of each i-th sensor, σ^2 as the noise power at the receiver of each sensor. The channel power gain of each i-th sensor in each j-th hovering place is [41]

$$h_i = \frac{h_0}{(X - x_i)^2 + (Y - y_i)^2} \tag{3}$$

where the h_0 represents the received power at the reference distance $d_0 = 1$ m. In each j-th hovering place, the achievable uplink data rate for each i-th sensor to the MEC server is given by

$$r_i = \frac{B}{N} \log_2 \left(1 + \frac{p_i h_i}{\sigma^2}\right), \quad \forall i \in \mathcal{N} \tag{4}$$

Moreover, the MEC server should receive enough emotional data of human beings in order to predict an accurate emotion. Thus, one can have

$$\alpha_i \geq \varepsilon_i, \quad \forall i \in \mathcal{N} \tag{5}$$

For each i-th sensor, we define α_i as the accuracy of the emotional prediction and ε_i is the minimum accuracy requirement. We fit the function of the emotional prediction accuracy as

$$\alpha_i = \zeta D_i + \beta, \quad \forall i \in \mathcal{N} \tag{6}$$

The detailed method of the fitting and the value of the linear parameters will be given in Section IV.

Furthermore, the required time for each i-th sensor's data processing at the MEC server is

$$t_i^c = \frac{F_i}{f_i}, \quad \forall i \in \mathcal{N} \tag{7}$$

The MEC server allocates its computing resources to all sensors. Thus, one can have

$$\sum_{i=1}^{N} f_i \le f_{max}, \quad \forall i \in \mathcal{N} \tag{8}$$

where f_i is the actual computation resource allocated by the MEC server. We define that f_{max} is the maximum computing capacity of the MEC server.

B. ENERGY CONSUMPTION MODEL OF THE SYSTEM

The energy consumption model of the emotional computing system consists of two parts, i.e., the computing energy of the MEC server and the wireless communication energy of sensors. We define the computing energy consumption of the MEC server for each task as $\kappa_i (f_i)^{\gamma_i} t_i^c$, where $\kappa_i \ge 0$ is the effective switched capacitance and γ_i is the positive constant. To match the realistic measurements, we set $\gamma_i = 3$ [42] here. The wireless communication energy of sensors is given as $\sum_{i=1}^{N} p_i t_i^u$. Thus, the total energy consumption (denoted by E) of the system can be given as

$$E = \sum_{i=1}^{N} p_i t_i^u + \sum_{i=1}^{N} \kappa_i (f_i)^{\gamma_i} t_i^c \tag{9a}$$

$$= \sum_{i=1}^{N} p_i t_i^u + \sum_{i=1}^{N} \kappa_i F_i f_i^2 \tag{9b}$$

$$= \sum_{i=1}^{N} p_i t_i^u + \sum_{i=1}^{N} \kappa_i \phi D_i f_i^2 \tag{9c}$$

$$= \sum_{i=1}^{N} p_i t_i^u + \sum_{i=1}^{N} \kappa_i \phi r_i t_i^u f_i^2 \tag{9d}$$

C. PROBLEM FORMULATION

Assume that the locations of the sensors and the UAV's hovering places are fixed and known [43]. Let $\boldsymbol{F} = \{f_i, \forall i \in \mathcal{N}\}$ and $\boldsymbol{T} = \{t_i^u, \forall i \in \mathcal{N}\}$. In the optimization problem below, we aim to jointly optimize the computing resources allocation (i.e., $\boldsymbol{F}$) and the data transmitting time (i.e., $\boldsymbol{T}$). Then, the optimization problem is formulated as

$$\mathcal{P}1: \ \underset{\boldsymbol{F},\boldsymbol{T}}{\text{minimize}} \ E \quad \text{s.t. (1), (5), (8)} \tag{10}$$

Notice that $\mathcal{P}1$ is a mixed-integer non-convex problem, which is difficult to find the optimal solution. We next transform $\mathcal{P}1$ into two convex problem, and we also develop an iterative algorithm to find the optimal solution.

TABLE 1. Results obtained based on MLP.

Iterations Number	Time (seconds)	Accuracy
1	3	81.86%
2	5	83.86%
3	7	84.72%
4	9	85.54%
5	11	85.91%
6	13	86.59%
7	15	86.85%
8	17	87.14%

IV. EMOTION SENSING AND PREDICTION

In order to complete the sensing and prediction of emotions with a small resource consumption, this section will fit the relationship between the amount of emotion analysis calculation data and the prediction accuracy. We will choose emotional analysis method based on deep learning to analyze IMDB movie reviews. The code of emotion analysis program is derived from a GitHub project [44], which is using the Python language, the deep learning framework Keras, with TensorFlow back end, running on the GPU server TITAN X, and the maximum calculation frequency is 2G cycles per second. The data set of IMDB is derived from website [45].

A. DATA PREPROCESSING

This data preprocessing method comes from the GitHub author [44]. There are 25,000 IMDB movie comments in total. In the data format, review refers to the comment text and sentiment refers to emotional classification label, in which 1 represents the positive and 0 represents the negative. After loading the data, we need to do some processing on the data, such as filtering out some non-ASCII characters, cleaning out some newline characters, and converting uppercase letters to lowercase, etc. Then we serialize the data and unify the length. The sentence length is unified to 1000 by rounding overage or padding 0. After that, we randomly scramble the data and divide it into training and validation sets (segment ratio 8:2). The index after serializing the data corresponds to the word Embedding of the words by using love.6B.100d, that is, each word is represented by a 100-dimensional vector.

B. FITTING DATA

The classification of IMDB based on MLP is a simple neural network application. After getting the word vector, we directly input it into the MLP network and perform softmax classification after multi-layer MLP training. The fitting will be based on the averaged data after using MLP. The results obtained based on this method are shown in the Table. 1.

Then we fit the time and the accuracy. It can be seen from Tab. 1 that the accuracy rate increases gently with the time passing by. Therefore we try to make a linear fit by least squares and the result of the linear fitting is as Fig. 3.

The linear formula is

$$\alpha = 0.0034 t^c + 0.8186 \tag{11}$$

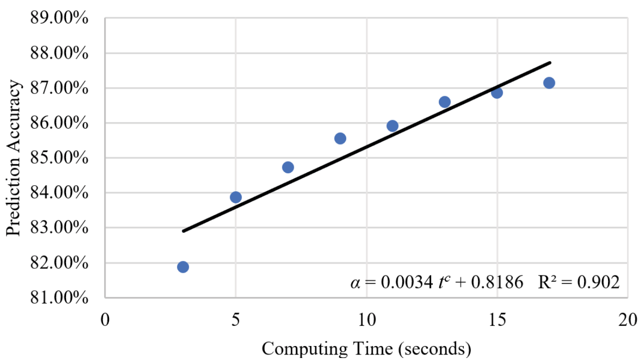

FIGURE 3. Linear fitting between the computing time and the prediction accuracy.

$R^2 = 0.902$ is the accuracy of the linear fitting. Therefore the fitting makes sense. In this paper, we choose the MLP method because it is both accurate and practical. Firstly, the accuracy of the MLP method is 0.902, which means the performance of MLP is very good. Moreover, compared with the other fitting methods, the MLP method is very simple and it has a very good structure to design an efficient algorithm. Therefore, the MLP method based fitting is very practical for engineering application.

According to the system model, we can further get the function between accuracy and the amount of data.

$$\alpha_i = 0.0034 \times \frac{\phi}{f} \times D_i + 0.8186 \quad (12)$$
$$= 1.7 \times 10^{-9} D_i + 0.8186 \quad (13)$$

V. RESOURCES ALLOCATION ALGORITHM

In this section, we investigate how can the MEC server allocate its computing capacity optimally. Moreover, we provide the system with optimal transmitting scheduling scheme. The optimal transmitting time of each sensor is given according to the emotional prediction accuracy.

A. RESOURCES ALLOCATION

Given any transmitting time $\boldsymbol{T}$, $\mathcal{P}1$ is reformulated as

$$\underset{\boldsymbol{F}}{\text{minimize}} \sum_{i=1}^{N} \kappa_i \phi r_i t_i^u f_i^2 \quad (14a)$$
$$\text{s.t.} \quad f_i \geq \frac{\phi r_i t_i^u}{t_i^{qos} - t_i^u}, \quad \forall i \in \mathcal{N} \quad (14b)$$
$$(8)$$

The constraint (14b) is obtained by simplifying the constraint (1). The objective function (14) is the sum of N convex functions and the constraint functions of (14b) and (8) are also convex. Therefore, problem (14) is a convex problem and can be solved by applying convex optimization technique such as the interior-point method [46]. To gain more insight, we next use the Lagrange dual method to obtain a well-structured solution for gaining essential engineering insights.

The Lagrange multipliers associated with the constraints (8) and (14b) are given as $\lambda(\lambda \geq 0)$ and $\boldsymbol{\mu} \triangleq \{\mu_i \geq 0, \forall i \in \mathcal{N}\}$, respectively. Thus, the Lagrangian function of problem (14) is

$$L(\boldsymbol{F}, \lambda, \boldsymbol{\mu}) = \sum_{i=1}^{N} k_i \phi r_i t_i^u f_i^2 + \lambda(\sum_{i=1}^{N} f_i - f_{max}) + \sum_{i=1}^{N} \mu_i (\frac{\phi r_i t_i^u}{t_i^{qos} - t_i^u} - f_i), \quad \forall i \in \mathcal{N} \quad (15)$$
$$= \sum_{i=1}^{N} [k_i \phi r_i t_i^u f_i^2 + (\lambda - \mu_i) f_i] - \lambda f_{max} + \sum_{i=1}^{N} \frac{\mu_i \phi r_i t_i^u}{t_i^{qos} - t_i^u}, \quad \forall i \in \mathcal{N} \quad (16)$$

Therefore, the KKT conditions are, for $i = 1, 2, \ldots, N$,

$$\frac{\partial L}{\partial f_i} = 2k_i \phi r_i t_i^u f_i + \lambda - \mu_i = 0 \quad (17)$$
$$\lambda(\sum_{i=1}^{N} f_i - f_{max}) = 0 \quad (18)$$
$$\mu_i (\frac{\phi r_i t_i^u}{t_i^{qos} - t_i^u} - f_i) = 0 \quad (19)$$
$$\sum_{i=1}^{N} f_i - f_{max} \leq 0 \quad (20)$$
$$\frac{\phi r_i t_i^u}{t_i^{qos} - t_i^u} - f_i \leq 0 \quad (21)$$
$$\lambda \geq 0 \quad (22)$$
$$\mu_i \geq 0 \quad (23)$$

From equation (18) and (20), one can notice that, once the MEC server provides sensors with enough computing resources, then $\sum_{i=1}^{N} f_i - f_{max} \leq 0$.

If $\sum_{i=1}^{N} f_i - f_{max} < 0$, then $\lambda = 0$. According to equation (17), $2k_i \phi r_i t_i^u f_i - \mu_i = 0$. One can notice that $2k_i \phi r_i t_i^u f_i > 0$. Therefore, one can have $\mu_i = 2k_i \phi r_i t_i^u f_i > 0$. Thus, $\frac{\phi r_i t_i^u}{t_i^{qos} - t_i^u} - f_i = 0$.

Moreover, if $\sum_{i=1}^{N} f_i = f_{max}$, then $\lambda > 0$. And we have $\mu_i > 0$ because of equation (17). Thus, according to equation (19), one can obtain $\frac{\phi r_i t_i^u}{t_i^{qos} - t_i^u} - f_i = 0$. Finally, the optimal resources allocation is given as

$$f_i^* = \frac{\phi r_i t_i^u}{t_i^{qos} - t_i^u}, \quad \forall i \in \mathcal{N} \quad (24)$$

B. TRANSMITTING SCHEDULING

Given any resources allocation $\boldsymbol{F}$, $\mathcal{P}1$ is reformulated as

$$\underset{\boldsymbol{T}}{\text{minimize}} \sum_{i=1}^{N} p_i t_i^u + \sum_{i=1}^{N} \kappa_i \phi r_i t_i^u f_i^2$$
$$\text{s.t.} \quad (1), (5) \quad (25)$$

For brevity, we simplify problem (25) as

$$\underset{\boldsymbol{T}}{\text{minimize}} \sum_{i=1}^{N}(p_i + \kappa_i \phi r_i f_i^2) t_i^u \tag{26a}$$

$$\text{s.t.} \quad \frac{\varepsilon_i - \beta}{\zeta r_i} \le t_i^u \le \frac{f_i t_i^{qos}}{f_i + \phi r} \tag{26b}$$

Note that the constraint (26b) is obtained by simplifying and combining constraints (1) and (5). One can notice that problem (26) is a linear programming (LP) problem, which can be solved by the well established optimization toolbox, e.g., CVX [47] optimally and efficiently. However, in this paper, the optimal transmitting time can be obtained quickly by the following calculation.

Problem (26) can be decomposed into N linear problems

$$\underset{\boldsymbol{T}}{\text{minimize}} \ (p_i + \kappa_i \phi r_i f_i^2) t_i^u \tag{27a}$$

$$\text{s.t.} \quad (26b) \tag{27b}$$

We know that the optimal solution of a linear problem can be always obtained at its boundary. Thus, the optimal solution of this minimization problem is obtained at the lower bound $\frac{\varepsilon_i - \beta}{\zeta r_i}$. Therefore, on can have

$$t_i^{u*} = \frac{\varepsilon_i - \beta}{\zeta r_i}, \quad \forall i \in \mathcal{N} \tag{28}$$

C. ENGINEERING INSIGHTS AND OVERALL ALGORITHM

In this subsection, we gain engineering insights of our proposed optimal solution. Moreover, we propose a very simple and efficient overall algorithm for the proposed non-convex problem.

Firstly, we give the iterative algorithm for the joint optimization problem as Algorithm 1.

Algorithm 1 The Iterative Algorithm for $\mathcal{P}1$

1: **Initialize** : $\boldsymbol{T}^0$ and let $k = 1$;
2: **Repeat** :
3: Use equation (24) to obtain $\boldsymbol{F}^k$;
4: Use CVX tool box to obtain $\boldsymbol{T}^k$;
5: Update $k = k + 1$;
6: **Until** : the fractional decrease of E is below a threshold ε or a maximum number of iterations ($k_{\max}$) is reached;
7: **Return** : The optimal computing resource allocation $\boldsymbol{F}^*$ and the optimal transmitting scheduling $\boldsymbol{T}^*$ for sensors.

For the non-convex problem, if the object function of the original problem is not block multi-convex [48], the result of the conventional iterative method (i.e. block-coordinate descent method) is relevant to the initial iteration point. However, in this paper, we have obtained the optimal solutions of two convex problems. Which means we can use the optimal solution $\boldsymbol{T}^*$ as the initial iteration point and then we can directly obtain the other optimal solution $\boldsymbol{F}^*$.

Therefore, for the computing resource allocation, we substitute the optimal t_i^{u*} into equation (24), and we have

$$f_i^* = \frac{\phi r_i(\varepsilon_i - \beta)}{\zeta r_i t_i^{qos} - \varepsilon_i + \beta}, \quad \forall i \in \mathcal{N} \tag{29}$$

Thus, we can obtain the overall algorithm (i.e., Algorithm 2) for the non-convex $\mathcal{P}1$ due to the closed form formulas (28) and (29).

Algorithm 2 Overall Algorithm for $\mathcal{P}1$

1: Use equation (28) to obtain the optimal $\boldsymbol{T}^*$;
2: Use equation (29) to obtain the optimal $\boldsymbol{F}^*$;
3: **Return** : The optimal computing resource allocation $\boldsymbol{F}^*$ and the optimal transmitting scheduling $\boldsymbol{T}^*$ for sensors.

One can notice that Algorithm 2 is much simpler than Algorithm 1 and it is very convenient for engineering application. Furthermore, according to equation (29), one can see that, the computing frequency will increase when the required emotional computing accuracy increases. Moreover, the QoS time is another important parameter to the optimal resources allocation scheme. When sensors require a strict QoS to enable the emotional prediction application, we need more computing resources so the f_i^* increases.

For the transmitting scheduling, according to equation (28), when the emotional prediction accuracy requirement ε_i increases, the transmitting time increases. Which means the MEC server needs more data to do the emotional prediction.

VI. SIMULATION RESULTS

In this section, we provide the simulation results to demonstrate the effectiveness of the proposed algorithm. We consider the system with one MEC server and multiple users, which are randomly and uniformly distributed within a 2D area of 100 × 100 m^2. Considering the statistic relevance of the simulation, the results in Section VI are obtained by 1000 simulation runs with random locations of the sensors. We set the channel power gain at the reference distance of 1 m as - 30 dB and the noise power at each sensor as - 60 dBm. The transmission power of each sensor is set as 200 mW. We set the effective switched capacitance $\kappa_i = 10^{-30}$ to match the realistic measurement. We run all the simulation on the computer with the 2.90 GHz CPU and 12 GB RAM. The simulation software is Matlab 2015a running on Windows 10.

In Fig. 4, we show the energy efficiency of our proposed algorithms. We set the system bandwidth as 2G Hz and the QoS requirement as 10 seconds. In the benchmark, the MEC server uses equal computing resource to predict each user's emotion. One can see that, with the increasing of the accuracy requirement, the energy consumption increases, as expected. Also, with the increasing of the number of sensors, the energy consumption of our proposed system increases, as expected.

However, one can see that the energy consumption of the average allocation scheme decreases, which is because the

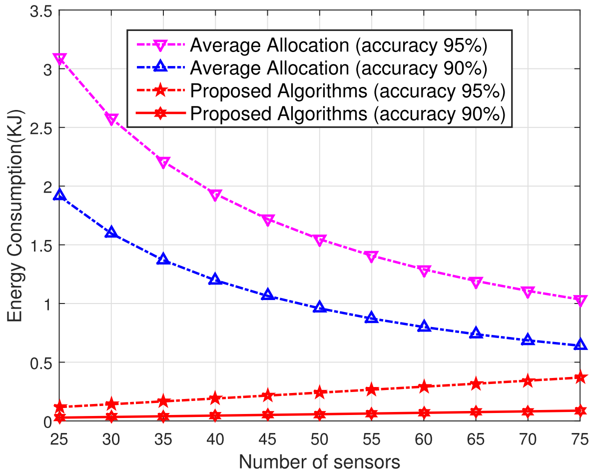

FIGURE 4. The system energy consumption versus the number of sensors.

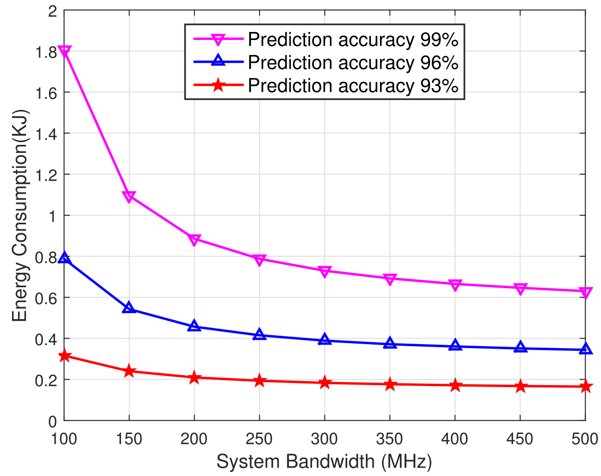

FIGURE 6. The system energy consumption versus the bandwidth *B*.

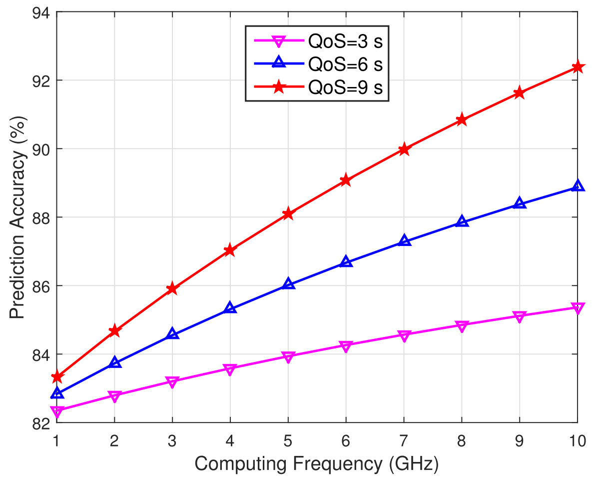

FIGURE 5. The average emotional prediction accuracy versus the average computing frequency of all sensors.

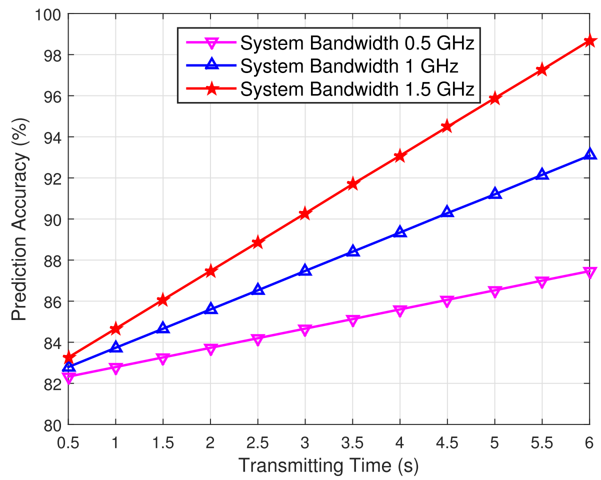

FIGURE 7. The average emotional prediction accuracy versus the average transmitting time of sensors.

computing capacity allocated to each sensor decreases and the benchmark will no longer meet the prediction accuracy requirement. Thus, the benchmark consumes more energy but still fails to meet the accuracy requirement of the emotional prediction. Therefore, our proposed algorithm outperforms the benchmark and it is very energy-efficient.

In Fig. 5, we set the system bandwidth as 2G Hz and the number of emotion sensors as 1000. One can see that, with the increasing of the QoS time, which is the time that our proposed system consumes to obtain the emotion of all users, the emotional prediction accuracy increases, as expected. Also, with the increasing of the average computing frequency, the average emotional prediction accuracy increases, as expected.

In Fig. 6, we set the number of emotion sensors as 50. One can see that, with the increasing of the system bandwidth, the energy consumption of our proposed system increases, as expected. Also, with the increasing of the accuracy requirement, the energy consumption increases, as expected.

In Fig. 7, we set the number of emotion sensors as 1000. One can see that, with the increasing of the system bandwidth, the emotional prediction accuracy of our proposed system increases, as expected. Also, with the increasing of the average transmitting time, the average emotional prediction accuracy of all users increases, as expected.

In Fig. 8, we set the number of emotion sensors as 500. One can see that, with the increasing of the QoS requirement, the energy consumption of our proposed system increases, as expected. Furthermore, with the increasing of the emotion prediction accuracy, the energy consumption of our proposed system also increases, as expected.

In Fig. 9, we show the time efficiency of our proposed overall algorithm (i.e., Algorithm 2). We compare the running time of Algorithm 1 and Algorithm 2. One can see that, with the increasing of the number of sensors, the running time saved increases, as expected. Therefore, our proposed overall algorithm is more efficient than the conventional iterative algorithm (i.e., Algorithm 1). Thus, our proposed overall algorithm is very convenient for engineering application.

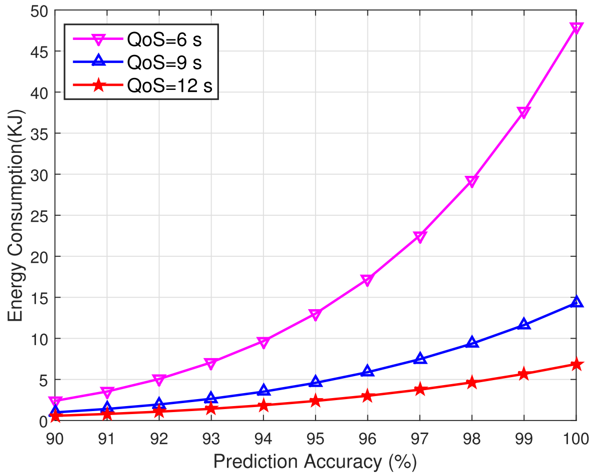

FIGURE 8. The system energy consumption versus the prediction accuracy α.

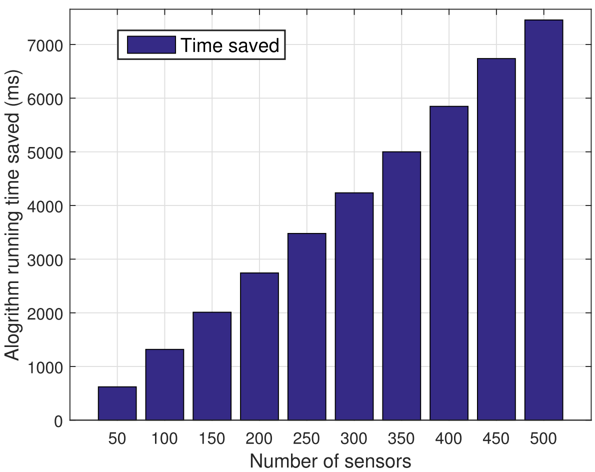

FIGURE 9. The average running time saved versus the number of sensors.

VII. CONCLUSION

In this paper, we perform emotion computing by using MEC technique. The formula of the emotional prediction accuracy is given. The closed form optimal solutions and the computing resource allocation algorithm are proposed. Thus, we minimize the total energy consumption in the communication and computing process. Simulation results show that the proposed scheme outperforms the benchmark and it improves the system performance and saves the total energy consumption.

REFERENCES

[1] V. Kanimozhi and T. P. Jacob, "Artificial intelligence based network intrusion detection with hyper-parameter optimization tuning on the realistic cyber dataset CSE-CIC-IDS2018 using cloud computing," in *Proc. Int. Conf. Commun. Signal Process. (ICCSP)*, Apr. 2019, pp. 33–36.

[2] Y. Du, K. Wang, K. Yang, and G. Zhang, "Energy-efficient resource allocation in UAV based MEC system for IoT devices," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2018, pp. 1–6.

[3] X. Qi, W. Zhang, and F. Hao, "Design of emotional construction–based life service APP for elderly people," in *Proc. Int. IEEE Conf. UIC/ATC/ScalCom/CBDCom/IoP/SmartWorld*, Jul. 2016, pp. 1045–1051.

[4] W. Hou, Y. Jin, and F. Yao, "Research on multi-agent system (MAS) model based on flow of affective computing (FAC)," in *Proc. 3rd Int. Conf. Pervasive Comput. Appl.*, vol. 2, Oct. 2008, pp. 869–874.

[5] R. Khosrowabadi, A. Wahab, K. K. Ang, and M. H. Baniasad, "Affective computation on EEG correlates of emotion from musical and vocal stimuli," in *Proc. Int. Joint Conf. Neural Netw.*, Jun. 2009, pp. 1590–1594.

[6] L. Deng and D. Yu, *Deep Learning: Methods and Applications*. Boston, MA, USA: Now, 2014. [Online]. Available: https://ieeexplore.ieee.org/document/8187230

[7] P. Ekman and H. Oster, "Facial expressions of emotion," *Annu. Rev. Psychol.*, vol. 30, no. 1, pp. 527–554, 1979. [Online]. Available: https://doi.org/10.1146/annurev.ps.30.020179.002523

[8] J. Jia, S. Zhang, F. Meng, Y. Wang, and L. Cai, "Emotional audio-visual speech synthesis based on PAD," *IEEE Trans. Audio, Speech, Language Process.*, vol. 19, no. 3, pp. 570–582, Mar. 2011.

[9] Madhusudan and A. K. Sharma, "Affective computing: A fuzzy approach," in *Proc. 4th Int. Conf. Parallel, Distrib. Grid Comput. (PDGC)*, Dec. 2016, pp. 154–159.

[10] J. Tang, Y. Zhang, J. Sun, J. Rao, W. Yu, Y. Chen, and A. C. M. Fong, "Quantitative study of individual emotional states in social networks," *IEEE Trans. Affective Comput.*, vol. 3, no. 2, pp. 132–144, Apr./Jun. 2012.

[11] J. Jia, X. Wang, Z. Ren, and L. Cai, "Emotional cognitive computing of Internet data," (in Chinese), *Proc. CCCF*, vol. 10, no. 2, pp. 38–43, Feb. 2014.

[12] J. Friedman, T. Hastie, and R. Tibshirani, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* (Springer Series in Statistics), vol. 1, no. 10. New York, NY, USA: Springer, 2001.

[13] T. S. Saini, M. Bedekar, and S. Zahoor, "Analysing human feelings by Affective Computing—Survey," in *Proc. Int. Conf. Comput. Commun. Control Autom. (ICCUBEA)*, Aug. 2016, pp. 1–6.

[14] J. A. K. Suykens and J. Vandewalle, "Least squares support vector machine classifiers," *Neural Process. Lett.*, vol. 9, no. 3, pp. 293–300, Jun. 1999. doi: 10.1023/A:1018628609742.

[15] B. Yegnanarayana, *Artificial Neural Networks*. New Delhi, India: PHI Learning Pvt. Ltd., 2009.

[16] S. Lawrence, C. L. Giles, A. C. Tsoi, and A. D. Back, "Face recognition: A convolutional neural-network approach," *IEEE Trans. Neural Netw.*, vol. 8, no. 1, pp. 98–113, Jan. 1997.

[17] C. Chin and D. E. Brown, "Learning in science: A comparison of deep and surface approaches," *J. Res. Sci. Teach., Off. J. Nat. Assoc. Res. Sci. Teaching*, vol. 37, no. 2, pp. 109–138, 2000.

[18] Z.-H. Zhou, *Ensemble Methods: Foundations and Algorithms*. London, U.K.: Chapman & Hall, 2012.

[19] R. Derakhshani and C. Lovelace, "An ensemble method for classifying startle eyeblink modulation from high-speed video records," *IEEE Trans. Affective Comput.*, vol. 2, no. 1, pp. 50–63, Jan./Jul. 2010.

[20] M. S. Hossain and G. Muhammad, "Emotion recognition using secure edge and cloud computing," *Inf. Sci.*, vol. 504, pp. 589–601, Dec. 2019.

[21] S. E. Kahou, X. Bouthillier, P. Lamblin, C. Gulcehre, V. Michalski, K. Konda, S. Jean, P. Froumenty, Y. Dauphin, N. Boulanger-Lewandowski, R. C. Ferrari, M. Mirza, D. Warde-Farley, A. Courville, P. Vincent, R. Memisevic, C. Pal, and Y. Bengio, "EmoNets: Multimodal deep learning approaches for emotion recognition in video," *J. Multimodal User Interfaces*, vol. 10, no. 2, pp. 99–111, 2016.

[22] D. Jiang, Y. Cui, X. Zhang, P. Fan, I. Ganzalez, and H. Sahli, "Audio visual emotion recognition based on triple-stream dynamic Bayesian network models," in *Proc. Int. Conf. Affect. Comput. Intell. Interact.* Berlin, Germany: Springer, 2011, pp. 609–618.

[23] Y. Kim, H. Lee, and E. M. Provost, "Deep learning for robust feature generation in audiovisual emotion recognition," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process.*, May 2013, pp. 3687–3691.

[24] M. S. Hossain, G. Muhammad, M. F. Alhamid, B. Song, and K. Al-Mutib, "Audio-visual emotion recognition using big data towards 5G," *Mobile Netw. Appl.*, vol. 21, no. 5, pp. 753–763, Oct. 2016. doi: 10.1007/s11036-016-0685-9.

[25] M. S. Hossain and G. Muhammad, "Audio-visual emotion recognition using multi-directional regression and ridgelet transform," *J. Multimodal User Interfaces*, vol. 10, no. 4, pp. 325–333, Dec. 2016. doi: 10.1007/s12193-015-0207-2.

[26] S. Zhang, S. Zhang, T. Huang, W. Gao, and Q. Tian, "Learning affective features with a hybrid deep model for audio–visual emotion recognition," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 28, no. 10, pp. 3030–3043, Oct. 2018.

[27] P. Rane, V. Mhatre, and L. Kurup, "Study of a home robot: Jibo," *Int. J. Eng. Res. Technol.*, vol. 3, no. 10, pp. 490–493, 2014.

[28] Z. Gao, C. Yao, and K. Xiao, "Mobile edge computing: Architectures, applications and challenges," (in Chinese), *ZTE Commun.*, vol. 25, no. 3, pp. 23–30, Jun. 2019.

[29] Y. C. Hu, M. Patel, D. Sabella, N. Sprecher, and V. Young, "Mobile edge computing a key technology towards 5G," *ETSI White Paper*, vol. 11, no. 11, pp. 1–16, 2015.

[30] M. Patel, B. Naughton, C. Chan, N. Sprecher, S. Abeta, and A. Neal, "Mobile-edge computing introductory technical white paper," Mobile-Edge Comput. (MEC) Ind. Initiative, Kochi, Kerala, White Paper, 2014, pp. 1089–7801.

[31] J. Li, H. Gao, T. Lv, and Y. Lu, "Deep reinforcement learning based computation offloading and resource allocation for MEC," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Apr. 2018, pp. 1–6.

[32] S. Li, N. Zhang, S. Lin, L. Kong, A. Katangur, M. K. Khan, M. Ni, and G. Zhu, "Joint admission control and resource allocation in edge computing for Internet of Things," *IEEE Netw.*, vol. 32, no. 1, pp. 72–79, Feb. 2018.

[33] K. Kumar and Y.-H. Lu, "Cloud computing for mobile users: Can offloading computation save energy?" *Computer*, vol. 43, no. 4, pp. 51–56, Apr. 2010.

[34] S. Barbarossa, S. Sardellitti, and P. D. Lorenzo, "Communicating while computing: Distributed mobile cloud computing over 5G heterogeneous networks," *IEEE Signal Process. Mag.*, vol. 31, no. 6, pp. 45–55, Nov. 2014.

[35] J. Guo, Z. Song, Y. Cui, Z. Liu, and Y. Ji, "Energy-efficient resource allocation for multi-user mobile edge computing," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2017, pp. 1–7.

[36] J. Liu, Y. Mao, J. Zhang, and K. B. Letaief, "Delay-optimal computation task scheduling for mobile-edge computing systems," in *Proc. IEEE Int. Symp. Inf. Theory (ISIT)*, Jul. 2016, pp. 1451–1455.

[37] W. Zhang, Y. Wen, K. Guan, D. Kilper, H. Luo, and D. O. Wu, "Energy-optimal mobile cloud computing under stochastic wireless channel," *IEEE Trans. Wireless Commun.*, vol. 12, no. 9, pp. 4569–4581, Sep. 2013.

[38] C. You, K. Huang, H. Chae, and B.-H. Kim, "Energy-efficient resource allocation for mobile-edge computation offloading," *IEEE Trans. Wireless Commun.*, vol. 16, no. 3, pp. 1397–1411, Mar. 2017.

[39] S. Jin, "Social language affective computing using sparse representation," in *Proc. 10th Int. Symp. Comput. Intell. Design (ISCID)*, vol. 2, Dec. 2017, pp. 387–390.

[40] L. Yang, J. Cao, S. Tang, T. Li, and A. T. S. Chan, "A framework for partitioning and execution of data stream applications in mobile cloud computing," in *Proc. IEEE 5th Int. Conf. Cloud Comput.*, Jun. 2012, pp. 794–802.

[41] S. Jeong, O. Simeone, and J. Kang, "Mobile edge computing via a UAV-mounted cloudlet: Optimization of bit allocation and path planning," *IEEE Trans. Veh. Technol.*, vol. 67, no. 3, pp. 2049–2063, Mar. 2018.

[42] K. Wang, K. Yang, and C. S. Magurawalage, "Joint energy minimization and resource allocation in C-RAN with mobile cloud," *IEEE Trans. Cloud Comput.*, vol. 6, no. 3, pp. 760–770, Sep. 2018.

[43] Y. Zeng, X. Xu, and R. Zhang, "Trajectory design for completion time minimization in UAV-enabled multicasting," *IEEE Trans. Wireless Commun.*, vol. 17, no. 4, pp. 2233–2246, Apr. 2018.

[44] GitHub. (May 2017). *Sentiment Analysis*.[Online]. Available: https://github.com/mpk001/Sentiment_analysis

[45] Kaggle. (Aug. 2015). *Bag of Words Meets Bags of Popcorn: Use Google's Word2Vec for Movie Reviews*. [Online]. Available: https://www.kaggle.com/c/word2vec-nlp-tutorial/data

[46] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[47] M. Grant and S. Boyd. (Jun. 2015). *CVX: MATLAB Software for Disciplined Convex Programming, Version 3.0*. [Online]. Available: http://cvxr.com/cvx

[48] Y. Xu and W. Yin, "A block coordinate descent method for regularized multiconvex optimization with applications to nonnegative tensor factorization and completion," *SIAM J. Imag. Sci.*, vol. 6, no. 3, pp. 1758–1789, 2013.

ZIYAN YANG received the bachelor's degree in information management and information systems from Jilin Normal University, in 2019. She is currently pursuing the master's degree with the School of Information Science and Technology, Northeast Normal University, China. Her research interests include emotional computing, mobile edge computing, and artificial intelligence.

YAO DU received the B.S. degree in communication engineering from the China University of Mining and Technology, in 2017. He is currently pursuing the M.S. degree with the School of Information and Communication Engineering, University of Electronic Science and Technology of China. His research interests include mobile edge computing, unmanned aerial vehicle, and convex optimization.

CHANG CHE received the B.S. degree in communication engineering from Sichuan University, in 2019. He is currently pursuing the M.S. degree with the School of Information and Communication Engineering, University of Electronic Science and Technology of China. His research interests include mobile edge computing and emotional computing.

WENYONG WANG received all his degrees from the Department of Computer Science, Jilin University, China. He is currently a Professor with the School of Information Science and Technology, Northeast Normal University, China. His research interests include computation theory, computer graphics, software engineering, machine learning, and artificial intelligence.

HAIBO MEI received the B.Sc. and M.Sc. degrees from the School of Computer Science and Engineering, University of Electronic Science and Technology of China, in 2005 and 2008, respectively, and the Ph.D. degree from the School of Electronic Engineering and Computer Science, Queen Mary University of London (QMUL), U.K., in 2012, where he was a Postdoctoral Research Assistant. He was a Senior R&D Engineer with Securus Software Ltd, U.K. He is currently a Lecturer with the University of Electronic Science and Technology of China. His research interests include resource efficiency and self-organization of wireless communications, intelligent transportation systems, and mobile cloud computing.

DONGDAI ZHOU received the B.Eng. and M.Sc. degrees from the Changchun University of Science and Technology, China, in 1992 and 1997, respectively, and the Ph.D. degree from Jilin University, China, in 2001. He is currently a Professor and the Dean of the School of Information Science and Technology, Northeast Normal University, China. His research interests include software architecture and software code auto-generation, especially the architecture design and codeless development of e-learning software.

KUN YANG (SM'08) received the B.Sc. and M.Sc. degrees from the Computer Science Department, Jilin University, China, and the Ph.D. degree from the Department of Electronic & Electrical Engineering, University College London (UCL), U.K. He is currently the Chair Professor with the School of Computer Science & Electronic Engineering, University of Essex, leading the Network Convergence Laboratory (NCL), U.K. He is also an affiliated professor with UESTC, China. Before joining the University of Essex at 2003, he was with UCL on several European Union (EU) research projects for several years. He manages research projects funded by various sources, such as UK EPSRC and EU FP7/H2020, and industries. He has published over 150 journal articles. He serves on the editorial boards of both IEEE and non-IEEE journals. His main research interests include wireless networks and communications, data and energy integrated networks, and computation and communication cooperation. He has been a fellow of IET, since 2009.