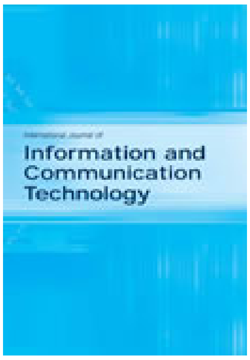

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Peidong He, Shuyu Deng, Xiaojun Li, Xianzhong Li, Chengcheng Yao

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Real-time frequency adaptation in carrier communication algorithm based on 2sVCNet network

Peidong He*, Shuyu Deng and Xiaojun Li

State Grid Sichuan Electric Power Company Marketing Service Center,
Chengdu, Sichuan 610045, China
Email: sccdjlzx@163.com
Email: dengfly001@aliyun.com
Email: zjhdlixiaojun@163.com
*Corresponding author

Xianzhong Li

State Grid Sichuan Electric Power Company,
Chengdu, Sichuan 610045, China
Email: lixz1637@sc.sgcc.com.cn

Chengcheng Yao

State Grid Sichuan Electric Power Company,
Information and Communication Company,
Chengdu, Sichuan 610045, China
Email: yaocc0729@sc.sgcc.com.cn

Abstract: With the rapid development of the internet, electricity meter engineering operation has become one of the most popular information dissemination electricity meter engineering operations nowadays, and the electricity meter engineering operation data on the internet is constantly increasing, and the following problem is that the improper use of electricity meter engineering operation is also becoming more and more extensive. The motion compensation module uses adaptive separable convolution to replace the traditional optical flow estimation algorithm, which can well handle the curve motion problem between pixels that cannot be solved by the optical flow method. For different electricity meter engineering operation frames, the motion compensation module predicts the convolution kernel that conforms to the image structure and the local displacement of the pixel, and realises the motion offset estimation and pixel compensation of the pixels of the following frame by means of local convolution. It is trained and tested on the same training set and test set as the current state-of-the-art multi-frame quality enhancement (MFQE) algorithm. The experimental results verify the proposed network has a good effect of electricity meter engineering operation artefacts.

Keywords: electricity meter engineering operation compressed; deep learning; convolution; multi-frame quality enhancement; MFQE.

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Biographical notes: Peidong He is a Master's student and a Professor Level Senior Engineer. His research field includes electric energy measurement, etc.

Shuyu Deng is a Master's student and Senior Engineer. His research interests include the calibration and verification of electrical energy standards.

Xiaojun Li is a Master's student and a Senior Engineer, specialising in research areas such as electricity metering.

Xianzhong Li is a Master's student and a Senior Engineer, specialising in research areas such as electric energy information data analysis.

Chengcheng Yao is a Master's student and Senior Engineer. Her research interests include data monitoring and analysis.

1 Introduction

The compressed sensing theory points out that the original signal can be recovered from a small number of observed values by appropriate reconstruction algorithm for compressible or sparse signals in a transform domain. Research on the reconstruction algorithm of compressed sensing is one of the key issues in the application of compressed sensing theory in practice (Tang et al., 2022). In image compression perception reconstruction algorithm, Gan and others put forward block compressed sensing algorithm (BCS) (Van Rozendaal et al., 2024) is an unit with image block to sampling and reconstruction of image, greatly reduce the stress coding on the storage and transmission, It is one of the basic processing frameworks (Xiong and Wang, 2022; Liu et al., 2020; Zhao et al., 2021) for image/electricity meter engineering operation compressed sensing reconstruction algorithm. Zhao et al. (2021) group sparse reconstruction algorithm was presented group based sparse representation (GSR), through similar block group sparse representation, image of local and non-local comparability, is currently has a better performance of the traditional image compression perception reconstruction algorithm. In recent years, deep neural network (DNN) has made a series of breakthroughs in image compression sensing reconstruction. Ding et al. (2021) for the first time uses the method of DNN to construct a reconstruction network composed of the full connection layer and the convolution layer to achieve image block compressed sensing reconstruction, which improves the reconstruction quality and reduces the reconstruction time by an order of magnitude. On this basis, the Ma and Li (2021) is proposed based on deep learning perception of image compression algorithm (CSNet), set up to study the convolution of sampling to retain more effective information network, and refactor end using convolution map, effectively reduce the block effect (Tan et al., 2020; Wang et al., 2020; Chang et al., 2021). The above algorithms reflect the advantages of deep learning in image compression sensing and reconstruction, and provide ideas for the development of Electricity meter engineering operation sensing and reconstruction algorithms. On the basis of CSNet (Wang et al., 2021b) reconstruction, Birman et al. (2020) introduced multilevel feature compensation convolutional network, which uses multilevel feature compensation of key frames to compensate non-key frames. However, neural network based on convolution is difficult to mine accurate motion information of electricity meter engineering operation signals, and the reconstruction performance is poor for fast and complex motion sequences. Optical flow estimation algorithm is a method to find the corresponding relationship between the last frame and the current frame by using the changes of images in the time domain and the correlation between adjacent frames in the image sequence and calculate the object motion between adjacent frames. For the traditional optical flow estimation method (Jiang et al., 2020; Song et al., 2020; Meng et al., 2020), prediction frames need to be obtained through optical flow graph estimation and pixel deformation. Due to the lack of real value of optical flow graph, the above methods have large errors. Wen (2020) points out that the optical flow graph estimation method is regarded as A fixed transmission map from point to point, that is, it is assumed that the movement of pixel point A to pixel point B is A straight line (and vice versa), but the curve movement of pixel points is not considered, and occlusion and blur occur in the process of Electricity meter engineering operation movement. The optical flow method may fail to obtain a relatively accurate motion path because the corresponding pixels in adjacent frames cannot be found (Pan, 2020). At present, most of the Electricity meter engineering operation quality enhancement methods still has some limitations. Some methods focus on the single-frame electricity meter engineering operation enhancement method, emphasising the use of image quality enhancement methods, while ignoring the temporal correlation and spatial correlation between electricity meter engineering operation frames. At the same time, some methods are considered to fuse CU information into the quality enhancement part, but the effect is still not ideal (Wu et al., 2020; Lyu et al., 2022). Other methods make use of the feature of inter-frame correlation, but ignore the low-quality feature of Electricity meter engineering operation decoded frames and do not consider the influence of compression artifacts of different sizes, so that feature extraction does not conform to the distribution characteristics, resulting in the final enhanced frame effect are not obvious.

Our method considering the above factors put forward a frame more attention quality enhancement MLAN network, including the main innovation points are as follows:

1. Adopt from global to local layer on the four layers of motion compensation network makes more dimension compression artefacts are perception, resulting in increased motion matching accuracy, makes the compensation distribution characteristics of frame is more conform to the requirements of the subsequent network.

2. Spatial attention and channel attention mechanisms are introduced to strengthen the focus the full-aspect feature extraction of the feature graph strengthens the key parts of each dimension, so as to achieve more sufficient feature extraction effect.

3. Taking advantage of the features of residual learning and dense connection, the deep mapping of features avoids gradient disappearance, accelerates the training speed, and thus realises strong suppression of compressed artefacts, retains the original details of electricity meter engineering operation frames to a large extent, and improves visual perception.

2 Construction of material method

2.1 Motion compensation module

The proposed network consists of motion compensation module and decompression artefact module. The former is used to realise inter-frame motion estimation and pixel information compensation, while the latter removes compressed artefacts of electricity meter engineering operation frames through pixel information fusion (Chen, 2020). The overall network structure is shown in Figure 1. The motion compensation module input two consecutive frames of compressed electricity meter engineering operation, and the last frame can be obtained after the motion compensation network motion compensation frame this The pixel offset information is learned and compensated for the current frame in the compressed electricity meter engineering operation And the next frame pixel defect information. Then, the prediction frame obtained in the motion compensation network with the original frame in the compressed electricity meter engineering operation connected as the input of the de compression artefact module, through the continuous learning process of the network, the output of the de compression artefact module is the original frame Results after removing compression artefacts. The next part will elaborate the network structure and principle used in this paper.

Cao (2019) proposed an adaptive separable convolution network for electricity meter engineering operation frame insertion, and achieved good results. In this method, the offset from frame I to frame I + 1 and frame I + 1 to frame I + 2 of the electricity meter engineering operation are learned through the network, and the predicted value of frame I + 1 is obtained by fusing the offset and the original input (frame I and frame I + 2). The process can be approximately expressed by equation (1):

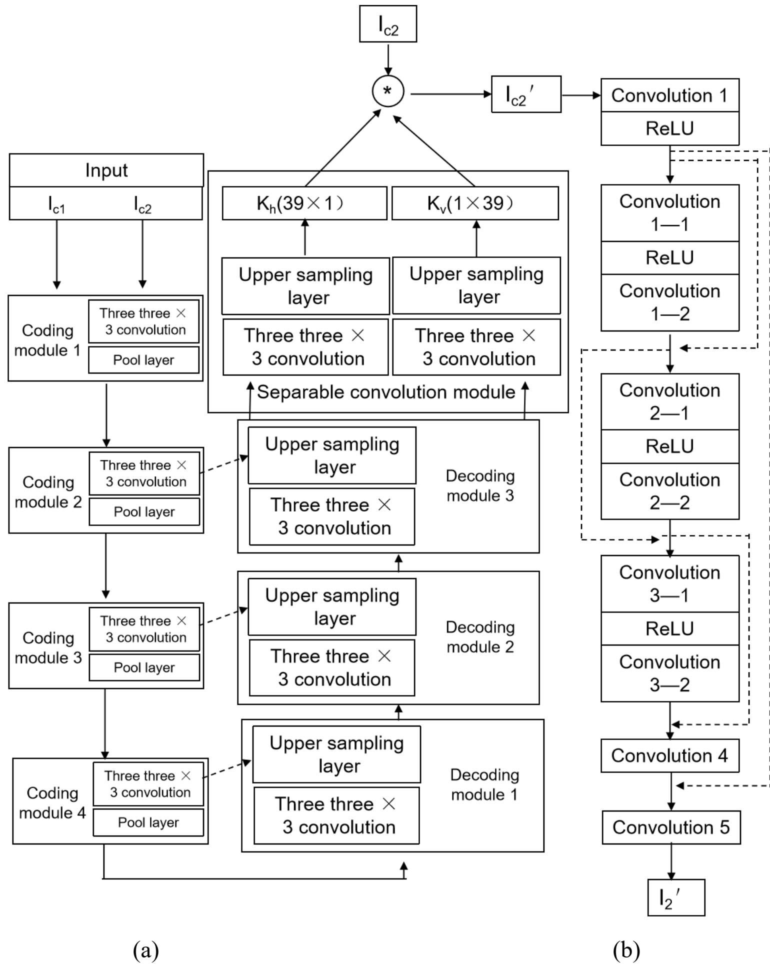
$$I_{c2}' = W_1^* \left(I_{c1} + \Delta_{i,i+1}\right) + W_2^* \left(I_{c3} + \Delta_{i+2,i+1}\right) \tag{1}$$

which I_{c1}, I_{c3} where: represents frame I and frame I + 2 respectively; I_{c2}' represents the prediction frame of frame I + 1; W1 and W2 represent the assigned weight defined as convolution operation; $\Delta_{i,i+1}$ and $\Delta_{i+2,i+1}$ represents the offset from frame I to frame I + 1 and from frame I + 2 to frame I + 1. From the ideas of Niklaus and others, we get the inspiration of motion compensation network in this paper. In this paper, the motion compensation network learns the motion offset of frame I and frame I + 1 of continuous Electricity meter engineering operation, so as to obtain the prediction value of frame I + 1 and realise the motion estimation between electricity meter engineering operation frames. This process can be represented as follows:

$$I_{c2}' = f\left(I_{c1}, I_{c2}\right) = I_{c1} + \Delta_{i,i+1} \tag{2}$$

which: I_{c1} I_{c2} represents frame I, frame I + 1 respectively represents the offset from frame I to frame I + 1, and f represents the mapping function learned by the network In this scheme, two consecutive frames are input into the motion compensation network I_{c1} and I_{c2}. The structure of motion compensation network is shown in Figure 1(a). The motion compensation network is composed of a plurality of coding modules, decoding modules and separable convolution modules. Each coding module is composed of multiple convolution layers and average pooling layers. Each decoding module is composed of convolution layer and upper sampling layer in turn, and combines the feature maps on different scales through jump connection operation.

Figure 1 Overall network structure, (a) motion compensation module, (b) de compression artefact module



In the encoding and decoding module, each encoding module consists of three 3 ×. It consists of three convolution layers and an average pool layer with a step size of 2. In this module, three convolution layers are stacked as a convolution block to obtain a larger receptive field, so as to extract more feature information. At the same time, the average pooling layer is used to reduce the characteristic map to 1/2 of the original, so as to ensure that the network can integrate more spatial information. Each decoding module consists of three 3 × 3 convolution layer and a bilinear upper sampling layer are arranged in turn. In view of the possible chessboard effect caused by the improper use of up sampling method in the process of image processing, this paper selects bilinear interpolation method for up sampling operation (Kong et al., 2022). The feature image is enlarged to twice the original by bilinear interpolation, which can effectively avoid the chessboard artefact in the reconstructed image. Finally, the skip connection operation combines the feature map obtained by the convolution block in each coding module with the feature map of the same size in the corresponding decoding block to enhance the feature information. By balancing the amount of training data and the depth and width of the network to maximise the network performance, this paper sets the number of output channels of each convolution block in the motion compensation module, as shown in Table 1. At the same time, in addition to the separation convolution operation, each convolution operation is followed by the nonlinear activation function ReLU (rectified linear units) to enhance the nonlinear expression ability of the network (Poyser et al., 2021).

Table 1 Parameter setting of each convolution block in motion compen sation module

Convolution block	*Convolution kernel size*	*Number of output channels*	*Step*	*Activation function*
Coding block 1	3×3	32	2	ReLU
Coding block2	3×3	64	2	ReLU
Coding block 3	3×3	128	2	ReLU
Coding block 1	3×3	256	1	ReLU
Coding block 2	3×3	128	1	ReLU
Coding block 3	3×3	64	1	ReLU
One dimensional separation convolution K_h	39×1	3	1	-
One dimensional separation convolution K_v	1×39	3	1	-

The output characteristic diagram obtained by the last decoder module is used as the input of the separable convolution module. In the separable convolution module, two separable convolution subnetworks are used to realise the one-dimensional convolution kernel $K_h(x, y)$, $K_v(x, y)$ prediction of among $K_h(x, y)$, $K_v(x, y)$. It can be approximately regarded as the horizontal and vertical vector representation of two-dimensional convolution kernel K. The relationship between two one-dimensional convolution kernels representing horizontal and vertical components and their corresponding two-dimensional convolution kernels can be approximately expressed as follows:

$$K(x, y) \approx K_{\text{h}}(x, y) * K_v(x, y) \tag{3}$$

Finally, the two one-dimensional convolution kernels obtained in the separable convolution module are connected with the original input of the next frame respectively. Convolution operation can get results after motion compensation. This process can be represented as follows:

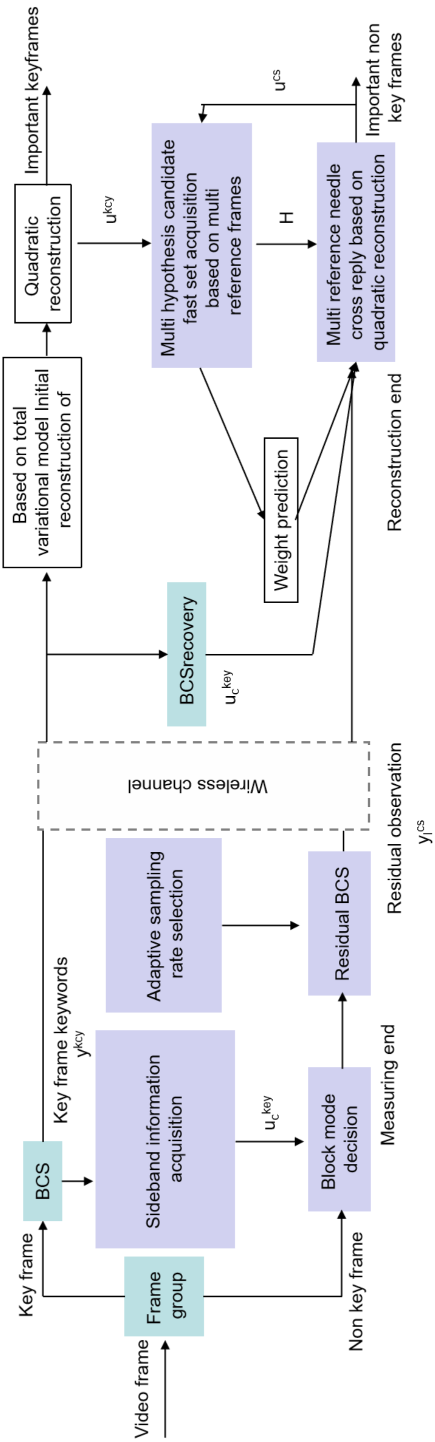
$$I_{c2}'(x, y) = K_{\text{h}}(x, y) * K_v(x, y) * I_{c2}(x, y) \tag{4}$$

where * indicates convolution operation. Through network self-learning, two one-dimensional convolution kernels are obtained $K_h(x, y)$. The motion displacement of two adjacent frames is captured and compensated by nonlinear feature mapping (Wang et al., 2019). At the same time, for size n ×. The convolution kernel $K(x, y)$ of n is involved in the convolution of network operation. The number of nuclear parameters decreased from N2 to n^2. The convolution operation part in the two sub network structures is consistent with the decoding module structure, which consists of three sub networks with a size of 3 × 3 convolution layer and 1 linear up sampling layer (Tian, 2019b). In the separation convolution operation, the size of one-dimensional convolution kernel is set to 39 respectively × 1 and 1 × 39. This is because in the training data adopted in this paper, since the maximum motion offset between adjacent electricity meter engineering operation frames is about 30 pixel values, this paper finds that the convolution kernel size of 39 can well adapt to most of the inter frame motion offset in the data set adopted in this paper (Tian, 2019a). Although the increase of convolution kernel can deal with larger offset, it will also lead to greater computation and increase the cost of network computing.

2.2 Performance index of electricity meter engineering operation observation and electricity meter engineering operation reconstruction

The combination of compressed sensing theory and electricity meter engineering operation communication technology can effectively reduce the cost of front-end acquisition, coding, processing and transmission. The sample representation of the whole block of information is conducive to the construction of a simple and effective anti channel error scheme. Liu et al. proposed an image communication system based on compressed sampling, which has achieved certain performance improvement when integrated into typical multi description codec (Matsubara and Levorato, 2021; Sengar and Mukhopadhyay, 2020; Wang et al., 2021a; Liang, 2019). Observation efficiency is a collaborative representation of rate distortion. At present, the optimisation goal of electricity meter engineering operation reconstruction of compressed sensing electricity meter engineering operation stream is to maximise pixel level fidelity for human vision, rather than improve semantic level indicators such as average recognition accuracy (map) for general machine vision. In terms of fidelity, the reconstruction quality of existing electricity meter engineering operation compressed sensing systems is low. If electricity meter engineering operation reconstruction still aims to recover the pixel details of the signal, the reconstruction quality will be difficult to exceed the electricity meter engineering operation decoding quality based on Shannon information theory (Qiu, 2019). After signal recovery, upstream streaming media needs to further perform various machine vision tasks, which is also a breakthrough to improve the reconstruction quality. Figure 2 shows a module diagram of an existing Electricity meter engineering operation compressed sensing system (Weng et al., 2018). Its performance indicators only include fidelity indicators such as peak signal-to-noise ratio (PSNR) and structural similarity (SSIM). Ukeye, ukey and UCS in the figure represent the key frames recovered at the measurement end, the key frames recovered at the reconstruction end and the non-key frames recovered at the reconstruction end respectively, and H represents the set of multi hypothesis candidate blocks, The system adopts the traditional technical framework of ‘single frame measurement + open-loop coding + fidelity guided reconstruction’. It has the advantages of low front-end power consumption and good fault tolerance in upstream streaming media applications, but it also faces the challenges of difficult control of observation efficiency and low reconstruction quality. It needs to build a new streaming aware framework to fully demonstrate its unique advantages for streaming media applications.

Figure 2 Module diagram of a electricity meter engineering operation compressive sensing system (see online version for colours)

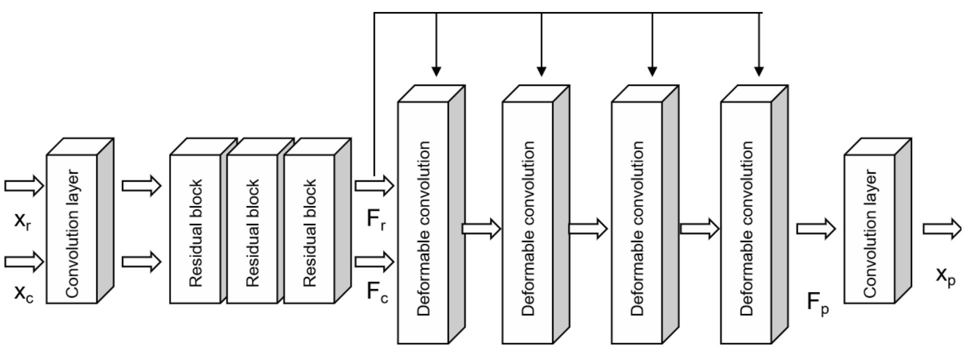


2.3 Two stage multi hypothesis enhanced reconstruction network for non-key frames

After the initial reconstruction within the frame of electricity meter engineering operation sensing, the key frames have high initial reconstruction quality due to their high sampling rate, while the initial reconstruction effect of more non-key frames is very poor. Therefore, the purpose of this section is to improve the reconstruction quality of non-key frames by using the time correlation between electricity meter engineering operation frames.

The traditional multi hypothesis prediction algorithm searches the hypothesis set in blocks and carries out weighted linear combination to obtain the prediction frame of the current frame. This study realises the multi hypothesis prediction based on pixels based on the concept of deep learning deformable convolution. Deformable convolution (Agustsson et al., 2020) is an optimised branch of traditional convolution. By learning the offset of pixels, the convolution layer obtains useful information from its regular receptive field, which improves the performance of convolution. The time-domain deformable convolution alignment network uses the deformable convolution layer to learn the motion offset between two frames (Li and Yu, 2018), and uses the offset to guide the alignment from the reference frame to the current frame to realise the motion compensation between two frames. In order to reduce the network burden, a simplified time-domain alignment prediction network is proposed in this study. As shown in Figure 3, the network is usually divided into three steps.

Figure 3 Structure of temporal deformable alignment network



Firstly, the feature extraction module is used to map the input reference frame and the current frame (X_C, X_R) to its feature domain (F_C, F_R) to make full use of high-order motion features to learn more accurate motion offset. The feature extraction module is usually composed of a 3 × 3 convolution layers and three residual learning blocks. K pixels through convolution operation, expressed as:

$$F_{r\to c}(p_0) = \sum_{k=1}^{K} w_k \cdot F_r(p_0 + p_k + \Delta p_k) \tag{5}$$

where w_k is the corresponding weight of the k^{th} sampling position obtained by learning. In order to ensure the motion correlation between the hypothesis set and the pixels to be predicted, the deformable convolution network looks for the matching pixels in the whole image, $p_0 + p_k + \Delta p_k$ represents the position information of the matching position, where PK is the convolution fixed offset, and Δp_k is a learnable motion offset, which depends on the motion relationship between the current frame and the reference frame, expressed as:

$$\Delta p_k = W_{pffsct}\left(F_r \oplus F_c\right) \tag{6}$$

where W_{pffsct} is the weight parameter of convolution layer, ⊕ indicates two frame channel splicing operation. In order to improve the prediction accuracy, this study uses four layers of cascaded deformable convolution to align the feature domain to obtain the feature domain prediction frame FP. Finally, in order to output the predicted image XP, a convolution layer is used to realise the mapping from feature domain to pixel domain. Compared with the traditional multi hypothesis prediction, the network has the following three advantages:

1 the network takes the pixel as the minimum unit for motion estimation and compensation, avoids the blocking effect and artefact caused by blocking, and improves the flexibility and accuracy of motion compensation

2 through end-to-end learning, the optimal offset vector in the feature domain is adaptively obtained, so as to obtain the optimal hypothesis set

3 the weight of linear weighting is obtained by convolution kernel parameter learning to improve the accuracy of hypothetical centralisation value.

In the specific experiment, $k = 9$ is set and the nuclear size is 3 × 3, and supervise the output prediction image in the training process to ensure the correct learning of the prediction network, and its loss function is:

$$L_{\mathrm{p}} = L\left(x^p, x^0\right) \tag{7}$$

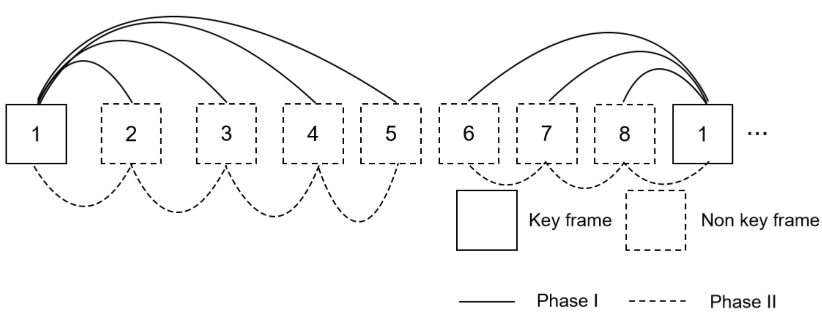
The multi hypothesis prediction network can well align the common information between the reference frame and the current frame, but it is difficult to achieve effective prediction for the unique information of the current frame. Therefore, this study introduces the residual reconstruction module again to compensate the missing operation information and detail information of the prediction frame by using the original observation value of the current frame, and also provides more accurate current frame information for the next stage of enhanced reconstruction. The network structure of the residual reconstruction module is the same as that in 2. The residual reconstruction module of resrecnet in Section 1 is the same, that is, after inputting the prediction frame XP, the module calculates the residual with the original observation value Y0 in the observation domain to obtain the residual reconstruction frame XR. In this process, the reconstructed network parameters in the residual reconstruction module will be retrained to meet the reconstruction requirements of more sparse residual signals. In the problem of compressed sensing, the closer the reconstructed image is to the original image, the more similar their observations will be. Therefore, this study will supervise the reconstruction process by combining the mean square error (MSE) loss of image domain and observation domain after obtaining the reconstructed frame, which is expressed as:

$$L_{\mathrm{r}} = L\left(x^r, x^0\right) + L\left(y^r, y^0\right) \tag{8}$$

Among y_r, y_0 respectively represent residual reconstruction frames x_r with original frame x_0 after Φ observations obtained by sampling.

In the process of motion compensation, the selection of reference frame is the key to obtain high-quality prediction frame. Based on the unbalanced quality of each frame and the difference of correlation between frames in the image group, a serial two-stage multi hypothesis enhancement and reconstruction mode is proposed in this study. In the first stage, because the initial reconstruction quality of key frames is much higher than that of non-key frames, key frames are selected as reference frames to provide more detailed information. In order to avoid the low correlation caused by the distance between the reference frame and the key frame, the first n/2 'non-key frames of each GOP. The key frame of the current GOP will be selected as the reference frame, while the key frame of the next GOP will be selected as the reference frame for the remaining frames. After the first stage of reconstruction, the difference in reconstruction quality between key frames and non-key frames is greatly reduced. Therefore, in the second stage, adjacent frames with higher correlation between frames are selected as reference frames to improve the matching efficiency (Wang, 2018). The selection scheme of reference frame in two stages is shown in Figure 4, in which the selection of reference frame in stage 1 is represented by solid arrow and the selection of reference frame in stage 2 is represented by dotted arrow. In the two-stage multi hypothesis enhanced reconstruction process, each enhanced reconstruction stage includes a multi hypothesis prediction network and residual reconstruction network to make full use of the time correlation between the selected reference frame and the current frame.

Figure 4 Selection of reference frames at each stage ($N = 8$)

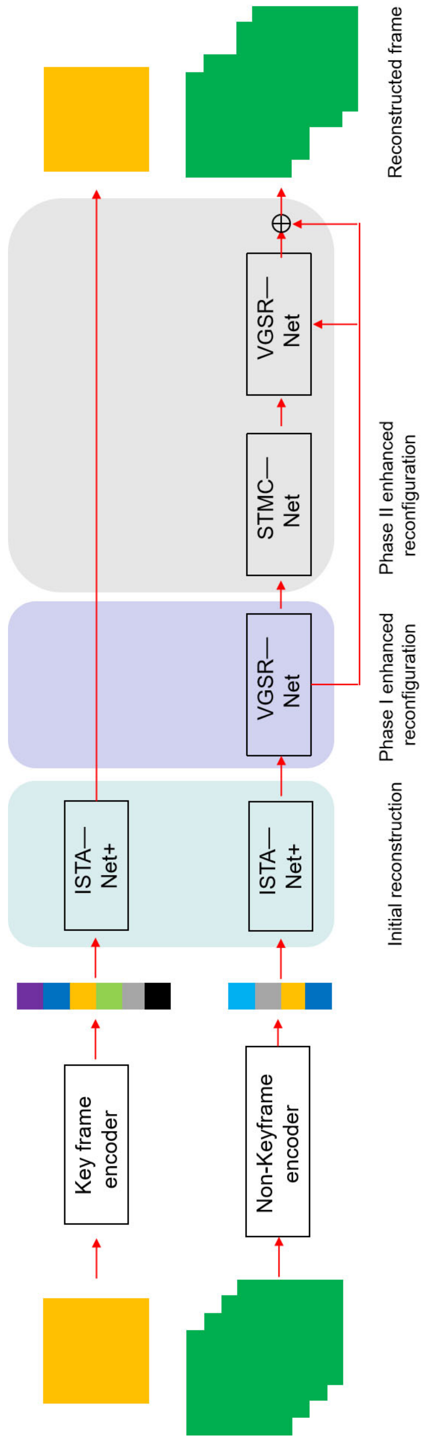


Due to the limitation of GPU Electricity meter engineering operation memory, this study shares the network parameters of the enhanced network in each stage, and fixes the sampling and initial reconstruction network parameters in the training process to train the enhanced reconstruction network independently. The loss function of the inter frame motion enhancement reconstruction network is expressed as:

$$L_{ER} = \sum_{i=1}^{2} L\left(x^{pi}, x^{0}\right) + L\left(x^{ri}, x^{0}\right) + L\left(y^{ri}, y^{0}\right) \tag{9}$$

Among x_{pi}, x_{ri}, y_{ri} respectively represent the observation domain representation of the prediction frame, residual reconstruction frame and residual reconstruction frame.

Figure 5 2sRER-VGSR-Net algorithm framework (see online version for colours)



2.4 Two stage recursive enhanced electricity meter engineering operation sensing reconstruction network

The traditional CVS algorithm obtains the optimal similar block group through iteration, which has the disadvantages of long running time and poor reconstruction effect at low sampling rate. To solve the above problems, this paper proposes a two-stage recursive enhanced neural network 2srer vgsr net, and the network structure is shown in Figure 5.

At the encoding end, the electricity meter engineering operation sequence is divided into image groups (GOP). The first frame of each GOP is a key frame with high sampling rate, and the other frames are non-key frames with relatively low sampling rate. According to the idea of BCS, each electricity meter engineering operation frame is sampled independently. In order to meet the rip constraint (Raj, 2018), this paper uses the random Gaussian observation matrix to sample the signal. At the decoding end, this paper is based on the concept of group sparsity, an inter group sparse representation sub network is designed. Based on this sub network, a two-stage recursive enhancement and reconstruction network is proposed, including the first stage enhancement and the second stage enhancement with motion estimation.

For a non-key frame, it is divided into n non-overlapping image blocks according to the way of coding end, and a electricity meter engineering operation inter frame similar block group is constructed for each image block, $t = 1, 2, \ldots, t$; $J = 1, 2, \ldots, N$, which represents the similar block group of the j^{th} image block in the t^{th} frame. The similar block group can be thinly represented by using the adaptive learning dictionary:

$$x_{VG_{tj}} = D_{VG_{tj}} \alpha VG_{tj} \tag{10}$$

Among αVG_{tj} is sparse coefficient. Therefore, the reconstruction of electricity meter engineering operation frame is to solve the optimisation problem of the following formula:

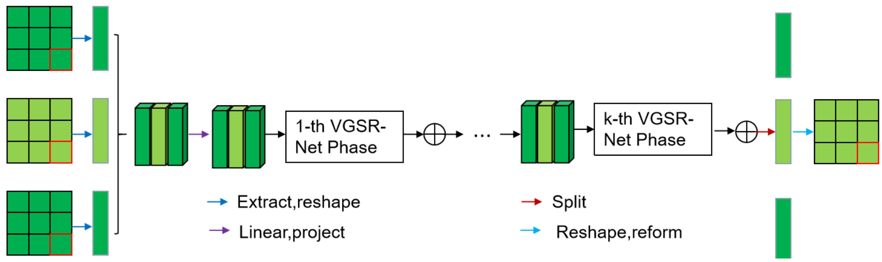
$$\min_{x} \frac{1}{2} \left\| \phi D_{VG_{tj}} \alpha_{VG_{tj}} - y \right\|_2^2 + \lambda \left\| \alpha_{VG_{tj}} \right\|_1 \tag{11}$$

In this paper, an electricity meter engineering operation inter group sparse representation sub network is proposed to solve the optimisation problem of equation (11). The adaptive sparse transformation dictionary is obtained by optimising the convolution network. The dictionary is used to map the low-dimensional signal to the higher-dimensional space, so that the distinction between similar structural features and non-similar features in similar block groups is more obvious. In the sparse domain, the larger coefficient is the main structural feature of similar block groups. Then the sparsity coefficient is:

$$\alpha_{VG_{tj}} = H\left(D\left(\alpha_{VG_{tj}}\right)\right) \tag{12}$$

Convolution neural network implementation of group sparse representation (vgsr net) this paper extends ISTA Net + and proposes a convolution network of group sparse representation of similar blocks between electricity meter engineering operation frames based on global correlation information. The structure is shown in Figure 6.

Figure 6 VGSR-Net frame (see online version for colours)



2.5 *Feature extraction and reconstruction of fusion attention mechanism*

Attention mechanism is an effective feature extraction method, which is mainly divided into channel attention (Wang, 2018) and spatial attention (Raj, 2018). The channel attention mechanism focuses the convolution process on the channels of the feature map. By adopting the learning based weighting method for each channel, the channel with a larger proportion in the feature map is given a larger weight value; on the contrary, the channel with a smaller proportion is given a smaller weight value, which can be expressed as:

$$Y = \delta\left(P\frac{1}{H \times W}\sum_{i}^{N} x_i\right) \times X \tag{13}$$

where X represents the characteristic diagram of a certain channel, and X_i is in the characteristic diagram.

At any point, P is the enhanced part of the network channel feature extraction, δ by Sigmoid function, y is the weighted characteristic graph, sigmoid. The function expression is:

$$\delta(\mathrm{x}) = \frac{1}{1 + e^{-x}} \tag{14}$$

Channel attention can well distinguish the importance of channels and channels, but the difference and correlation between feature points in a single feature map cannot be well represented, and spatial attention mechanism can well solve this problem. By focusing on the weighting of feature points in the feature map, the feature points with greater loss will be given greater weight value; on the contrary, the feature points with less impact will be given smaller weight value, which can be expressed as:

$$Y = \delta\left(P\left(cat\left(\frac{1}{C}\sum_{i}^{C} x_i, x_{\max}\right)\right)\right) \times X \tag{15}$$

where X represents a feature map, X_i is the feature point at the same position on each channel feature map, $x_{\max}$ is the maximum feature point at the same position on each channel feature map, *cat* is a cascade operation, and P is the spatial feature extraction enhancement part of the network, and Y is the weighted characteristic graph. Because the action dimensions of channel attention mechanism and spatial attention mechanism are different, the probability distribution of the feature map after one attention operation in other dimensions will not change. Considering the independence of the scope of space and channel dimensions, the series attention mechanism is adopted to extract the features of electricity meter engineering operation frames. The configuration of this part is shown in Table 2. Considering that the network task is to improve the quality of the current frame, additional pixel distribution learning is carried out for the current frame, and the same concatenation mechanism is adopted to make the two training stages similar.

Table 2 Set of channel-spatial attention

Serial number	*Convolution kernel*	*Number of channels*	*Step*	*Degree of expansion*
1	3×3	64	1	1
2	3×3	64	1	1
3	1×1	64	1	1
4	1×1	1	1	1
5	3×3	64	1	2

Figure 7 Channel-spatial attention (see online version for colours)

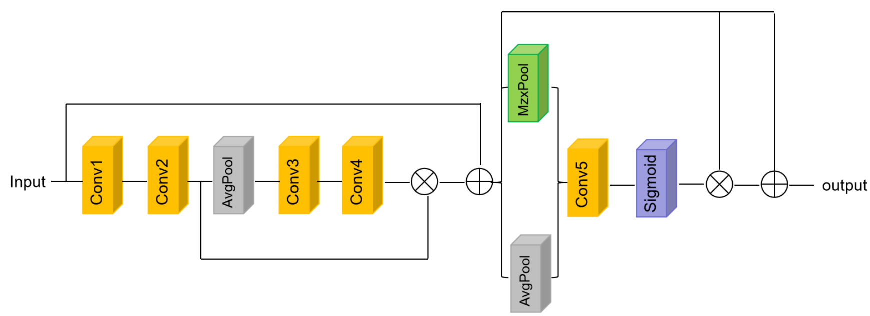
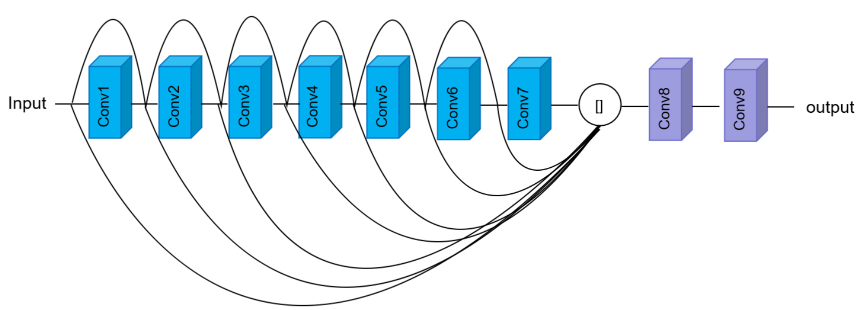


Figure 8 Feature mapping and reconstruction (see online version for colours)

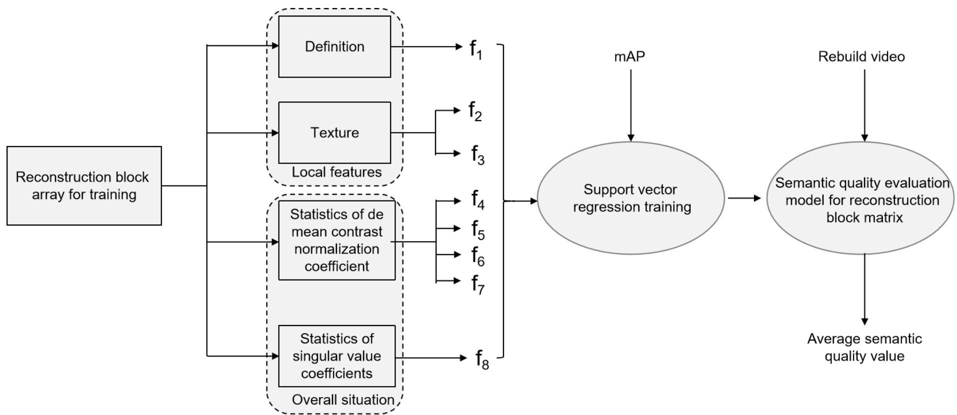


After obtaining the output features of the fusion attention mechanism, it is also necessary to map and reconstruct the features. Considering the advantages of residual learning (Yang, 2018) in suppressing gradient dispersion and the advantages of densenet (Wang et al., 2024) in feature fusion, we choose to construct dense and residual connections as shown in the figure, in which all convolution cores are 3 × 3, and the activation function is relu. The output feature map of each layer in this part will be used as the input of the last two convolution layers after cascade fusion, and the image will be reconstructed into the number of target channels.

2.6 Semantic quality evaluation

In upstream streaming media applications, sensing electricity meter engineering operation signals often come from unknown scenes and the front end cannot obtain the original signal. Electricity meter engineering operation reconstruction cannot obtain the front-end reference signal during operation, so it is difficult to use reference quality evaluation.

Figure 9 Training process of a semantic quality assessment model



In recent years, machine based upstream streaming media has shown its development potential. A large MSQ value means that the reconstructed electricity meter engineering operation has high semantic quality. At present, there are no research results on how to integrate sparse a priori modelling and streaming data-driven deep learning to reconstruct continuous dynamic images with the help of semantic quality guidance (Zhu and Yang, 2018).

3 Experiment and analysis

3.1 Data preparation and experimental setup

The algorithm in this paper is based on the database proposed by MFQE (Song et al., 2020). The original uncompressed training and test electricity meter engineering operations in the database are from the joint collaborative team on electricity meter engineering operation coding (jct-vc) (Wang et al., 2019). Both training electricity meter engineering operation and test electricity meter engineering operation use ffmpeg (fast forward MPEG) command and are compressed according to hevc standard, and the quantisation parameter (QP) is set to 37. The original training electricity meter engineering operation and the corresponding compressed electricity meter engineering operation are frame extracted, and the training data set is composed of about 15,000 consecutive compressed electricity meter engineering operation frames, including about 100,000 training samples. Because the size of hevc encoding macroblock is 4×4, 8×8, 16×16, 32×32, so this experiment divides the training samples into 64×64 image blocks to ensure that the training set data can include artefact information of different scales.

In this experiment, Charbonnier function (Matsubara and Levorato, 2021) is used to replace MSE as the loss function of the network. Charbonnier function introduces additional variables on the basis of MSE calculation formula ε. It can better preserve the image edge information to avoid image edge blur, avoid the discontinuity caused by input, and effectively help the stable convergence of the network. It has been proved that using Charbonnier function in image super-resolution reconstruction can obtain better visual effect (Sengar and Mukhopadhyay, 2020). The calculation formula of Charbonnier function is as follows:

$$l(\theta) = \frac{1}{N}\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(F\left(I_{c2}^{*};\theta\right) - I_{c2}^{g}\right)^{2} + \varepsilon^{2}} \tag{16}$$

where $F(I^*C2); \theta)$ indicates the output of the network; θ represents the weight and bias of each filter in the network; $I^g{}_{c2}$ represents the original uncompressed electricity meter engineering operation frame corresponding to the current frame I_{C2} in the compressed electricity meter engineering operation; N refers to batch processing quantity; ε is a regularisation term used to preserve image edges.

Table 3 Comparison of reconstruction results between 2sVCNet and several deep learning based algorithms

r	*Algorithm*	*PSNR/SSIM*						
		Lena	*Baby*	*Pepper*	*Butterfly*	*House*	*Barbara*	*Average*
0.1	CSNet	32.15/ 0.8218	33.70/ 0.8453	31.89/ 0.8130	27.02/ 0.8383	31.72/ 0.8042	23.24/ 0.7137	30.62/ 0.713
	ResRecNet	32.29/ 0.8250	33.98/ 0.8591	32.38/ 0.8117	27.29/ 0.8352	32.53/ 0.8107	23.33/ 0.7217	30.97/ 0.722
	ResRecNet	31.45/ 0.8145	34.03/ 0.8497	31.63/ 0.8989	27.26/ 0.8461	32.17/ 0.8105	23.32/ 0.2203	30.48/ 0.721
0.2	CSNet	35.49/ 0.8542	36.66/ 0.8729	35.11/ 0.8367	30.66/ 0.8730	35.61/ 0.8367	24.77/ 0.8076	32.88/ 0.808
	ResRecNet	35.66/ 0.8551	36.83/ 0.8741	35.30/ 0.9381	30.95/ 0.9746	35.83/ 0.8399	24.94/ 0.8127	33.09/ 0.813
	ResRecNet	35.66/ 0.8561	36.82/ 0.8742	35.22/ 0.8377	31.13/ 0.8752	35.89/ 0.8401	24.86/ 0.8116	33.10/ 0.812
0.3	CSNet	37.36/ 0.8658	38.55/ 0.9829	36.48/ 0.9477	32.72/ 0.9822	37.69/ 0.8519	28.01/ 0.8071	34.97/ 0.807
	ResRecNet	37.75/ 0.8677	38.87/ 0.8844	36.70/ 0.8485	33.50/ 0.8845	38.26/ 0.8566	28.37/ 0.8123	35.41/ 0.812
	ResRecNet	37.83/ 0.8691	38.90/ 0.8856	36.82/ 0.8499	33.68/ 0.8952	38.33/ 0.8566	28.62/ 0.8191	35.53/ 0.828

3.2 Performance analysis of multi hypothesis enhanced reconfiguration network

In order to verify the performance of each module of the multi hypothesis enhanced reconstruction network, the initial reconstruction frame of 2sVCNet is listed in this paper. The PSNR reconstruction results of the two-stage prediction frame and residual reconstruction frame are shown in Table 3. It can be seen from Table 3 that the multi hypothesis prediction network and residual reconstruction network in the two stages have realised their established functions, which is conducive to the improvement of reconstruction quality. In order to make full use of the time correlation, a serial two-stage reconstruction is introduced in this study. As can be seen from Table 3, the average sampling rates are 0.5% respectively 150 vs. which prove the superiority of the reconstruction mode in fast and complex motion scenarios.

Table 4 Reconstruction results of predicted frames and residual reconstructed frames at each stage of 2sVCNet dB

r	*Test sequence*	*Initial restructure*	*Phase I*		*Phase II*	
			Forecast	*Residual*	*Forecast*	*Residual*
0.150	Fast movement	29.92	31.93	32.15	32.31	32.40
	Slow motion	30.72	35.59	35.96	35.88	37.01
0.038	Fast movement	24.65	26.14	26.32	26.56	26.60
	Slow motion	24.43	28.07	31.37	30.28	30.33

4 Conclusions

Based on the idea of traditional multi hypothesis motion compensation, the two-stage multi hypothesis enhanced reconstruction network first introduces the deep learning time-domain deformable convolution alignment network to realise the pixel based multi hypothesis prediction and improve the prediction accuracy. And enhance the interpretability and portability of compressed sensing machine learning, and open up a quantitative evolution technology path for giving full play to the unique advantages of compressed sensing electricity meter engineering operation stream. The visual observation effect is greatly improved, and the quality of the electricity meter engineering operation sequence itself is enhanced only by using the decoded electricity meter engineering operation stream.

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References

Agustsson, E., Minnen, D., Johnston, N. et al. (2020) ‘Scale-space flow for end-to-end optimized Electricity meter engineering operation’, *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp.8503–8512.

Birman, R., Segal, Y. and Hadar, O. (2020) ‘Overview of research in the field of electricity meter engineering operation using deep neural networks’, *Multimedia Tools and Applications*, Vol. 79, No. 7, pp.11699–11722.

Cao, J. (2019) ‘Application of electricity meter engineering operation technology in smart prison’, *China Security Technology and Application*, Vol. 25, No. 6, pp.20–21.

Chang, S., Liu, J., Liu, Z. and Tian, S. (2021) 'Design of image compression platform based on SVD algorithm', *Electronic Quality*, Vol. 13, No. 8, pp.41–44.

Chen, X. (2020) 'Research on application of BMP color image compression based on DCT', *Computer Programming Skills and Maintenance*, Vol. 39, No. 11, pp.142–143.

Ding, D., Ma, Z., Chen, D. et al. (2021) 'Advances in electricity meter engineering operation system using deep neural network: a review and case studies', *Proceedings of the IEEE*, Vol. 109, No. 9, pp.1494–1520.

Jiang, Y., Wei, R. and Lu, C. (2020) 'Research on laser spectral image compression based on deep learning network', *Laser Journal*, Vol. 41, No. 12, pp.176–180.

Kong, M., Guo, Y., Alkhazragi, O. et al. (2022) 'Real-time optical-wireless electricity meter engineering operation surveillance system for high visual-fidelity underwater monitoring', *IEEE Photonics Journal*, Vol. 14, No. 2, pp.1–9.

Li, R. and Yu, K. (2018) 'HDR electricity meter engineering operation algorithm based on inter frame correlation', *Journal of Zhejiang University of Technology*, Vol. 46, No. 6, pp.622–626 + 649.

Liang, N. (2019) 'Design of electricity meter engineering operation acquisition and compression system based on arm', *Journal of Beijing Institute of Technology*, Vol. 18, No. 4, pp.32–34.

Liu, K., Liu, W., Ma, H. et al. (2020) 'A real-time action representation with temporal encoding and deep compression', *IEEE Transactions on Circuits and Systems for Electricity Meter Engineering Operation Technology*, Vol. 31, No. 2, pp.647–660.

Lyu, Z., Zhang, D. and Luo, J. (2022) 'A GPU-free real-time object detection method for apron surveillance electricity meter engineering operation based on quantized MobileNet-SSD', *IET Image Processing*, Vol. 16, No. 8, pp.2196–2209.

Ma, H. and Li, S. (2021) 'Adaptive teaching electricity meter engineering operation based on surfacelet transform and motion estimation', *Journal of Dalian Jiaotong University*, Vol. 42, No. 5, pp.106–110.

Matsubara, Y. and Levorato, M. (2021) 'Neural compression and filtering for edge-assisted real-time object detection in challenged networks', *2020 25th International Conference on Pattern Recognition (ICPR)*, IEEE, pp.2272–2279.

Meng, F., Zhang, H., Liu, C. and Dong, J. (2020) 'Design of embedded image compression device based on high frame rate', *Electronic Devices*, Vol. 43, No. 6, pp.1385–1390.

Pan, L. (2020) 'Research on image compression sensing fusion technology', *Computer Knowledge and Technology*, Vol. 16, No. 35, pp.202–203.

Poyser, M., Atapour-Abarghouei, A. and Breckon, T.P. (2021) 'On the impact of lossy image and Electricity meter engineering operation on the performance of deep convolutional neural network architectures', *2020 25th International Conference on Pattern Recognition (ICPR)*, IEEE, pp.2830–2837.

Qiu, H. (2019) *High Magnification Electricity Meter Engineering Operation and Storage Technology based on ZVR*, Zhejiang Province, Zhejiang Zhongxin Power Engineering Construction Co., Ltd., 16 January.

Raj, P. (2018) *Bell Image Compression Method based on JPEG2000 Standard*, Shaanxi Province, Xi'an University of Electronic Science and technology, 1 December.

Sengar, S.S. and Mukhopadhyay, S. (2020) 'Motion segmentation-based surveillance electricity meter engineering operation using adaptive particle swarm optimization', *Neural Computing and Applications*, Vol. 32, No. 15, pp.11443–11457.

Song, Z., Wu, F., Liu, X. et al. (2020) 'Vr-dann: real-time electricity meter engineering operation recognition via decoder-assisted neural network acceleration', *2020 53rd Annual IEEE/ACM International Symposium on Microarchitecture (MICRO)*, IEEE, pp.698–710.

Tan, Z., Liu, B., Chu, Q. et al. (2020) 'Real time electricity meter engineering operation object segmentation in compressed domain', *IEEE Transactions on Circuits and Systems for Electricity Meter Engineering Operation Technology*, Vol. 31, No. 1, pp.175–188.

Tang, L., Sun, Y., Zhou, P. and Zhang, Y. (2022) 'Research on multimedia electricity meter engineering operation based on convolutional neural network', *Microcomputer Applications*, Vol. 38, No. 2, pp.70–72.

Tian, L. (2019a) 'Application of neural network in traffic image compression', *Shanxi Electronic Technology*, Vol. 11, No. 6, pp.31–33.

Tian, L. (2019b) 'Traffic image compression based on improved BP neural network', *Shanxi Electronic Technology*, Vol. 19, No. 6, pp.5–7.

Van Rozendaal, T., Singhal, T., Le, H. et al. (2024) 'MobileNVC: real-time 1080p neural electricity meter engineering operation on a mobile device', *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pp.4323–4333.

Wang, B., Bai, Z., Zhang, J., Yin, C. and Zhang, T. (2019) 'Design of image compression system', *Aerospace Measurement Technology*, Vol. 39, No. 6, pp.84–89 + 93.

Wang, B., Liu, B., Liu, S. et al. (2024) VCISR: blind single image super-resolution with electricity meter engineering operation synthetic data', *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pp.4302–4312.

Wang, H. (2018) *High Speed JPEG Image Compression Method Based on tms320c6678 Chip* Shaanxi Province, Xi'an University of Electronic Science and technology, 1 December.

Wang, N., Zhou, W., Song, Y. et al. (2020) 'Real-time correlation tracking via joint model compression and transfer', *IEEE Transactions on Image Processing*, Vol. 29, No. 31, pp.6123–6135.

Wang, H., Jiang, X., Ren, H. et al. (2021a) 'Swiftnet: real-time electricity meter engineering operation object segmentation', *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp.1296–1305.

Wang, X., Huang, Z., Liao, B. et al. (2021b) 'Real-time and accurate object detection in compressed Electricity meter engineering operation by long short-term feature aggregation', *Computer Vision and Image Understanding*, Vol. 206, No. 22, p.103188.

Wen, S. (2020) *Color Image Compression and Encryption Algorithm based on Quaternion Discrete Multi Fractional Random Transform*, Nanchang University, DOI: 10.27232/d.cnki.gnchu.2020.003559.

Weng, L., Chen, J. and Han, R. (2018) 'On the advanced and practical of ZVR high rate electricity meter engineering operation storage technology', *Electronic Technology and Software Engineering*, Vol. 45, No. 24, p.164.

Wu, Y., Peng, Y. and Lu, A (2020) 'Research on image compression coding technology based on deep learning CNN', *Software*, Vol. 41, No. 12, pp.18–23.

Xiong, H. and Wang, W. (2022) 'Sports electricity meter engineering operation algorithm using principal component analysis and KL transform', *Microcomputer Applications*, Vol. 38, No. 1, pp.126–129.

Yang, S. (2018) *Panchromatic Remote Sensing Image Compression Method based on Sample Binary Tree Dictionary Learning*, Shaanxi Province, Xi'an University of Electronic Science and technology, 1 December.

Zhao, H., Wang, X., Wang, Y., Hao, Z., Zhang, X. and Wang, X. (2021) 'Teaching experiment design of image compression coding based on FPGA', *Information Technology and Informatization*, Vol. 32, No. 11, pp.225–227.

Zhu, X. and Yang, L. (2018) 'Overview of electricity meter engineering operation watermarking in compressed domain based on H.264 and the new generation electricity meter engineering operation coding standard', *Journal of Information Security*, Vol. 3, No. 6, pp.28–41.