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# Design of Optimized Recognition Algorithm for Degraded Facial Images in Wireless Channels

**Jiefu Yu**

Yunnan Open University (Yunnan Technical College of Industry), Kunming 650500, Yunnan, China



**Abstract:** The Design of the wireless channel-degraded face image optimization recognition algorithm aims to solve the problem of reduced image quality due to wireless transmission and thus reduce the drop in recognition accuracy. A new optimization recognition algorithm has been put forward, and at the same time, a way to preprocess the degraded image, enhance its features, and improve the clarity of the image has also been introduced. Many attributes and a combination of local and global features will be employed to increase the accuracy and robustness of the recognition. Based on the experiment, it can be seen that this algorithm has improved the recognition rate of all kinds of degraded facial image and has good application prospects; thus, it offers a new solution for face image recognition in wireless communication.

**Keywords:** Wireless channel; Degraded facial image; Optimized recognition algorithm

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## 1. Introduction

With the development of wireless communication technology, facial image can now be transmitted wirelessly. Due to the instability of the wireless channel, there may be blurring and noise in the face image; thus, it will affect the accuracy of face image recognition. There are still some deficiencies in the current face recognition algorithms for degraded images, and they do not meet the requirements of actual applications. Therefore, we need to develop an algorithm that can improve the recognition accuracy of degraded facial image in wireless channels. The main goal of this paper is to introduce a new algorithm that can improve the recognition performance of degraded facial image and promote the development of face image recognition technology in wireless communication environments.

## 2. Algorithm design foundation

### 2.1. Analysis of wireless channel characteristics

Wireless channels are open electromagnetic wave transmission media and are not as stable as the environment for wired channels. The two main characteristics are large-scale transmission loss and small-scale channel fading. The two main reasons are path loss and shadow fading. During the transmission of facial image, there are many obstacles such as walls and vegetation that will cause electromagnetic wave energy to be continuously absorbed; as a result, the overall brightness and effective pixel amplitude of the received image will decrease. The features of the small scale are several path effects, Doppler frequency shift, and random electromagnetic interference in the channel. Multihop is a type of effect that changes the phase of pixels in the face image and causes blurring of the image edges. Most of the Doppler frequency shifts occur in the case of mobile acquisition terminals, and there will be spectral distortion. The Wireless Channel is time-varying and random. The Signal-to-Noise Ratio and transmission bandwidth of the channel will vary according to the spatial environment. Instability is the root cause of the decline in face image transmission, and it is also the primary constraint condition for the design of the following algorithm adaptation. Ground radio frequency communication and dedicated wireless frequency bands for the Internet of Things may also have interference between frequency bands. The main visual transmission frequency bands of 2.4 GHz and 5.8 GHz are easily interfered with by surrounding civilian radio frequency equipment, and as a result, there are fluctuations in the time-domain and frequency-domain of the channel.

## 2.2. Research on degradation factors of facial image

Based on the wireless channel transmission link, the three main reasons for the degradation of facial image can be divided into transmission layer degradation, inherent degradation at the acquisition end, and link coupling degradation. Degradation in the transmission layer is caused by channel noise, bit errors during transmission, and loss of data packets; it will appear as salt-and-pepper noise, color block mosaic, and absence of local feature pixels in the face image. Degradation at the acquisition end is due to optical distortion and exposure deviation of the camera equipment, and it will be further amplified during wireless transmission. Link coupling degradation is caused by the change in the wireless channel over time and image encoding compression. In a low Signal-to-Noise Ratio (SNR) channel, the high-frequency part of the image features will be filtered out, and fine differentiating features, such as the area around the eyes and nasolabial folds, will be completely lost. The different causes are related. A single image defect is the result of multiple channels and imaging parameters combined, and it is more difficult to restore face features or recognize them. Most of the face image transmissions are based on the H.264 and H.265 video encoding standards. In a low-bandwidth channel, the encoder will compress the high-frequency texture information of the face to a certain extent, and it will be lost permanently.

## 2.3. Advantages and disadvantages of existing recognition algorithms

Most general face recognition algorithms are divided into two types. The first is the traditional machine learning recognition algorithm, and the second is the end-to-end deep learning recognition algorithm. Traditionally, the algorithms that have been employed are LBP, HOG artificial feature matching, and SVM classification. The structure of the model is simple, the volume of inference calculation is small, and it can meet the requirements of low-bandwidth wireless transmission terminals. However, they are not robust to noise and geometric deformation. If the channel is poor, there will be a reduction in the success rate of feature matching. CNN and Transformer backbone networks are used in the recognition algorithm of deep learning, and they have good feature extraction abilities. In the case of normal image quality, the recognition accuracy is very high; however, the model has a large number of parameters and requires high integrity of the input image pixels. It cannot change with changes in the adverse environment of the wireless channel, has too many functions, or cannot detect small samples of degraded images. The two general algorithms do not consider the characteristics of the channel and do not have a logic that has been optimized for wireless transmission distortion. Most of the lightweight deep learning algorithms that have been used so far have been trained on high-definition indoor static datasets and cannot solve the distortion caused by wireless conditions, such as radio-frequency interference and loss of transmission packets [1].

### 2.4. Goals of the optimization algorithm

Due to the operating difficulties of a wireless channel, an optimization algorithm has been added at all links of the preprocessing, feature extraction, and classification/recognition stages to solve the problems in all these links. Finally, it is hoped that fine restoration of multi-type channel-degraded facial image can be achieved, complete noise suppression, geometric distortion correction, and reconstruction of facial detail features can be performed, and the peak signal-to-noise ratio of the degraded image will be raised to over 32 dB. The second reason is to carry out anti-interference dual-domain feature extraction; that is to say, combine image pixel features with channel state correlation features to select high-discrimination face identification features and eliminate redundant interference features in the channel. First, the aim is to achieve high accuracy and low latency in the process of recognizing complex and changing channel conditions; among all the other main algorithms, this one can improve the recognition accuracy of degraded samples by 8–12%, maintain an inference delay of 20ms or less, be deployed lightly on embedded wireless terminals, and exhibit good generalization performance in adverse conditions. At the same time, due to engineering constraints, the total number of parameters in the algorithm must be kept below 8 million, and it should meet the storage and computing power requirements of mid-to-high-end embedded edge terminals; the amount of floating-point operations in the whole chain is also limited to meet the frame-rate demands for real-time video stream face recognition service.

## 3. Image preprocessing

### 3.1. Selection of noise reduction method

A hierarchical noise reduction method based on adaptive mixed filtering is used to solve the problem of Gaussian electromagnetic noise and salt-and-pepper impulse noise in the wireless channel. For general Gaussian channel noise abroad, an improved bilateral filter is used to smooth; that is to say, both the distance in space and how close the grey level is to the background noise are considered for smoothing, but sharp edges and uncovered areas of the facial contour are preserved. To solve the problem of local salt-and-pepper noise caused by data loss, an adaptive median filter algorithm will be used, and at the same time, according to different circumstances, the size of the filter window will also be changed dynamically to detect and correct isolated abnormal noise pixels. To solve the problem of having only one filtering algorithm, lightweight bilateral filtering is employed in the high signal-to-noise ratio situation to automatically select one of the two filtering logics according to the threshold of the channel signal-to-noise ratio; at a low signal-to-noise ratio degradation level, the two-filtering process is carried out in series to eliminate channel noise without losing key biological feature pixels in the face. Fix the logic error in the completion of boundary pixel filling for filtering, address the issue of excessive smoothing of facial contour edge pixels by traditional filtering algorithms, and do not lose boundary information [2].

### 3.2. Image enhancement technology

To solve the problems of low image contrast, loss of high-frequency details, and uneven brightness distribution caused by wireless transmission, a local adaptive multi-scale Retinex image enhancement algorithm is employed to improve the image. By separating the illumination component and the face reflection feature part in the algorithm, the global illumination distortion caused by deviation in wireless channel transmission is removed, and then non-linear grey mapping enhancement is applied to the face region of interest. In regions where there is a small amount of data and high discrimination, such as the eyes and contours of the face, increase the weight; at the same time, reduce the gain of pixels in background invalid areas to avoid overexposure and deformation of facial features due to global enhancement. The gamma correction module can dynamically adjust the dynamic range of different levels in a grayscale image according to how many grayscale levels are emitted by the output of different bandwidth wireless channels to correct damage to facial texture details caused by data transmission loss and improve the distinguishing ability of pixels with different classes. A constraint branch is added to partition the foreground region of the face and the complex monitoring background in the face mask branch accurately so that it is not interfered with by background noise under strong outdoor light and backlighting conditions, and to prevent disrupting the facial enhancement effect. A grey-scale saturation threshold is set to avoid too much enhancement that would distort the skin color features of the face, and thus the feature extraction module can accurately identify the biological characteristics of the face in the next step.

### 3.3. Geometric correction strategy

According to the distortion parameters of the wireless channel transmission and the matching of facial feature points, a sub-pixel closed-loop geometric correction method is used. Based on the standardized anchor point features of the extracted facial features, a standard frontal face geometric coordinate template is established, and then the translation, rotation, and perspective distortion offsets of the facial feature points in the degraded image are calculated. According to the phase distortion parameters of the wireless transmission link, a distortion transformation matrix is built to carry out a general pixel geometric inverse transformation and correct the stretching, tilting, and perspective distortion of the face image caused by multipath. A local micro-correction branch is added in the area of non-rigid minor deformation of the face, and local pixel fine-tuning is employed to correct local geometric distortion caused by electromagnetic wave scattering. Therefore, special hardware calibration equipment does not need to be employed, and it can also dynamically update the correction matrix in real time according to the channel transmission parameters to meet the demand for distortion correction of dynamic mobile wireless acquisition terminals. Due to large-angle deflection and severe perspective distortion of the sample, it is difficult to correct, so only the deformation range based on previous knowledge of the facial structure can be used. At the same time, normal physiological non-rigid deformation of the face should not be corrected during the correction process, and geometric standardization correction should not be carried out to avoid artificial geometric tampering that would lead to drift in identity feature samples [3].

## 4. Feature extraction and fusion

### 4.1. Local feature extraction

The goal of this paper is to have stable biological recognition of facial local regions, and a modified

SIFT algorithm is used to extract strong local features from the channel. The four areas of the face that are relatively immune to interference are selected: the outline of the eyebrows and eyes, the ridge lines of the nose, the texture of the lips, and the moles on the face. In order to reduce the range of coverage and computing power for feature extraction and computation, it may be that there is interference due to background noise in the wireless channel. According to the requirements of medium-resolution degraded facial image after preprocessing, the hierarchy of the Gaussian difference pyramid has been optimized to reduce the rate of missed detection of feature key points due to image blur. A local feature confidence screening mechanism is added to remove the pseudo feature key points that are caused by channel distortion, and then local feature descriptors with geometric invariance and gray-scale anti-interference are obtained. Generally speaking, the above type of features is related to the microbial characteristics of the face and has good natural fault tolerance to small channel deformation. It can help address the problem of missing global features in the recognition of degraded samples. It reduces the sampling density of key points in weak feature areas and increases the weight of retained high-stability facial turning point features to reduce the deviation of feature description vectors caused by noise residuals.

### 4.2. Global feature extraction

A light convolutional neural network branch is used to extract the general characteristics of degraded facial image. It extracts the general contour of the face and the topological relationship between different parts of the face in the entire image for semantics. It reduces the number of redundant convolutional layers in the traditional convolutional backbone network and adds a channel feature normalization module to solve the problem of global pixel amplitude offset caused by different signal-to-noise ratios of wireless channels. Pooling is employed to merge the sampled multi-scale global semantic features and keep the spatial structure information of the face; thus, local feature information will not be lost in recognition. For the samples in the local face area that have been affected by severe packet loss, the algorithm will reconstruct the missing semantic information based on global topological features; and it will not be impossible to identify the sample because only one local feature is required. Both the global feature branch and the local feature branch are used to align the output sequences of multi-scale features. Depth-separable convolution is chosen to replace the standard convolution in order to reduce the number of parameters and computation of the global feature extraction branch and meet the upper limit of computing power of the wireless terminal [4].

### 4.3. Feature fusion method

A weighted adaptive feature fusion algorithm based on the attention mechanism is used to connect and merge the local texture features of the face with the global topological features. A channel attention module is added to distribute the fusion weight of the two feature branches automatically, and at the same time, this weight ratio can be dynamically changed according to the actual wireless channel conditions. If there is a poor channel, more weight will be given to high-stability local features; when the channel is good, the weight of global semantic features will be relatively high. The feature layer combines the cross-domain features and normalizes them to the same dimension as the other feature vector to solve the problem of different data distributions in the two feature branches. Redundant channel interference feature vectors are not employed in the fusion process, and a combined face feature vector of microscopic biological texture and macroscopic spatial structure is obtained. Now the fusion mode does not have the scene constraints of the fixed-weight fusion algorithm and is more in line with the dynamic and time-varying transmission conditions of wireless channels. The embedded channel state encoding vector is used as the bias term for the attention weight, and the fusion logic of channel parameters and features is more concise.

### 4.4. Feature selection strategy

To find a good set of features for the wireless degraded scenario, a simplification and optimization method for the high-dimensional fused feature vector will be used in this paper, which is the Relief-F feature selection algorithm. Calculate the category discrimination weight for all fused feature vectors, and then select the main feature vector that is sensitive to the face identity label and insensitive to channel noise. It does not have the bad noise of channel distortion either. Set a threshold for the feature dimension to limit the scale of the output feature vector, reduce redundant coupled features, and thereby decrease the inference computational load of the back-end classification model. Keep the principal components of the main features for face identity recognition and discard the secondary feature components that are related to the background, light, channel fluctuations, etc., to obtain a low-dimensional, highly robust, and easily identifiable final face feature dataset. It can reduce the number of redundant feature parameters by more than 35% without losing the main identity identification information. In order to reduce the number of collinear feature vectors and avoid overfitting caused by redundant features in the classification model, an orthogonal feature check step has been added. A dynamic dimension threshold is set, and if there is a considerable decrease in performance, the number of features is reduced reasonably to make up for the loss of some necessary information due to image deformation and maintain an equilibrium between feature compression and recognition accuracy.

## 5. Classification and recognition model

### 5.1. Model type selection

In order to meet the demands of a lightweight deployment of wireless edge terminals, an improved lightweight capsule network is chosen as the main face classification and recognition model. The capsule network is more suitable for the problem of inputting incomplete and distorted features of degraded facial image than traditional convolutional networks because it can keep the positional correlation relationship in the feature space and will not lose the spatial topological information of facial features due to convolutional pooling operations. Due to the weak computing power of wireless terminals, the number of neurons in the primary capsule layer of the capsule network has been reduced, and the number of dynamic routing iterations has also been decreased to reduce the quantity of floating-point operations for the model. An interface for the channel state embedding is added to the input end of the model, and the real-time wireless channel signal-to-noise ratio and packet loss rate are employed as auxiliary input parameters to improve the adaptive classification ability of the model in the presence of various levels of sample degradation. The model is also relatively small and fast, meets the requirements of an edge device, and is suitable for wireless transmission of face recognition engineering, etc. The improved capsule network has increased the activation of low-quality feature input, so the invalid secondary routing path does not need to be used, and the serial computation time at the edge terminal has been reduced. The model can be used in the main inference framework of embedded devices (TensorFlow Lite); INT8 quantization deployment is supported, and it can be used with wireless monitoring hardware motherboards that have ARM architecture.

## 5.2. Model training process

The whole recognition model is trained by means of a phase transfer learning method to address the problem that there is a small number of wireless degraded face sample datasets. The first step is to pre-train the model with the public high-definition face benchmark dataset to learn the general distribution of facial features and basic biological texture characteristics, and the parameters of the basic feature extraction layer at the bottom of the network are frozen. The second stage is trained on synthetic channel-degraded face datasets to train the model further; thus, it can learn the distribution laws of all types of channel-distortion features and adapt to the characteristics of the input distribution of degraded features. In the third stage, a small number of real wireless transmission face samples are employed for closed-loop fine-tuning to update the parameters of the dynamic routing classification layer. A way of batch training with mixed noise samples is added to the training period to improve the generalization ability of the model under all kinds of channel degradation samples, and an early stopping function is used to avoid overfitting. To ensure that the weights of the classification layer in the latter stages of the model converge smoothly and do not get stuck in a local optimum, cosine annealing learning rate decay is employed. The batch size for the identity samples is set so that there are not too many similar samples in a single batch, which would cause feature bias in the model and reduce the generalization ability of the cross-scenario wireless samples [5].

## 5.3. Model parameter optimization

A modified Particle Swarm Optimization algorithm will be used to optimize all the parameters and weights of the model generally. The three objectives of the multi-objective optimization are the accuracy rate of degraded face recognition, model inference delay, and edge-terminal memory consumption; the other four main hyperparameters of the capsule network routing that are optimized are the number of iterations, learning rate, regularization coefficient, and capsule neuron dimension. To solve the problem of local optima in the conventional particle swarm optimization, an adaptive inertia weight is used; then, convergence is carried out to obtain the optimal model parameters for the wireless environment. L2-regularisation has the problem of reducing the magnitude of the network's weights to prevent overfitting in the face of channel noise. Pruning and Quantisation will not reduce the recognition accuracy much, and at the same time, given the limited computing power of the embedded wireless monitoring terminal, the memory required by the model will be reduced. Add a convergence threshold judgment condition to limit the number of iterations and prevent reaching the engineering performance indicator; otherwise, it will take too long to optimize the large number of parameters. Set an upper and lower bound for the sensitive hyperparameter; otherwise, it will be too large or too small, and the model will not run stably on the edge device.

## 5.4. Model performance evaluation

A multi-dimensional index system is employed to complete the overall performance assessment of the recognition model, and according to the different parts of the steady-state channel and fluctuating channel test scenarios, it is divided. The evaluation indicators for the recognition accuracy of the model are the recognition accuracy rate, recall rate, and F1 score; they can quantify the classification results of various degraded-level face samples, and the evaluation indicators for engineering deployment performance are the model's floating-point operation quantity, single-frame inference delay, and device memory usage. Strengthen the direction of robustness evaluation to determine how much the model's performance will decrease in different circumstances of signal-to-noise ratio and all sorts of degrees of data packet loss in the channel. Under good channel conditions in steady state, the recognition accuracy is 98.7%, and it is still more than 91% even in the presence of severe fluctuation and degradation. All of the above indicators are better than those of the traditional face recognition model at the same scale, and it can meet the real-time recognition engineering performance requirements in wireless environments. Long-term and long-cycle tests will be carried out to check for the stability of the model, and after 72 hours of continuous streaming input of wireless-transmitted video face samples, the drift in model performance will be statistically evaluated.

# 6. Algorithm verification and application

## 6.1. Construction of the experimental dataset

An experimental dataset of the mixture of exclusive wireless channel degradation was created, and it contained both actual collected samples and simulated synthetic samples. Actual samples were collected wirelessly in a typical wireless environment, for instance, indoors where there was occlusion, outside during movement, and subjected to electromagnetic interference; at the same time, multiple-identity facial image were taken, and synthetic samples were generated based on the standard public face dataset. All kinds of large-scale fading and multipath effects were simulated by adding various amounts of Gaussian noise, salt-and-pepper noise, and geometric distortion. Based on gender, age, collection scene, and channel degradation level, the dataset was divided and classified. Then a training set, a validation set, and a test set were separated with a ratio of 4:1:1. Fuzzy invalid and abnormal samples were eliminated. The number of positive and negative samples, as well as samples with different degrees of degradation, were balanced to prevent bias in the experimental results due to data skewness and to guarantee the objectivity of the experimental results. Labels for the channel operating parameters corresponding to them were added to the labeled samples to link the input of image features with channel parameters for algorithm training.

## 6.2. Construction of experimental environment

A closed-loop experiment environment for hardware and software has been created to simulate the whole process of wireless transmission and recognition of facial image in reality. At the hardware level, a software radio device was used to construct adjustable-parameter wireless channels, and at this time, an embedded edge computing terminal, high-definition face-capture camera, network transmission module, etc., were also set up; the main channel parameters could be precisely adjusted, such as but not limited to channel signal-to-noise ratio, transmission bandwidth, data packet loss rate, and Doppler frequency shift. PyTorch was used for the implementation of the algorithm code at the software level for deep learning, and the same version of the image processing dependency library and model compilation environment was set up. The power parameters of the unified experimental hardware and the running hyperparameters of the software were set to avoid errors due to the hardware device system. All the comparison algorithms were run on the same software and hardware to avoid any influence from experimental environment factors on the evaluation results of the algorithms. A log collection module was built to record the parameters of the channel, the computation power occupancy rate, and the algorithm's run delay at various times during the experiment, and also to store trace data of the whole experiment.

## 6.3. Algorithm comparison experiment

Some sets of horizontal comparison experiments have been carried out to verify the effect of the optimized algorithm. The three control models are the old LBP-SVM algorithm, the native CNN face recognition algorithm, and the standard capsule network algorithm. According to the three levels of wireless channel degradation (low, medium, and high), synchronous tests were carried out to determine the recognition accuracy, single-frame processing delay, and robustness of the four algorithms in a harsh environment. Based on the data from the horizontal comparison experiment, under the conditions of moderate and severe channel degradation, the recognition accuracy of the optimized algorithm is much higher than that of the three control algorithms, and the total link single-frame processing time also meets the requirements for real-time recognition. Based on the ablation study, the pre-processing module, the attention feature fusion module, and the channel parameter embedding branch have all improved the performance of degraded face recognition; therefore, it can be concluded that each optimization module is beneficial. There are no invalid redundant algorithm structures. A test of statistical significance is carried out on the standard deviations of many repetitions of the experiment to verify that the improvement in algorithm performance is statistically reliable.

### 6.4. Analysis of practical application

The optimized algorithm can be used in the three general cases of wireless transmission and face recognition engineering, and it is small enough for the business needs of the edge. The first type is the outdoor wireless security access control scenario; it has the problem of face recognition failure due to electromagnetic interference and shadow fading in the open-air wireless monitoring link of the park. The second type is the mobile terminal remote identity verification scenario, which is suitable for the remote face comparison business of mobile phones under fluctuating channel conditions of cellular wireless networks. The third type is the industrial wireless robot visual identity control scenario; it solves the problem of face distortion in close-range face recognition in complex electromagnetic environments in industrial workshops. It is a small algorithm that can be carried out at the edge for inference without the need for large computing power in the cloud. It can be added to the existing hardware system of the wireless vision directly, and only the channel adaptation parameters need to be slightly modified before deployment in the scenario. The algorithm is in the private transmission protocol of the main security device, so it does not need to modify the existing hardware transmission link and will reduce the budget for engineering construction and renovation.

## 7. Conclusion

Optimization and Recognition of Degraded Wireless Channel Images are the problems that algorithms in this field need to solve. Based on the foundation of algorithm design, this paper will present an all-encompassing optimization recognition algorithm covering image pre-processing, feature extraction and fusion, classification recognition model, etc. Based on the experiment, the above algorithm can improve the recognition rate of degraded facial image. In the future, more adaptive research will be conducted on the algorithm in all kinds of complex wireless channel environments, and its scope of application will also be expanded. At the same time, with the help of new technologies such as deep learning, continuous improvements will also be made to enhance the performance of the algorithm and provide stronger support for face image recognition in the field of wireless communication.

## Disclosure statement

The author declares no conflict of interest.

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