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Research Article

Video Recognition of Government Community Management Cases Based on Partial Differential Equation Method

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With the development of urban economic construction and urban planning, higher requirements are put forward for the government community in the corresponding community management, community service, and other related things. As an important technical means to assist the government and community in management, video recognition technology plays an important role in the accurate management and service of the government and community. Traditional algorithms based on partial differential equations will destroy image edges and image details in video recognition. Based on this, this paper improves the traditional partial differential equation algorithm of image recognition, selects the GAC model based on image segmentation in the main function, and innovatively optimizes the stop function of its equation function, so as to improve the effect of community case image segmentation. In the image smoothing layer, this paper innovatively selects the second derivative based on image processing as the inherent feature of image recognition, so as to solve the rough problem of image edge and improve the processing efficiency of the algorithm. In order to further maintain the details of the relevant images of community cases, this paper integrates the Gaussian curvature driving function on the improved partial differential equation algorithm, so as to protect the details of the smooth region of the relevant recognition video and solve the disadvantages of the traditional algorithm. The experimental results show that the improved partial differential equation algorithm proposed in this paper improves the accuracy of video recognition by about 5% compared with the traditional algorithm. At the same time, the new algorithm can well ensure the detail integrity of the recognized video.

1. Introduction

The digitization of government community management is the trend of community development. The digitization of community management depends on the corresponding digital technology, including video recognition and Internet of Things. Accurate, reasonable, and efficient community video recognition technology is conducive to strengthening the government's efficient management of the community and improving the quality of relevant public services in the community [1–3]. With the continuous development of video recognition technology, the corresponding traditional mainstream video recognition technology mainly includes video processing, stochastic modeling method, video digital signal processing algorithm, and partial differential equation algorithm [4, 5]. The corresponding digital signal processing algorithm mainly relies on the wavelet analysis algorithm for image processing and recognition. The corresponding wavelet transform analysis algorithm realizes the processing and analysis of dynamic signals on the basis of the original Fourier transform algorithm. At the same time, the wavelet transform analysis also has the ability to distinguish time, space, and corresponding frequency; however, the wavelet transform algorithm has serious defects in the edge protection of the recognized video or image. It only has certain advantages in specific image processing fields such as image noise reduction and segmentation [6–8]. The traditional partial differential equation algorithm is more and more widely used because it has strong anisotropic diffusion performance, so it can protect the edge information of the recognized video. However, the traditional partial differential equation image processing algorithm still can not meet the requirements of today's community video management in image processing details and corresponding image processing accuracy; therefore, the improved algorithm based on the traditional partial differential equation algorithm is very meaningful.

The traditional partial differential equation image processing algorithm essentially instructs the recognized image to change continuously according to a specific partial differential equation. The final mathematical solution obtained by continuous calculation and iteration based on this partial differential equation is the final image processing result [9, 10]. The conventional image processing technology based on partial differential equation includes the active contour algorithm, nonlinear diffusion model algorithm, and corresponding level set algorithm. Under the above three core processing concepts, a variety of partial differential equation algorithms are derived [11, 12]. The core of the corresponding active contour algorithm is to establish the corresponding energy function by using the internal and external force constraints of the recognized image and make the corresponding curve continuously approach the processed image by using the joint action of the corresponding internal and external forces [13]. The core idea of the corresponding level set algorithm is to treat the corresponding recognized image as a level set curve [14]. The corresponding core idea of the corresponding nonlinear diffusion model algorithm is to use the nonlinear function whose diffusion function changes with the local properties of the corresponding image to process the corresponding image or video [15]. The conventional partial differential equation processing algorithm can give the continuity model of the recognized image or video, so as to transform the processing process corresponding to the processed image into an image processing problem varying with time, so that the gray level corresponding to the corresponding recognized image depends on a mathematical partial differential function and realize the connection of the image physical process through continuous iteration, so as to visually analyze the gradient, level set, curvature, and other features of the corresponding video or image. Compared with other algorithms, the traditional partial differential equation algorithm has good adaptability in the corresponding local video processing. It can protect the image texture and edge details while processing the video or image [16, 17].

In view of the disadvantages of the above traditional partial differential equation in video or image processing, this paper will improve the traditional partial differential equation image recognition algorithm, select the GAC model based on image segmentation on the main function, and optimize its corresponding stop function, so as to improve its corresponding image segmentation effect; at the level of image smoothing, this paper selects the second derivative based on image processing as the inherent feature of the recognition image, so as to solve the rough problem of image edge and improve the processing efficiency of the algorithm. In order to further maintain the details of the recognized image, this paper integrates the Gaussian curvature driving function on the improved partial differential equation algorithm, so as to protect the details of the smooth region of the relevant recognized video. The experimental results show that the improved partial differential equation algorithm proposed in this paper improves the accuracy of video recognition by about 5% compared with the traditional algorithm. At the same time, the new algorithm can well ensure the detail integrity of the recognized video.

The structure of this paper is as follows: in Section 2, the current research status of traditional partial differential image recognition algorithms will be analyzed and studied. In Section 3, the improved partial differential image recognition algorithm is analyzed and studied, and the Gaussian curvature driving function is analyzed and studied in detail. Section 4 of this paper will experiment with the algorithm proposed in this paper and analyze the experimental results. Finally, this paper will be summarized.

2. Correlation Analysis: Research Status of Image Recognition Algorithm Based on Partial Differential Equation

At the corresponding level of image recognition, the partial differential equation algorithm has been studied and optimized by a large number of scholars and research institutions because of its natural advantages of detail protection. European and American researchers first proposed an image model based on anisotropic diffusion, which directly replaces the isotropic diffusion in Gaussian smoothing. Based on this model, such as the P-M diffusion model, nonlinear diffusion model, partial differential equation of image processing based on impulse filter, and image denoising algorithm based on TV total variation continue to appear, thus, the relevant partial differential equation algorithm is introduced [18–20]. In order to further explore the deficiency of the uniform linear diffusion image processing model in the conventional partial differential equation algorithm, the nonuniform diffusion equation is gradually introduced. The model can make the corresponding recognized image have a relatively large diffusion coefficient at the corresponding flat place and a smaller diffusion coefficient at the corresponding image edge. However, this algorithm will be seriously disturbed by noise when routinely using image gradient to judge the corresponding image edge, resulting in large error in the result [21]. In order to solve the above error problems, relevant American researchers proposed a nonlinear diffusion model equation, which proposed a large number of anisotropic nonlinear diffusion partial differential equations and selected the diffusion coefficients in different directions based on the anisotropic diffusion equation, so as to remove the image noise and protect the corresponding features of the image edge [22]. In order to solve the shortcomings of the above uniform linear diffusion image processing model, the diffusion coefficient must take into account the structural characteristics and important detail information of the image to be processed and construct a structure that can reduce the diffusion at the edge according to the structural and detail characteristics of the image to be processed, so as to effectively retain the important features of the image while denoising. Based on this, the nonuniform diffusion equation is proposed and applied by the research community. The corresponding essential core idea is to construct an appropriate diffusion coefficient function, so that there is a relatively large diffusion coefficient at the flat part of the image and a small diffusion coefficient at the edge of the image, so as to solve the problems of unclear local detail processing in the nonlinear diffusion partial differential equation. However, when using a gradient to judge the edge, this method will be greatly affected by noise and produce large deviation. In order to further overcome the shortcomings of the above nonuniform diffusion equation, relevant researchers further proposed an improved nonlinear diffusion equation model, which can effectively avoid the error caused by the noise of the abovementioned nonuniform diffusion equation. At the same time, relevant follow-up researchers further studied the image processing model of nonlinear diffusion equation, proposed some anisotropic nonlinear diffusion partial differential equations, and further improved the improved nonlinear diffusion partial differential equation. The corresponding essential principle is that the anisotropic nonlinear diffusion equation uses the diffusion coefficients in different directions. It can remove noise and maintain image features such as edges. In order to further solve the image edge blur problem corresponding to the traditional partial differential equation algorithm, relevant researchers proposed an image processing model of forward and backward diffusion equation. Its main core idea is to select the corresponding negative value at the edge of the recognized image as the diffusion coefficient, so as to realize the edge sharpening of the processed image and realize the final noise reduction of the image [23–25].

3. Improved Partial Differential Equation Video Recognition Algorithm Based on Gaussian Curvature Driving Function

This section mainly analyzes and studies the corresponding principle of the improved partial differential equation video recognition algorithm and analyzes and studies its key technologies. The corresponding algorithm analysis system is shown in Figure 1. It can be seen from Figure 1 that the improved algorithm selects the GAC model based on image segmentation on the main function and optimizes its corresponding stop function, so as to improve its corresponding image segmentation effect. At the level of image smoothing processing, this paper selects the second derivative based on image processing as the inherent feature of the recognition image; so as to solve the problem of rough image edge, the processing efficiency of the algorithm is improved. In the image edge processing part corresponding to the whole system, the Gaussian curvature driving function is mainly used to process and analyze the image edge. The Gaussian curvature driving function further optimizes the detail processing of the recognized video or image to a certain extent, so as to improve the performance of the recognition algorithm to a certain extent.

3.1. Gaussian Curvature Driving Function. In order to further optimize the detail processing of the recognized video, the denoising model used in the improved algorithm is an improved model based on the Gaussian curvature driving function. The corresponding core principle is to treat the recognized image or video as a two-dimensional surface in the three-dimensional space corresponding to the coordinate axis, so as to introduce the geometric characteristics corresponding to the image into the corresponding denoising partial differential equation for processing; at this time, the corresponding image or video noise is identified as a local Gaussian curvature function, and it can be effectively eliminated and replaced by other corresponding functions. The original function of the corresponding Gaussian curvature driving function is shown in formula (1). All conventional coefficients in the following formula (1) are real values greater than zero. The corresponding mathematical symbol t represents the time variable of the system, the mathematical symbol m represents the image gradient of the recognized image, and the mathematical symbol n represents the corresponding divergence operator.

$$m_t = \operatorname{div} \frac{\phi\left(m_{ij}\left(m_{ii} - m_{ij}\right)\right)}{\left(1 + m_i + m_j\right)\left(1 - m_i + m_j\right)} \nabla m(x, y). \tag{1}$$

It is optimized and improved based on the above formula. The corresponding improvement process is shown in Figure 2. It can be seen from the figure that it is mainly divided into two levels: the establishment of the model and the numerical solution optimization algorithm of the improved model. In the process of establishing the corresponding model, the corresponding mathematical expression of the improved model is shown in formula (2), and the specific definition of the corresponding key function is shown in formula (3); the corresponding mathematical symbol definition in the formula is unified with the above formula. At this moment, the corresponding function model will control the diffusion of the function according to the Gaussian curvature and the corresponding gradient. When the corresponding Gaussian curvature is in the area where the corresponding value is zero, the corresponding model will stop the diffusion operation, and when the value corresponding to the corresponding Gaussian curvature is not zero, the corresponding diffusion speed will be accelerated. Based on this, it can be seen that the diffusion speed of the improved model can be well controlled compared with the traditional model, and the edge details of the recognized video or image can be better protected compared with the traditional Gaussian curvature model.

$$\frac{dm}{dt} = \operatorname{div}\left(\varphi(H) * (\nabla m)^2 * \nabla m(x, y)\right), \tag{2}$$

$$\begin{cases} \phi(H) = \ell - (2\ell - 1)\left(\dfrac{x}{\lambda}\right)^2 + (\ell + 1)\left(\dfrac{x}{\lambda}\right)^4, -\lambda < x < \lambda, \\ \cdots \\ 0, \quad x \geq \lambda \text{ or } x \leq -\lambda. \end{cases} \tag{3}$$

The numerical solution algorithm level in the corresponding improved Gaussian curvature driving function algorithm model is mainly the corresponding model formula

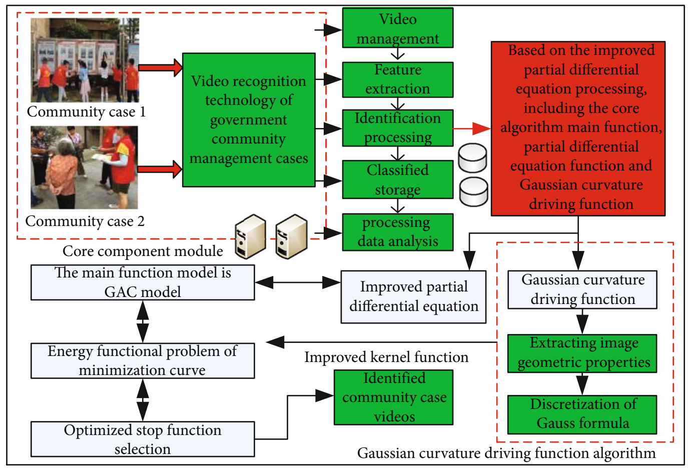

Figure 1: Principle block diagram of the improved partial differential equation video recognition algorithm.

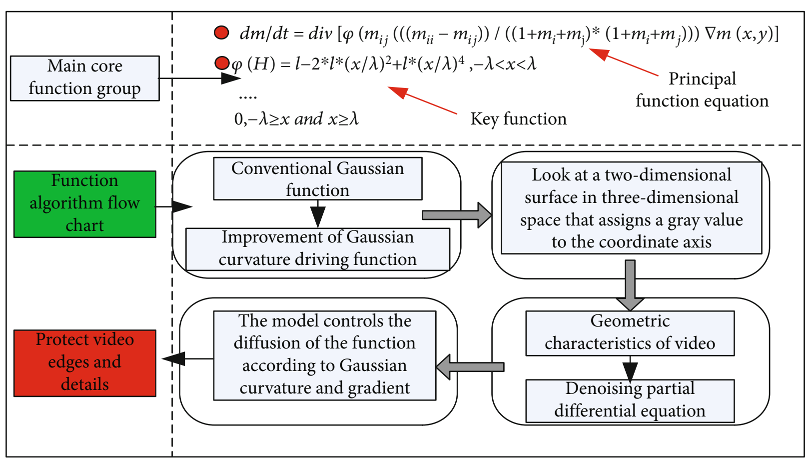

Figure 2: Flow chart of the improved Gaussian curvature driving function algorithm.

in discretization formula (2). Based on this, the corresponding new solution formula is shown in formula (4), in which the formula details corresponding to function formula G are shown in formula (5), and the corresponding final solution result will be continuously approximated by formula (6); finally, the desired solution is obtained.

$$\begin{cases} m^2 = m^1 + \left(\operatorname{div}\left(\phi(H)*\nabla m*(\nabla m)^0\right)\right), \\ \cdots \\ m^{i+1} = m^i + \left(\operatorname{div}\left(\phi(H)*\nabla m*(\nabla m)^{i-1}\right)\right), \end{cases} \quad (4)$$

$$\operatorname{div}\left(\phi(H)\nabla m(\nabla m)^i\right) = \left(\phi(H)(\nabla m)^{i-1}\frac{\partial H}{\partial x}\right)_t + \left(\phi(H)(\nabla m)^{i-1}\frac{\partial H}{\partial y}\right)_t, \quad (5)$$

$$\begin{cases} \phi(H) = \ell - (2\ell - 1)\left(\dfrac{x}{\lambda}\right)^2 + (\ell+1)\left(\dfrac{x}{\lambda}\right)^4, -\lambda < x < \lambda, \\ \cdots \\ 0, \quad x \geq \lambda \text{ or } x \leq -\lambda. \end{cases} \quad (6)$$

From the expression of the above formula, it can be seen that the improved Gaussian curvature driving function model is essentially to calculate the product of the principal curvature corresponding to the model. When the corresponding principal curvature is zero, the corresponding regions are all zero, and the corresponding Gaussian curvature corresponding to the region where the so-called average curvature is not zero may also be zero, Therefore, based on this point, the problem that the corresponding detail structure and corresponding image features cannot be retained in the case of corresponding average curvature can be well solved. In essence, in the corresponding main algorithm flow, the Gaussian curvature driving function model is used as the front and back filters of the image input. Compared with the traditional filter, the improved Gaussian curvature driving function model can effectively remove most of the noise.

3.2. Analysis of Improved Partial Differential Equation Video Recognition Algorithm. The main function model used in the selection of the improved partial differential equation video recognition algorithm is the GAC model. In essence, it is to segment the recognized image or model and gradually transform the corresponding image segmentation problem into the energy functional problem of the corresponding minimization curve. The corresponding function of the corresponding improved GAC model is shown in formula (7). In the corresponding formula, s represents the parameter function, and the corresponding function g is the subtraction function.

$$P[c(s)] = b_1 * \int_0^t g(s(p) * \nabla q) dt + b_2 * \int_0^t |s(p)| dt). \tag{7}$$

Based on this, the corresponding image curve segmentation is essentially similar to light propagation. It needs to use the corresponding minimization formula to determine the contour of the object in the relevant image. The corresponding calculation formula is shown in formula (8). The corresponding $L(c)$ function in the formula represents the arc length corresponding to the closed curve C, and the corresponding $LR(c)$ function represents the corresponding target minimum functional. The image gradient descent function stream corresponding to equation (7) is shown in

$$\frac{\partial(s)}{\partial(t)} = \bar{d} * \left((s) - \nabla g * \bar{d}\right). \tag{8}$$

Based on the analysis of the above basic formula, the action behavior demonstration diagram of the corresponding GAC model is shown in Figure 3. From the figure, it can be seen that the corresponding model behavior is mainly divided into two parts. The corresponding first part is essentially the result of the interaction between the average curvature motion and the nonnegative scalar factor. In this result, when the corresponding curvature is positive, the corresponding curve moves inward, and when the corresponding curvature is negative, the corresponding curve moves outward. At the same time, the total length of the corresponding curve will continue to shorten and gradually tend to be smooth; at this time, the corresponding nonnegative scalar factor will gradually tend to 1, and the corresponding trend formula is shown in formula (9). At the same time, the nonnegative scalar factor near the corresponding image edge will tend to 0. At this time, the corresponding trend formula is shown in formula (10). The corresponding second part mainly discusses the two dominant forces of the GAC model at this time, which correspond to internal force and external force, respectively. The corresponding internal force mainly makes the control curve shape, the corresponding curve smooth and round, and the corresponding external force mainly drives the curve close to the boundary area in the image; finally, the curve stops at the boundary of the object in the recognized video or image.

$$\nabla g \longrightarrow 0 \succ g \approx 1, \tag{9}$$

$$\nabla g \longrightarrow r \succ g \approx 1. \tag{10}$$

The energy minimization processing method is followed when actually using the GAC model for video or image processing. The main factors considered are as follows: conventional community video can be understood as the deformation of corresponding abstract data under the action of internal and external forces, and the physical essence of corresponding video or image is expressed by energy function based on the processing model itself. When the internal and external functions corresponding to the corresponding processed image reach a certain balance, the identified video or image will minimize the energy. At this time, the image solution obtained by the model is the corresponding best output video or image solution. The corresponding energy minimization method is mainly to find the partial differential description equation Euler Lagrange equation corresponding to the main function GAC model. The corresponding way of seeking energy minimization is mainly based on the variational idea, and the relevant equations are solved based on the energy generalization extreme value problem. The corresponding processing steps are as follows:

Step1: analysis considers the properties of the recognized video or image, the smoothness of the corresponding restored image or video and its consistency with the corresponding ideal output image, as well as the details and edge protection of the corresponding image or video edge.

Step2: makes a reasonable and effective mathematical language description based on the properties obtained in step 1, so as to obtain a preliminary energy generalization function. At the same time, different mathematical description models are established for different community scenes. At the same time, the existence, stability, and uniqueness of the relevant models are analyzed and described, and finally, the corresponding Euler Lagrange solution equation is obtained.

Step3: focuses on solving the corresponding solutions when solving the corresponding partial differential equations. In this paper, the iterative method is selected for equation solving. In the actual operation, attention should be paid to the rational use of algorithms and sample data, so as to avoid a large number of operation processing and unnecessary waste of resources.

In the stop function of the corresponding algorithm, select the stop function shown in formula (11) and formula (12), and its corresponding function performance is shown in Figure 4. It can be seen from the figure that the corresponding stop function will rapidly decline within a certain range under the corresponding appropriate parameters, so as to meet the requirements of the main function.

$$gs1(i) = 1 - \left(\frac{(i/k)^2}{\left(1 + (i/k)^2\right)}\right), \tag{11}$$

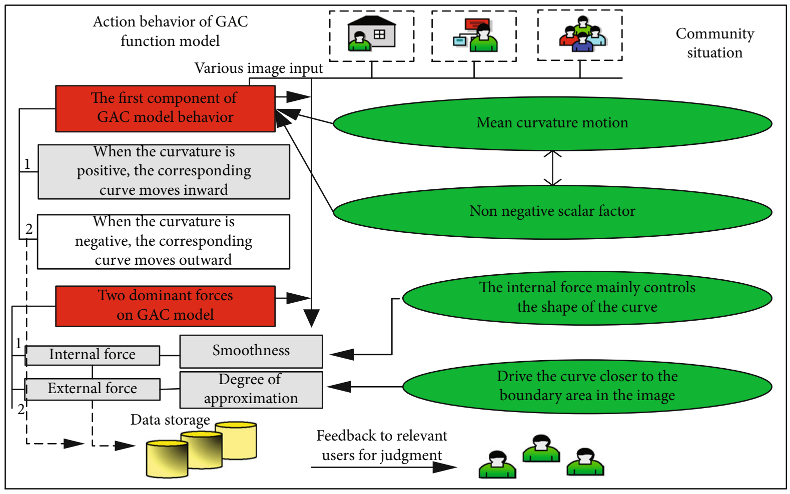

Figure 3: Action behavior of GAC model.

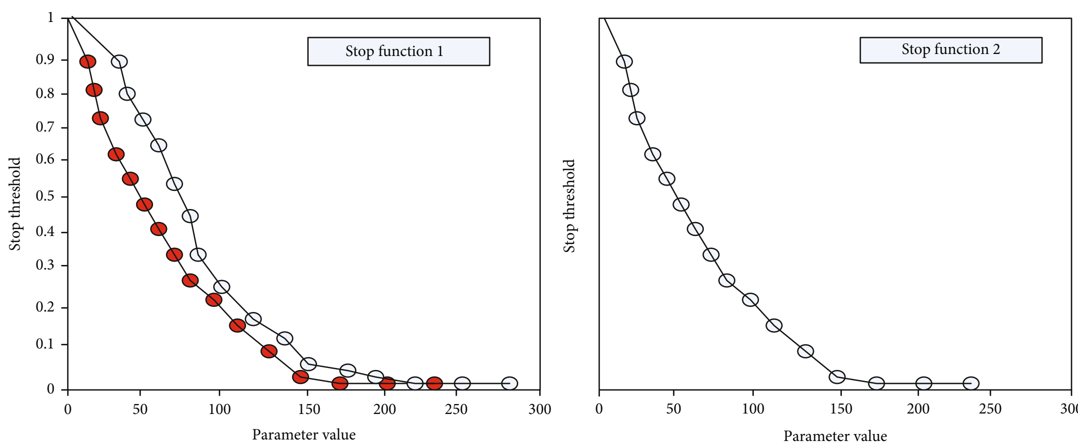

Figure 4: Behavior diagram of the stop function of the improved partial differential equation video recognition algorithm.

$$gs2(i) = \sqrt{-\left(\frac{i * i}{(k * k)^2}\right)}. \quad (12)$$

In order to further denoise the corresponding recognized video and image, an adaptive denoising model based on traditional wavelet transform is added at the end of the main algorithm, and the denoising model is regarded as the filter at the end. The corresponding denoising model function is shown in formula (13); in the corresponding formula, the detail functions corresponding to function $P(m)$ and function $Y(m)$ are shown in formula (14) and formula (15).

$$\min \longrightarrow e(m) = P(M) + Y(M), \quad (13)$$

$$P(M) = \iint \left(\frac{\lambda}{(1 + (M/(k * k)))}\right), \quad (14)$$

$$Y(M) = \iint |M(x, y) - m_o(x, y)|^2. \quad (15)$$

The system outputs the final processed video and image level and further adds a frequency filter for filtering processing. In this module, the corresponding image frequency is combined with the corresponding image gradient. When the corresponding recognized image or a small part of the video has a local gradient, the corresponding here is the corresponding smooth area. Then, the corresponding image frequency is relatively low. Based on this, the image frequency is used to distinguish the edge and noise of the corresponding recognized image or video, so as to more finely reflect the local features of the image, and further distinguish the image edge features and the smooth region of the image.

4. Experiment and Analysis

In order to further verify the superiority of this algorithm, this paper makes an experimental analysis based on the video samples corresponding to a large government community. The corresponding experimental samples are four groups of government community management-related videos, and the comparative experimental algorithms are three, corresponding to the traditional wavelet transform analysis algorithm, the traditional algorithm based on the partial differential equation, and the improved algorithm of

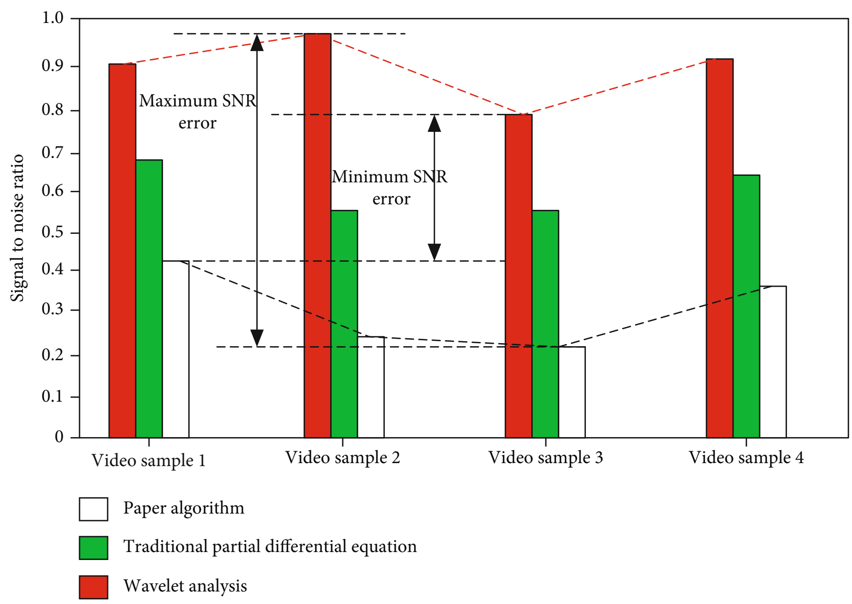

Figure 5: Experimental curve of signal-to-noise ratio of different algorithms under four groups of sample videos.

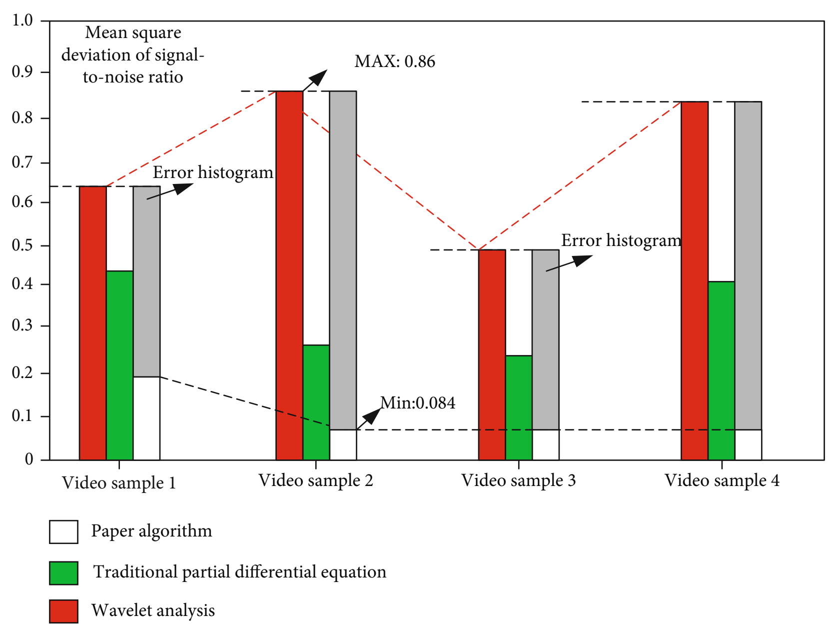

Figure 6: Experimental curves of mean square deviation of different algorithms under four groups of sample videos.

the partial differential equation in this paper. The signal-to-noise ratio experimental curves and corresponding mean square deviation curves of the corresponding three different algorithms under four groups of videos are shown in Figures 5 and 6. It can be seen from the figure that the algorithm proposed in this paper can not only visually reflect the effect of the original image but also obtain a higher image signal-to-noise ratio, and the corresponding image denoising effect is better and excellent. Further analysis of the signal-to-noise ratio experimental curves and the corresponding mean square deviation curves corresponding to Figures 5 and 6 shows that the signal-to-noise ratio advantages of the wavelet analysis algorithm and traditional partial differential equation algorithm are not distinguished in some video samples, and the signal-to-noise ratio stability of the two algorithms in different video samples is relatively low; the improved partial differential equation algorithm proposed in this paper adds a lot of auxiliary processing algorithms, so its corresponding signal-to-noise ratio is relatively stable when dealing with different video samples.

In order to verify the recognition accuracy of the algorithm for specific videos, specific target accuracy experiments are also carried out based on the above four groups of sample videos, and the accuracy is determined by taking the criminal cases in the image as the target (mainly defining whether there are police, police cars, and other landmark

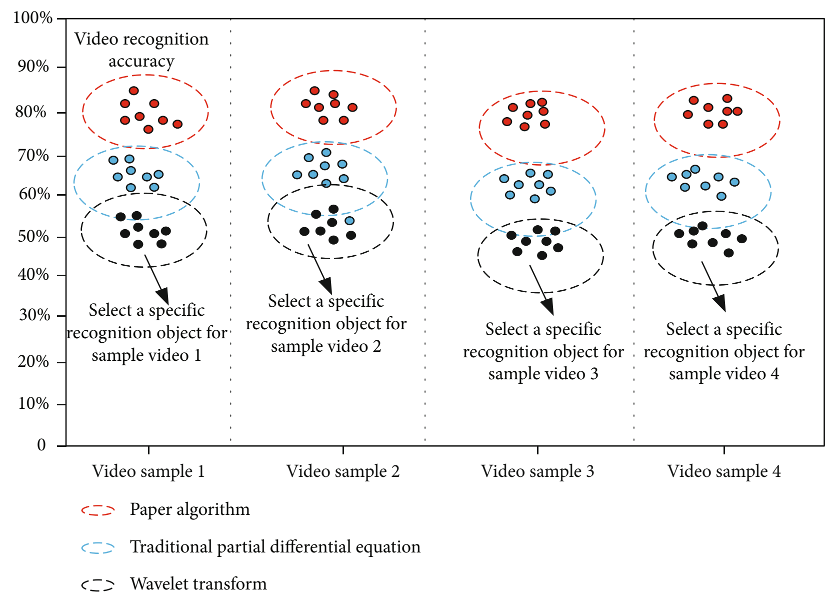

Figure 7: Curve of recognition accuracy of different algorithms for established targets under four groups of sample videos.

objects). The corresponding experimental results are shown in Figure 7; it can be seen from the figure that the algorithm proposed in this paper is closer to the real situation, and its recognition accuracy is improved by about 5% compared with the traditional algorithm. At the same time, by further analyzing the accuracy curves of the three algorithms under the condition of four groups of sample videos, it can be found that when identifying one or several established videos, the accuracy difference between the wavelet analysis algorithm and the traditional partial differential equation algorithm is small, and even the accuracy corresponding to some video samples overlaps; this shows that these two algorithms have disadvantages in terms of video recognition accuracy. Correspondingly, the accuracy of the improved partial differential equation algorithm proposed in this paper has obvious advantages compared with the other two algorithms, which benefits from the enhancement of some weak details by the auxiliary algorithm, which increases the discrimination conditions of the algorithm and improves the accuracy of the algorithm in identifying relevant video frequencies.

When the corresponding sample environment is further deteriorated, the corresponding environmental noise is increased. At this time, a comparative experiment is carried out for the above three algorithms. The corresponding experimental accuracy is shown in Figures 8(a) and 8(b). It can be seen from the figure that the accuracy of the algorithm proposed in this paper still has obvious advantages in complex environment. Through careful analysis, it can be found that in the video samples with Gaussian white noise, the accuracy performance of wavelet analysis algorithm and traditional partial differential equation algorithm is relatively less affected, mainly because the algorithm itself does not pay attention to the accuracy problem. The recognition accuracy of the corresponding improved partial differential equation algorithm for specific video decreases relatively slightly, and the same situation also occurs in the situation of increasing shot noise, which further shows that the design of the algorithm in this paper has full consideration at the corresponding filter level. Considering that the conventional community environment is relatively complex, please note that the corresponding noise interference may be superimposed by a variety of noises. Therefore, further thinking from the perspective of decreasing accuracy, it can be found that the improved algorithm in this paper actually has some factors of unstable anti-interference performance, which will be paid more attention in the follow-up research.

Based on the above experiments and the corresponding result analysis, it can be concluded that this algorithm not only improves the traditional partial differential equation algorithm but also further solves the disadvantages of the traditional algorithm, so as to realize the advantages of image and video recognition in accuracy and signal-to-noise ratio, which has obvious practical significance.

Due to the complexity of the corresponding environment of community-related video cases, in the community cases with problems in the corresponding light or lighting, this paper adds auxiliary image or video processing algorithms for special scenes. The algorithm module mainly processes based on the change of the gradient field of the recognized image or video, places the corresponding recognized image or video in the gradient domain in the module for consideration, and improves the comparison of the processed image or video by changing the corresponding gradient field distribution; through the corresponding gradient field of image enhancement, the detail enhancement processing of the image or video in the environment with relatively poor relevant conditions is realized, the edge details of the image or video with relatively small occurrence times are strengthened, and the problems of image darkening or brightening caused by light problems are improved. The processing steps of the auxiliary processing algorithm are

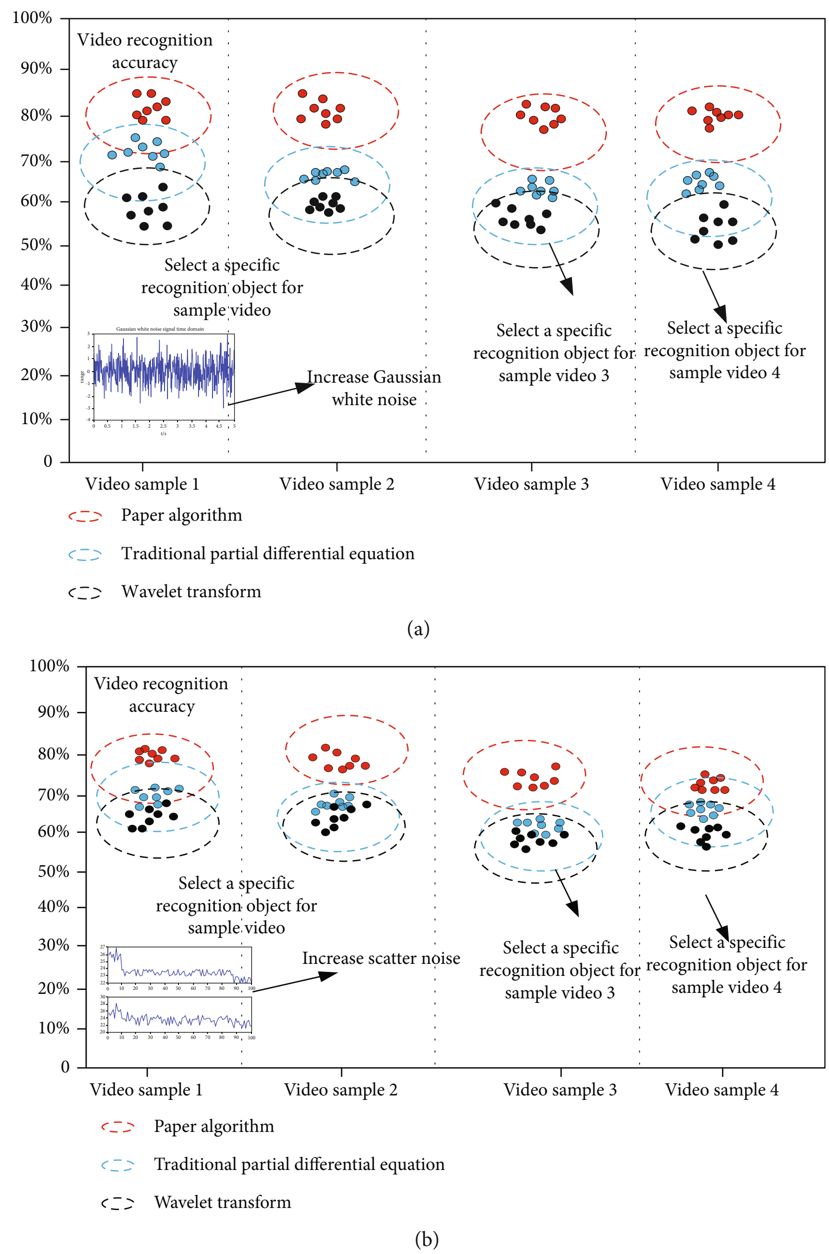

Figure 8: (a) Recognition accuracy curve of different algorithms for given targets under four groups of sample videos in complex environment (Gaussian white noise). (b) Recognition accuracy curve of different algorithms for given targets under four groups of sample videos in complex environment (shot noise).

as follows: using the image gradient field enhancement function to enhance the image gradient of the processed image or video, while keeping the corresponding gradient direction unchanged, and limiting the value range of the corresponding image gradient modulus in the transformation process.

5. Summary

This paper mainly analyzes the relevant technical analysis of current government community video recognition, analyzes and studies the video recognition algorithm of partial differential equation, and points out its corresponding research status. Based on the current disadvantages, this paper selects the GAC model based on image segmentation on the main function of the improved partial differential equation and optimizes its corresponding stop function, so as to improve its corresponding image segmentation effect. At the level of image smoothing processing, this paper selects the second derivative based on image processing as the inherent feature of the recognition image; thus, the rough problem of image edge is solved and the processing efficiency of the algorithm is improved. In order to further maintain the details of the recognized image, this paper integrates the Gaussian curvature driving function on the improved partial differential equation algorithm, so as to protect the details of the smooth region of the relevant recognized video. The experimental results show that the improved partial differential equation algorithm proposed in this paper improves the accuracy of video recognition by about 5% compared with the traditional algorithm. At the same time, the new algorithm can well ensure the detail integrity of the recognized video. In the follow-up research, this paper will conduct experimental verification for community cases in a complex environment to verify whether the algorithm in this paper still has advantages in this environment. At the same time, it will improve its shortcomings, reduce the consumption of computing resources, improve the iterative performance of the algorithm, and improve the performance of human-computer interaction.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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