Research on target recognition method based on multi-feature information fusion decision

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In order to improve target tracking stability and target recognition rate, this paper proposes a multi-feature fusion recognition algorithm based on BP neural network and D-S evidence theory, extracts the target features by RGB color weighted histogram and Sobel edge weighted histogram, establishes the decision rule model by combing BP neural network and D-S evidence theory, utilizes the BP neural network to evaluate the reliability of evidence source, according to the characteristic of reliability evaluation, obtains the target multi-feature information fusion decision and recognition of the target by the D-S combination rule. Through experimental comparison, the results show that the target recognition rate is about 95.5% and the misjudgement rate is about 4.5% by using multi-feature information fusion decision under the same conditions, in addition, the recognition results validate that the proposed image multi-feature information fusion decision method can improve effectively the target recognition rate.

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1. Introduction

The target tracking and recognition are the important research points in the dynamic target detection and recognition. The diversity of environmental factors and target cause the tracking instability, the tracking loss, and the tracking error in the target tracking system, it is necessary to research a reliable method for the target tracking and the target recognition. In the target tracking system, there is an essential processing link after target detection, the link is target recognition [1], the target recognition rate restricts the reliability of target tracking. In the target recognition algorithm, the BP neural network is a more common recognition method, because the recognition result of BP neural network is only a classification value of target's attribute [2], the classification value does not represent the exact probability of target's attribute, and expresses subjective concept or fuzzy concept, this method can inaccurately classify for the diversity of target, and could not fully obtain the feature information of target tracking, so it is necessary to study an improved BP neural network processing algorithm. Some experts put forward the D-S evidence theory fusion recognition algorithm for inaccurate and unknown information recognition of the target, but the D-S evidence theory recognition method has some limitations, cannot perfectly gain multiple features of target to solve the impact of environmental factors for target recognition [3].

In order to improve target recognition rate by using BP neural network and D-S evidence theory, and enhance target tracking stability, this paper proposes a multiple feature fusion recognition algorithm based on BP neural network and D-S evidence theory.

2. Image feature extraction of target

2.1. The color weighted histogram

We calculate the ratio of different colors in the entire image, these ratio express the spatial distribution of different colors in the image, the ratio is called a color histogram [4], the color histogram divides the whole color space into a number of cells, each color cell is called bin. This paper selects the RGB color histogram of the target as one of the extraction features, among, the channel R is quantized as L levels, the channel G and the channel B is quantized as $L/4$ level respectively, so the number of bin is $L\times(L/4)^2$.

Assuming that the number of pixels is n in the target area, the pixel set of the target region is $\{x_i\}, i=1,2,...n$, the central coordinates of the target region is x_0, the feature values of the target template on the R component are $\{u=0,1,2...,L-1\}$, the feature values on the G component and the B component are $\{u=0,1,2...,L/4-1\}$, therefore, the RGB color weighted histogram is shown in formula (1).

$$\begin{cases} p_c(u)=\sum_{i=1}^{n}K\left(\left\|\dfrac{(x_i-x_0)}{w_t}\right\|^2\right) & b(x_i)=u \\ 0 & b(x_i)\neq u \end{cases} \tag{1}$$

In (1), $K(\cdot)$ is the kernel function of each pixel weight value, w_t is the window bandwidth, $b(x_i)$

expresses the feature value at the pixel point for x_i.

In order to reduce the influence of the environment on the target area, the pixel of target center is closer, the weight of pixel set bigger, meantime, and we can select appropriate window bandwidth to accurately extract the color feature of the target. For the same type target, when the target attitude changes, the target can be recognized by using the target color feature. In a complex environment, multiple targets of the same type have the same color histogram; we should utilize other features of the target to further recognize.

2.2. The edge weighted histogram

If the spatial structure of the target changes, and the structure of the target change obvious, that is, the type of the target changes, the recognition of the target is easy to misjudge by the color feature, and needs to combine the edge feature to recognize target.

In the Sobel operator, the edge gradient values can be decomposed into two categories of horizontal direction and vertical direction [5]. These two edge gradient values have their own common templates respectively, these templates can be expressed by G_x and G_y [6]. When we detect the first frame, first the binarization of image, then calculate the gradient amplitude of the target image at the edge and the edge direction by using the template of G_x and G_y, G is the gradient amplitude of the target image, θ_e is the edge direction.

$$\begin{cases} G = \sqrt{{G_x}^2 + {G_y}^2} \\ \theta_e = \arctan\left(\dfrac{G_y}{G_x}\right) \end{cases} \tag{2}$$

In (2), the range of the edge direction is from -90°to 90°.

Supposing that the total number of edge pixels is n', the edge pixel sets are $\{x_g\}$, among, $g = 1,2,...n'$, the center coordinates of the target area is x_0, the direction of the edge are quantized into M_e equal points, therefore, the feature values of the target template in the each equal points direction are $\{u = 0,1,...,180 / M_e - 1\}$, the distribution function of the target edge weighted histogram is expressed by formula (3).

$$\begin{cases} p_e(u) = G\sum_{g=1}^{n'} K\left(\left\|\dfrac{(x_g - x_0)}{w_t}\right\|^2\right) & b(x_g) = u \\ 0 & b(x_g) \neq u \end{cases} \tag{3}$$

In (3), $b(x_g)$ is the feature values at the pixel point for x_g.

While the external environment changes, the gray value of the acquired target image also changes, and the edge features of the same target have some change because of the changing environment. In order to enhance the anti-interference ability of the edge features, for the extracted edge information of the target, we can use these measures, which are filtering, expanding and refinement, these processing measures can not only filter out the weak and false boundaries in the edge, but also extract the real boundary, the recognition ability of the target is effectively improved by using processed edge image.

3. The preprocessing classification of BP neural network

In order to prove the classification ability of the BP neural network, we define the BP neural network as a nonlinear and separable problem for the geometric structure, reduce the constraints of the correct classification, calculate the weight value by the counter propagation, then make the preselected cost function minimum, achieve the correct classification of the target by reducing constraint conditions [7]. Supposing that the neuron algorithm converges to the weight vector and the threshold, thus, we need to classify the two types of unknown feature vector.

If $x = [x_1, x_2, x_3, ..., x_l]$ is the element of the feature vector, θ is the threshold, the input node of the network is the element of the feature vector, each element multiplies the corresponding weight, the multiply results add, then reduce the threshold, activate the result by a nonlinear function. The nonlinear function is also known as the activation function, and is essentially a step function, namely, the activation result can divide the corresponding feature vector into one of the two classes. The multilayer result can be regarded as the extension of the basic neuron, which is called the two level forward feed neural network, among, the two neurons of the first layer form the hidden layer to complete calculation of the first stage, the single neuron of the second stage constitutes the output layer to achieve the final calculation. The input layer corresponds to the node of the input data, so the number of input nodes is equal to the dimension of the input space. If there are more than two neurons in the hidden layer and the input layer, the multi-layer neural network structure can be expanded into the l dimension input vector.

When we design the BP neural network, should consider the number of network layers, the number of neuron nodes in each layer, the learning rate, the input layer and the output layer.

1) The number of network layers

In fact, the BP neural network with three level can approximate any rational function, we increase the number of layers to further reduce errors and improve accuracy, at the same time, make the network complicated, the purpose is to increase the training time of network weights, we improve accuracy of the error by adding the number of neurons in the hidden layer, in general, should increase the number of neurons in the hidden layer.

2) The number of hidden layer nodes

If h is the number of hidden layer nodes, m is the dimension of the input matrix, c is the dimension of the output matrix, q is the constant, which is from 1 to 10. According to the empirical formula $h=\sqrt{m+c}+q$ and $h=\log_2^m$ [8], we can calculate the range of the number of hidden layer nodes, adjust the number of nodes by experiment. In the specific design, the number of hidden layers is two times for the number of input layers, then adds a little number.

3) The learning rate

The learning rate determines the generated amount of weights in each training cycle. If we set learning rate high, make convergence of the network fast to cause system instability. If the learning rate is low, which lead to the longer training time, the slower convergence of the network, so the learning rate is generally between 0.01 and 0.8.

4) The input matrix

Assuming that X is the input matrix, n is the total number of samples, then X is a matrix of $n\times m$, the input matrix stores the characteristics of all training samples, the characteristics of each sample occupy one row.

$$X=\begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,m} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,m} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,m} \end{bmatrix} \tag{4}$$

5) The output matrix

The belonging species of each sample is known in the actual training process, if Y is the output matrix, the number of species have C classes, the output matrix is set to a matrix of $n\times c$, each row shows the expected output of a sample, the corresponding column of the sample is set to 1, and the others are 0.

4. D-S evidence combination and decision rules

We use multi-layer perceptive network to recognize the feature for each characteristic information of the suspected target area, obtain the recognition result based on the attribute of the feature. When we extract the multiple feature information, generate multiple recognition results of the same target by multiple multi-layer perceptive networks, decide and fuse these results by multiple feature information fusion, form the final attribute decision of target.

The D-S evidence theory is an inexact reasoning theory, which satisfies axioms less than probability theory. We use the trust function instead of the probability as a measure in the theory of evidence, so distinguish the difference of uncertainty and unknown, and can express the degree of unknown information [9]. When the D-S evidence theory completes the fusion of inaccurate information, we give the basic probability values by the input evidence and the basic probability assignment function, combine the propositional evidence by the combination of the evidence theory, decide and recognize according to the combined basic probability values, obtain the target recognition results.

If there is a problem, which needs to adjudicate, there are many adjudicative results, all adjudicative results without relevance are called the recognition framework Θ, 2^{Θ} is a set of all subsets (propositions/evidence) by Θ, there are N elements in Θ, there are 2^N-1 elements in 2^{Θ}. For every evidence, there is a basic probability assignment function (BPA), $m(\cdot)$ expresses the BPA, $m(A)$ is the basic probability assignment function of the proposition A, which indicates a certain degree support for A. Supposing that there are n propositions, these propositions satisfy $P(e_1\cap e_2\cdots\cap e_n)=P(e_1e_2\cdots e_n)=P(e_1)P(e_2)\cdots P(e_n)$, these corresponding basic probability assignment functions are $m_1m_2\cdots m_n$, the n propositions are combined by using the Dempster rules, the joint probability density assignment function of the proposition A is obtained as in (5).

$$m(A)=\frac{\sum\limits_{\substack{\bigcap_{i=1}^{n}A_i=A \\ A_i\in 2^{\Theta}}} m_1(A_1)m_2(A_2)\cdots m_n(A_n)}{1-k} \tag{5}$$

$$k=\sum_{\bigcap_{i=1}^{n}A_i=A} m_1(A_1)m_2(A_2)\cdots m_n(A_n) \tag{6}$$

In (5) and (6), k is the global conflict factor, $1-k$ is the sum of the joint credibility of all propositions, these propositions are nonempty sets, which are supported by all evidences, and are also the normalization factor of the synthetized proposition reliability.

We get the credibility that each proposition synthesize by the D-S combination rule, need to give the decision rule to determine whether this proposition is true. At present, the most commonly decision criterion is the criterion based on the basic probability assignment function in the evidence theory, that is, the optimal choice proposition is determined by calculating the basic probability assignment function, the decision must satisfy the following three conditions:

1) The type of testing target should have the maximum basic probability assignment value.

2) The basic probability assignment difference

between the type of testing target and the type of other target is greater than the threshold, ε_1 is the threshold.

3) The uncertain basic probability assignment must be less than the threshold, ε_2 is the threshold.

If the value of the joint probability assignment function of proposition A does not satisfy one of three conditions, we cannot obtain accurate target recognition result. If the threshold is not suitable, it is easy to misjudge; therefore, the threshold needs to be determined according to the characteristics of the actual target, when the type of target changes, we must properly adjust these thresholds to obtain accurate recognition.

5. The target recognition model based on multi feature information fusion decision

Target recognition is correct classification for recognition of the detection image area, whether target should track by the recognition result, meantime, the accuracy of target recognition has a great influence in the stability and reliability of target tracking. Therefore, in the target tracking system, it is very necessary to improve the recognition rate of the target.

We can not accurately recognize the target by using single feature of the target, and should utilize the multi-feature information of detection target image to further classification, this measure can make up the deficiency of the single target feature, and accurately obtain whether the region is a real target, and can reduce the misjudgment rate.

This paper obtains the preliminary recognition results of the target based on the extracted target color features and target edge features by the BP neural network, two feature recognition results cannot represent the probability value of the target attribute, it is fuzzy concept, and needs to further decisions, the reasoning and calculation of the inaccurate data is obtained by D-S evidence theory. Therefore, after obtaining the preliminary recognition results of the neural network, the recognition results of two features are used as propositions, and the basics probability assignment function of each proposition is constructed, we combine the propositions with the D-S evidence fusion rules, and determine the calculation results according to the D-S evidence decision criteria, and obtain the recognition results.

The multi-feature information fusion recognition aims to complete the classification of the dynamic target area, namely, the dynamic target area belongs to the pedestrian or the vehicle, so the multi-feature information fusion recognition model must be able to correctly classify the multi-feature information of the dynamic target area. Considering the diversity of pedestrian and vehicle, it is difficult to derive and set up multi-feature information fusion recognition model by the characteristic quantity from the mathematical analysis. Therefore, this paper establishes the corresponding fusion decision recognition model by statistical analysis of sample data from the sample data.

5.1. The basic probability assignment function

The D-S theory has the ability of dealing with uncertain and incomplete information, but it is a difficult point, which is the structure of $m(A)$ by the D-S evidence theory, the traditional method needs the support of experience knowledge [10]. The D-S evidence theory constructs the basic reliability assignment by the distance function and exponential function, but the construction method has large computation, low real time and lack of ability of online learning. The artificial neural network has the characteristics of self-organization, self-learning and self-adaptive, can constantly adjust the connection weights of the network through learning to achieve the purpose of recognition and classification. The trained artificial neural network has a certain distinguishment ability of the domain experts, so it is feasible to use neural network to construct a source of evidence for each discrimination image, the source of evidence is $m(A)$ [11], On the other hand, the neural network can be trained off-line, on-line and real-time calculation, $m(A)$ can solve the many calculation problem by using the neural network [12]. This paper uses BP neural network to preprocess and recognize target, tries to establish corresponding relationship between the results of pre-processing and BP neural network, solves the difficult problem of construct $m(A)$ in D-S evidence theory.

In the multi-feature information fusion recognition model, if Θ is the recognition framework of target, Θ is composed of C0 and C1, so four propositions are produced:

1) A_1 ={C0}, A_1 shows that the recognition target is vehicle.

2) A_2 ={C1}, A_2 shows that the recognition target is pedestrian.

3) A_3 ={C0, C1}, A_3 indicates that the recognition target is both pedestrian and vehicle, namely, the recognition target is uncertainty.

4) A_4 ={ϕ}, A_3 means that the recognition target is neither pedestrian nor vehicle.

The correct construction of the basic probability assignment function is the key to the D-S evidence theory. If (y_1, y_2) is the output value of single neural network, for each of four propositions, in the neural network, the sum of the absolute value of given output value according to the target color feature and the absolute value of given output value according to the target edge feature is called the constraint condition, when the constraint condition changes, the corresponding basic probability assignment function of each proposition is different. If the constraint condition is less than 1.5, the corresponding basic probability assignment function to each proposition is as shown in equation (7). If the constraint condition is greater than 1.5, the corresponding basic probability assignment function to each proposition is as shown in formula (8).

$$\begin{cases} m_i(A_1) = \dfrac{|y_{i1}|}{|y_{i1}|+|y_{i2}|} \\ m_i(A_2) = \dfrac{|y_{i1}|}{|y_{i1}|+|y_{i2}|} \\ m_i(A_3) = 0 \\ m_i(A_4) = 0 \end{cases} \quad |y_{i1}|+|y_{i2}| \le 1.5 \qquad (i=1,2) \quad (7)$$

$$\begin{cases} m_i(A_1) = 0 \\ m_i(A_2) = 0 \\ m_i(A_3) = 1 \\ m_i(A_4) = 0 \end{cases} \quad |y_{i1}|+|y_{i2}| > 1.5 \qquad (i=1,2) \quad (8)$$

In (7) and (8), $m(A)$ represents the corresponding basic probability assignment function of each proposition, the basic probability assignment function of each proposition is determined by the output value of neural network, i is the *i-th* neural network, $i=1$ indicates color feature recognition network, $i=2$ represents the edge feature recognition network.

Therefore, in the target tracking system, multi-feature information fusion is used for target recognition, the constraint conditions is determined according to extracted features of the target, that is, the quantity and type of extracted target features are different, and the constraint conditions are correspondingly changed.

According to the evidence combination rule of (7) and (8), we get the joint probability assignment expression of all propositions under the fusion characteristics, which is expressed by (9).

$$\begin{cases} m(A_1) = \dfrac{m_1(A_1)\times m_2(A_1)+m_1(A_1)\times m_2(A_3)+m_1(A_3)\times m_2(A_1)}{1-[m_1(A_1)\times m_2(A_2)+m_1(A_2)\times m_2(A_1)]} \\ m(A_2) = \dfrac{m_1(A_2)\times m_2(A_2)+m_1(A_2)\times m_2(A_3)+m_1(A_3)\times m_2(A_2)}{1-[m_1(A_1)\times m_2(A_2)+m_1(A_2)\times m_2(A_1)]} \\ m(A_3) = \dfrac{m_1(A_3)\times m_2(A_3)}{1-[m_1(A_1)\times m_2(A_2)+m_1(A_2)\times m_2(A_1)]} \end{cases} \quad (9)$$

5.2. Target recognition model of fusion decision

In order to extract a variety of feature information, if a variety of feature information input the same network to process, the increment of the input dimension makes the structure of network become complex and uncertain, causes the network training time long and less effect, and it is difficult to guarantee the learning and generalization ability of the network, affects the recognition effect of neural network [13]. In order to make use of the classification advantages of the multi-layer perceptive network and eliminate the adverse impact of the oversize network input dimension, this paper preprocesses and recognizes a large number of features from extracting dynamic target area, that is, each feature use the corresponding network to recognize classification, the high dimension input recognition network is transformed into multiple low dimensional input recognition network. The input vector classification reduces the number of dimensional to greatly simplify the structure of network and improves the generalization ability of network, but also produces multiple network recognition results, needs further comprehensive processing [14]. Based on this method, this paper establishes the multi-feature information fusion decision recognition model with two levels based on BP neural network and D-S evidence theory, as shown in Fig. 1.

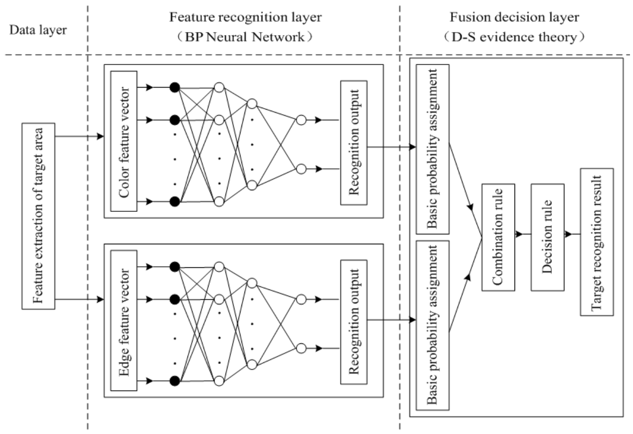


Fig. 1. The multi-feature information fusion decision recognition model

In Fig. 1, the multi-feature information fusion recognition model consists of data layer, feature recognition layer and fusion decision layer. The information source of data layer is from the image data of the dynamic target area, obtains the information of color and edge by using different feature extraction methods, a set of feature vectors describes each feature. The feature recognition layer is a multi-layer perceptive network, establishes the corresponding multilayer perceptive network for each feature, realizes the target recognition by the feature. The fusion decision layer uses the D-S evidence theory to make decision fusion of the output results of the multi-layer perceptive network, the discriminant result is the recognition result of the whole identification system. From the multi-feature information fusion recognition model based on the two levels of neural network and evidence theory, we find that the number of units of the hidden layer is easy to be determined because of the reduction of the input unit for each neural network of the feature recognition layer. When the error is counter propagation, we reduce the weight and the amount of calculation to accelerate the speed of convergence and reduce the learning cycle, meantime, the neural networks of different feature trains individually without mutual influence, the independence of the training is similar to the distribution operation, which can improve the recognition efficiency of the whole recognition system, in particular, when there is a change of the individual feature information or the new feature information, we only need to train or add an recognition network, not only reduce workload, but also make the whole fusion recognition model easily expand. Therefore, the algorithm flow is shown in Fig. 2.

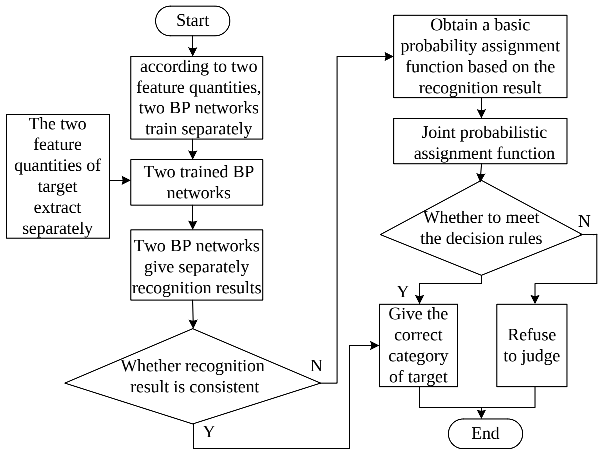


Fig. 2. The algorithm flow of fusion recognition model

6. Experiment and analysis

6.1. Preliminary recognition and result analysis of BP neural network

In order to verify the effect of neural network for target recognition, this paper constructs a BP neural network recognizer for the target color features and target edge features, selects 600 images, which contains vehicle and pedestrian, vehicle and pedestrian have 300 sample images respectively, we extract the corresponding feature vectors as the sample set, among, select 300 images include pedestrian and vehicle, vehicle and pedestrian have 150 sample images respectively, assuming that vehicle is C0, pedestrian is C1, the 300 samples are used as the training set of the network, the other 300 samples are used as the testing set of the network.

For color feature information, the input layer dimension of the recognition network is 256, the number of hidden layer neurons is 7, the dimension of the output layer is 2. For the edge feature information, the input layer dimension of the recognition network is 36, the number of hidden layer neurons is 6, and the dimension of the output layer is 2. Therefore, the target feature trains input matrix and output vector of network, which can be expressed by (10).

$$\begin{cases} X = [F_{c0}, F_{c1}]^T \\ Y = [Y_{c0}, Y_{c1}]^T \\ F_{ck} = \begin{bmatrix} p_{150k+1,1} & \cdots & p_{150k+1,m} \\ p_{150k+2,1} & \cdots & p_{150k+2,m} \\ \cdots & \cdots & \cdots \\ p_{150k+150,1} & \cdots & p_{150k+150,m} \end{bmatrix} \quad (k=0,1) \\ Y_{ck} = \begin{cases} zero(150,2) \\ (:, k+1) = 1 \end{cases} \end{cases} \tag{10}$$

In the learning and training phase of the BP neural network, we initialize the network weights with a small random value, if the initial weight is too large, it is easy to cause the network not to be trained. We set the network configuration parameters, then the neural network training is successful when the error of learning is equal to setting error of target, otherwise, it is necessary to judge whether the number of training times is maximum number of iterations, if the maximum number of iterations is reached, the training ends, otherwise, the training continues. The part of the network configuration parameters are shown in Table 1.

Table 1. The part of network configuration parameters

Network parameter name	Recognition network parameters of color feature	Recognition network parameters of edge feature
Raining target error of neural network	0.001	0.001
Maximum number of iterations	5000	10000
learning rate	0.01	0.01
Weight training algorithm	traingdm	traingdm
The number of nodes / excitation functions of the first hidden layer	7/tansig	6/tansig

In the training network, we constantly adjust the threshold to achieve the minimum training error. The recognition network structure diagrams of color and edge feature are shown respectively in Fig. 3(a) and 3(b).

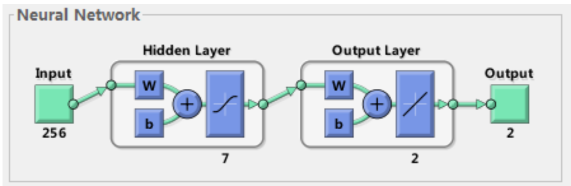


Fig. 3. (a) The neural network structure diagram of color feature

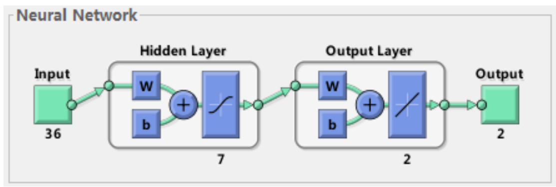


Fig. 3. (b) The neural network structure diagram of edge characteristic

In order to investigate the training network recognition of the color feature and the edge feature, the image features of the network testing store in the network input matrix of learning and training, then obtain the output vector by the trained BP neural network, the vector is a row vector of 1×2, each row shows its similarity with the class, the range of similarity degree is from 0 to 1, which is the source of belief data of proposition in D-S evidence decision. (y_1, y_2) expresses the output results, the recognition result is the vehicle when $(y_1, y_2) > u_{th1}$, the recognition result is pedestrian when $(y_1, y_2) < u_{th2}$, gets the maximum value of the output matrix, namely, $u_{th1} = u_{th2} = 0$, obtains the preliminary recognition results of the target. There are four typical results in the recognition process of BP neural network, list and analyze these four typical results, as shown in Table 2 and Table 3.

Table 2. The typical results of color feature recognition network

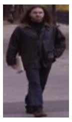
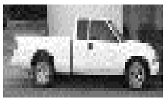
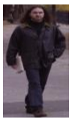
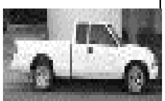
Input image	Color feature					Network output	Recognition result
	1st bin	2nd bin	3rd bin	...	256th bin		
	-2.874	-1.847	-1.245	...	-2.941	(-0.146，0.901)	C1
	-2.256	-1.978	-1.763	...	-2.369	(1.292，0.013)	C0
	-0.676	-0.134	-0.841	...	13.760	(0.037，1.124)	C1
	-0.366	-1.691	-1.968	...	10.356	(0.281，0.624)	C1

Table 3. The typical results of edge feature recognition network

Input image	Edge feature					Network output	Recognition result
	-90°	-85°	-80°	...	90°		
	0.738	0.350	-0.095	...	1.832	(0.158，1.007)	C1
	-0.076	-0.886	-0.733	...	-0.742	(1.169，0.249)	C0
	0.363	-0.270	-0.863	...	0.985	(0.968，0.731)	C0
	-0.932	-0.466	-0.908	...	-0.897	(0.964，0.071)	C0

From Tables 2 and 3, the results indicate that the recognition results of the first and the second input images are correct either color or edge according to $u_{th1} = u_{th2} = 0$, but the third image is recognized as C0 in the color recognition network, the fourth image is recognized as C1 classes in the edge recognition network, this is misjudgment phenomenon, two networks have respective recognition rates under the large statistical samples. We count 200 image samples from the network testing set, including 100 pedestrians and vehicles, use 200 images to show the actual recognition result of each class of the test sample, each row indicates the number of wrong recognition. Assuming that the recognition rate of the network is the ratio of the correct recognition samples number of the testing sample and the testing samples number, we obtain the recognition rate of each category in each network by counting the recognition results of each category, the recognition results are shown in Table 4(a) and 4(b).

Table 4. (a) The recognition results of color feature

Category	Original quantity	recognition result of color feature	
		C0	C1
C0	100	83	17
C1	100	10	90
Recognition rate		86.5%	

Table 4. (b) The recognition results of edge feature

Category	Original quantity	recognition result of edge feature	
		C0	C1
C0	100	82	18
C1	100	13	87
Recognition rate		84.5%	

The comprehensive analysis from Tables 2, 3, 4(a) and 4(b) can find that when the judgment condition is $u_{th1} = u_{th2} = 0$, the single feature recognition network has a certain misjudgment rate. Therefore, we should make full use of the multi-feature information to further fuse the output of neural network, reduce the error recognition probability of the target.

6.2. Recognition result and analysis of target multi-feature information fusion decision

In the multi-feature information fusion recognition model, we use the color feature and texture feature to recognize the feature, each result is independent evidence to decision. In order to verify the effect of multi-feature information fusion recognition, select four images of Table 2 and 3 as experimental data. We know from Table 4(a) and 4(b) that when the judgment condition is $u_{th1} = u_{th2} = 0$, the recognition method is a single feature network, the recognition results have a certain error rate by comparing the network output, the third image is misjudged into the C0 in the color recognition network, the fourth image is misjudged into the C1 in the edge recognition network. Obviously, if multi-feature decision fusion and recognition operation is not used, it is difficult to improve the recognition rate of the system. We adopt the multi-feature information fusion recognition method, the result of each feature recognition network is an evidence, construct a basic probability value of each proposition for each evidence, if m_1 is the basic probability assignment function of the color feature recognition evidence, m_2 is the basic probability assignment function of the edge features recognition evidence, the basic probability assignment of different features and different propositions as shown in Table 5(a) and 5(b).

Table 5. (a) The basic probability assignment of each proposition for color features

Input image	Basic probabilistic assignment of each proposition for color features			
	$m_1(A_1)$	$m_1(A_2)$	$m_1(A_3)$	$m_1(A_4)$
The first image	0.139	0.861	0	0
The second image	0.990	0.010	0	0
The third image	0.032	0.968	0	0
The fourth image	0.310	0.690	0	0

Table 5. (b) The basic probability assignment of each proposition for edge features

Input image	Basic probabilistic assignment of propositions for edge features			
	$m_2(A_1)$	$m_2(A_2)$	$m_2(A_3)$	$m_2(A_4)$
The first image	0.136	0.864	0	0
The second image	0.824	0.176	0	0
The third image	0.570	0.430	0	0
The fourth image	0.931	0.069	0	0

Combining with the basic probability assignment of different characteristics and different propositions in table 5(a) and 5(b), if $\varepsilon_1 = 0.7, \varepsilon_2 = 0.2$, the joint probability assignment and fusion decision results of different propositions under different features can be obtained, as shown in Table 6 and Table 7.

Table 6. The joint probability assignment and fusion decision results of different propositions under fusion feature

Input image	Basic probability assignment of propositions under fusion feature				Judgment result
	$m(A_1)$	$m(A_2)$	$m(A_3)$	$m(A_4)$	
The first image	0.025	0.975	0	0	C1
The second image	0.998	0.002	0	0	C0
The third image	0.042	0.958	0	0	C1
The fourth image	0.858	0.142	0	0	C0

From the fusion decision results of Table 5(a), 5(b) and 6, we find that for the first image and the second image, namely, the correct result is obtained by the single feature BP neural network. The result is also correct by multiple feature information fusion, the result indicates that the feature fusion decision model is available. For the third image and the fourth image, that is, the output result of the third image is error in color feature recognition network, the output result of the fourth image is error in the edge recognition network, then utilize multi-feature information fusion decision to revise the error correction results. The target detection result is recognized by using the model of multi-feature information fusion decision, and the judgment result is C1, that is, the recognition result is correct.

In order to further analyse the target recognition by using multi-feature information fusion decision, we count 200 image samples of the network testing set, including 100 pedestrians and 100 vehicles. The BP output of the testing sample set is comprehensively re-stated by using D-S evidence theory, the recognition results are shown in Table 7.

Table 7. The recognition results of statistical fusion decision

Category	Original quantity	Recognition result of fusion decision	
		C0	C1
C0	100	95	5
C1	100	4	96
Accuracy recognition rate	95.5%		
misjudgment rate	4.5%		

The accuracy recognition rate of the model is 95.5%, compared with the recognition results of the single network model, the accuracy recognition rate improves 10%. Therefore, the multi-feature fusion decision recognition model can reduce the target misjudgment rate and improve the accuracy recognition of target.

7. Conclusions

This paper analyzes the image feature of target according to the color weighted histogram and the edge weighted histogram, gives the preprocessing classification of BP neural network and D-S evidence combination and decision rules, establishes multi-feature fusion decision recognition model with three structures, the model comprises the data input layer of the mixed Gauss model, and the feature recognition layer by using the BP neural network, and the fusion decision layer of the D-S evidence theory. The multi-feature fusion decision recognition model can automatically recognize the category of the target, through the preliminary recognition result analysis of BP neural network and recognition result analysis of multi-feature information fusion decision, we find that the recognition result of multi-feature information fusion decision makes the target recognition rate improve, the target recognition rate is about 95.5%, meantime, reduces the misjudgments rate, the architecture of multi-feature fusion decision recognition model is easy to implement, and is flexible and open.

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