Construction and Optimization of Multi-Scenario Autonomous Call Rule Models in Emergency Command Scenarios

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***Abstract*—In response to the slow processing speed, weak anti-interference, and low accuracy of autonomous call models in current emergency command scenarios, the research focuses on the fire scenario, aiming to improve the emergency response efficiency through technological innovation. The research innovatively integrates digital signal processing algorithm and two-tone multi-frequency signal detection algorithm to develop a hybrid algorithm. Then, a novel autonomous call model based on the hybrid algorithm is constructed. The comparative experimental results indicated that the accuracy of the hybrid algorithm was 0.9 and the error rate was 0.05, which was better than other comparison models. The average accuracy and comprehensive performance score of the model were 0.95 and 97 points, respectively, both of which were better than comparison models. The results confirm that the autonomous call model proposed in this study can accurately and quickly judge emergency scenarios and handle calls, and provide new ideas and theoretical basis for emergency command and rescue of fire and other disasters, with broad application prospects.**

***Keywords*—Digital signal processing algorithm; dual tone multi-frequency signal detection algorithm; fire; autonomous call model**

I. Introduction

The emergency command in the field of emergency rescue faces many challenges, including signal interference, inaccurate prediction, and slow response. These problems are particularly acute during disasters, which may result in delayed rescue operations and wasted resources. With the continuous progress of digital and intelligent technology, the autonomous calling model is increasingly being applied in various industries. In emergency command and rescue, attempts have also been made to introduce autonomous call rule models [1]. Many domestic and foreign scholars have explored the application of autonomous call models. For example, Zardini et al. proposed a new on-demand autonomous call mobile model to solve the existing large transportation demand and road congestion. The results showed that the proposed autonomous call mobile model saved 70% of the travel time [2]. In addition, to address the low efficiency of hazard perception and recognition in autonomous vehicles, Ghosh et al. proposed a machine learning algorithm-based autonomous hazard call model for self-driving vehicles, which was used to test the model in real situations. The results showed that the hazard recognition efficiency of autonomous vehicles based on this model increased by 22.1% [3]. To solve the problem that UAV is difficult to accurately reach the accident site during emergency rescue, Shaheenzh et al. proposed a new autonomous call to air channel model. The results showed that this model had good practical application effects [4]. However, these autonomous call models still have low detection efficiency and weak anti-interference ability, so it is also necessary to optimize the above autonomous call models [5]. Therefore, proposing an autonomous call model that can improve the prediction accuracy and prediction efficiency of emergency scenarios is an urgent problem.

The Analytic Hierarchy Process (AHP) is simple to calculate and has strong applicability, but when dealing with large-scale problems, it is subjective and prone to significant calculation errors [6]. Although Surface Acoustic Wave (SAW) technology can improve the accuracy of signal filtering and enhance anti-interference, it still has high filter insertion loss and low SAW filter performance in the high frequency range. The above two methods are also not applicable to the current autonomous calling model [7].

The Dual Tone Multi-Frequency (DTMF) signal detection algorithm has fast dialing speed, high reliability, and strong anti-interference ability [8]. The high-precision characteristics of the Demand Side Platform (DSP) signal processing algorithm can reconstruct signals and avoid interference from other signals. The flexibility of this algorithm is also beneficial for its processing, analysis, and modification of complex signals [9]. Many scholars have analyzed the above algorithms. Maity et al. designed an improved DTMF algorithm to address the weak noise resistance and low efficiency in signal detection in telecommunications equipment. Comparative experiments were conducted between this improved algorithm and previous algorithms. The results showed that the noise resistance and efficiency were improved by 79% and 87%, respectively [10]. Oluwole et al. proposed a home automation technology based on DTMF to solve the high energy consumption and low transmission speed in home appliance control. The improvement in transmission speed was not significant [11]. In addition, Fan designed a DSP signal processing algorithm to improve the machine learning accuracy. The results showed that the model improved machine learning performance [12]. To improve the computational speed of digital signal processing systems, Seshadri proposed a signal processing algorithm based on DSP. The results demonstrated that this algorithm improved the signal processing speed [13]. Nisha et al. also proposed a denoising method based on DTMF to improve the denoising effect of MRI images. The results showed that the denoising effect of this method was significantly better than that of traditional methods [14].

In summary, some scholars have now analyzed the autonomous calling model. Although the autonomous calling model has been optimized, there are still some problems with the above model. For example, the autonomous call mobile model proposed by Zardini et al. still has low model prediction accuracy. The vehicle hazard autonomous call model proposed by Ghosh et al. still has long computation time-consuming. The autonomous call-to-air channel model designed by Shaheenzh et al. still has slow call speed. The above research shows that the current model has some limitations, such as low detection efficiency and weak anti-interference ability, and needs to be further optimized. To meet this demand, an innovative autonomous call model is proposed, aiming to build a solution suitable for complex emergency scenarios by combining the high precision and flexibility of DSP algorithm with the speed dial, high reliability and strong anti-jamming ability of DTMF signal detection algorithm. This motivation stems from the significant advantages and complementarity of the two in signal processing: DSP algorithms are good at processing and analyzing complex signals, while DTMF technology ensures stable communication in emergency situations. Compared with the subjectivity of AHP and the low filtering performance of SAW technology in the high frequency range, the proposed model shows significant advantages in solving the problems of signal interference, inaccurate prediction and slow response.

The main contribution and influence of the research is that the proposed hybrid algorithm autonomous call model not only makes up for the shortcomings of the existing model in prediction accuracy, response speed and anti-interference ability, but also proves its excellent performance in multi-scenario applications through the experimental verification of actual fire simulation scenarios. This innovation not only provides a more efficient and accurate solution for emergency command and rescue, but also opens up new ideas and methodological references for subsequent research, and is expected to promote the overall progress in the field of emergency rescue. Specifically, the proposed model improves the accuracy and response speed of disaster early warning, optimizes resource allocation, and enhances the reliability and stability of emergency communication, thus minimizing casualties and property losses when disasters occur. The argument of the research is that the disaster autonomous call warning model based on DSP and DTME signal detection technology can improve the accuracy of disaster warning and reduce disaster casualties. The argument is based on the high accuracy and flexibility characteristics of DSP algorithms, as well as the theoretical foundations of high anti-interference, high reliability and fast dialing speed. The contribution of the research lies in the fact that the autonomous call model in emergency scenarios can improve warning and response speed, optimize resource allocation, and enhance emergency communication reliability and stability, thereby reducing the loss of life and property caused by disasters.

II. Methods and Materials

A. DTMF Signal Detection Algorithm Integrated with DSP Algorithm

The current autonomous call rule model in emergency command scenarios has problems such as slow dialing speed and susceptibility to external influences, which seriously affects the timeliness and accuracy of emergency command. Therefore, strengthening the overall performance of the autonomous call rule model is of great significance for improving the effectiveness of emergency command. The DTMF signal detection algorithm has fast dialing speed, high reliability, and strong anti-interference ability. Given these advantages, the DTMF is applied to the multi-scenario autonomous call model to improve the model speed and anti-interference ability, enhancing the emergency command effectiveness. Among them, the signal generation principle in the DTMF signal detection algorithm is shown in Eq. (1) [15].

$$f_{(t)} = A\sin 2\pi f_{(1)}t + A\sin 2\pi f_{(2)}t \tag{1}$$

In Eq. (1), $f_{(1)}$ and $f_{(2)}$ respectively represent any two selected frequencies. A represents the amplitude. t represents the continuous time variable, which represents each each time point at which the signal is generated. The principle of DTMF signal generation is shown in Fig. 1.

In Fig. 1, the principle of DTMF signal generation is as follows. The input information is fed into the oscillator. The high-frequency oscillation signal generated by the oscillator is transmitted to two counters, respectively. When the value in the counter reaches the preset value, the counter inverts the signal to form a low-frequency square wave and then outputs. The low-frequency square wave output is a sinecure, and the amplitude of the square wave is controlled. Then, the processed two signals are transmitted to the signal mixer for signal mixing processing, and finally outputted. The system function of the oscillator in the DTMF signal generation is shown in Eq. (2).

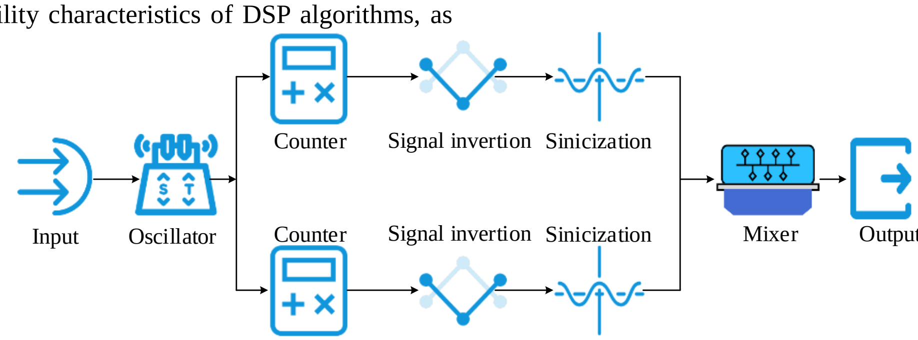


Fig. 1. Schematic diagram of DTMF signal generation.

$$H_{(z)} = \frac{b}{1 + a_1 z^{-1} + a_2 z^{-2}} \tag{2}$$

In Eq. (2), a and z respectively represent row audio signals and column audio signals. b represents the amplitude under the normalized digital frequency, as shown in Eq. (3).

$$\begin{cases} b = A\sin\omega \\ \omega = f_0 / f_a \end{cases} \tag{3}$$

In Eq. (3), f_0 represents the sine wave frequency. f_a represents the sampling frequency. ω is the normalized digital frequency. a_1 and a_2 in Eq. (2) are shown in Eq. (4).

$$\begin{cases} a_1 = -2\cos\omega \\ a_2 = 1 \end{cases} \tag{4}$$

The unit sampling response corresponding to the oscillator is shown in Eq. (5).

$$h(n) = A\sin((n+1)\omega)u(n) \tag{5}$$

In Eq. (5), n represents the sampling point. The difference equation of the oscillator is shown in Eq. (6).

$$g(n) = 2\cos\omega g(n-1) - g(n-2) \tag{6}$$

The signal synthesis in the DTMF signal detection algorithm is shown in Eq. (7).

$$y(n) = A_0 + A_1 \sin\frac{2\pi d t_0}{t_s} + A_2 \sin\frac{2\pi d t_1}{t_s} \tag{7}$$

In Eq. (7), t_0 and t_1 represent the high-frequency and low-frequency of the generated signal, respectively. A_0 and A_1 represent the amplitude of t_0 and t_1. t_s is the sampling frequency. d is the number of sampling points. Afterwards, it is subjected to sinusoidal processing. The sine function is shown in equation (8).

$$\sin(x) = \sin(x1) + \frac{[\sin(x2) - \sin(x1)(x2 - x1)]}{256} \tag{8}$$

In Eq. (8), $x1$ and $x2$ represent two segmentation points, but the level difference between the high-frequency and the low-frequency affects the experimental results. The level difference is shown in Eq. (9).

$$S_H = -20\lg(\frac{V_H}{V_0})S_L(1 < S_H - S_L < 2) \tag{9}$$

In Eq. (9), S_H represents the level of the high-frequency signal. S_L represents the level of the low-frequency signal. V_H and V_L represent high-frequency voltage and low-frequency voltage, respectively. DAC is shown in Eq. (10).

$$DAC(n) = 12.8 \times (1023A_0 + A_1 A + A_2 B) \tag{10}$$

In Eq. (10), A and B are shown in equation Eq. (11).

$$\begin{cases} A = 1023\sin(\frac{2\pi d t_0}{t_s}) \\ B = 1023\sin(\frac{2\pi d t_1}{t_s}) \end{cases} (d = 0,1,2.....) \tag{11}$$

In Eq. (11) and Eq. (12), t_0 and t_1 represent the high-frequency and the low-frequency in DTMF, respectively. d is the number of sampling points. t_s is the sampling frequency. Although the DTMF signal detection algorithm has fast dialing speed and strong reliability, it has high requirements for signal-to-noise ratio, easy signal leakage, and low detection accuracy. The high precision of DSP algorithms makes signal reconstruction possible and avoids interference from other signals. The flexibility of this algorithm is beneficial for its processing, analysis, and modification of complex signals [16]. The basic structure diagram of the DSP algorithm is shown in Fig. 2.

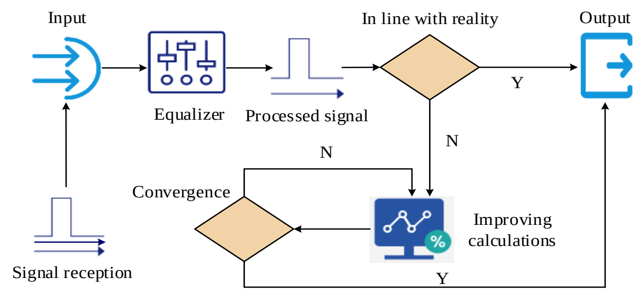


Fig. 2. Basic flowchart of DSP algorithm.

From Fig. 2, the DSP algorithm first receives the signal, and then extracts and processes the received signal through a digital equalizer at the receiving end of the DSP algorithm. The processed signal is compared with the output sequence to determine whether the processing result of the equalizer matches the actual situation. If it matches, the processing result is output. If it does not match, the equalizer cannot converge successfully. The DSP is improved. After improving, it is judged until it matches the actual situation, and the processed signal is output. The transmission calculation for the received signal is shown in Eq. (12).

$$y_a(i) = s(i) \cdot h_a(i) + w(i) \tag{12}$$

In Eq. (12), $y_a(i)$ represents the transmitted signal. $h_a(i)$ represents the time-domain function. The relationship between the transmitted signal and the output signal of the equalizer is shown in Eq. (13).

$$z(j) = \lambda s_a[(j-k)T_s] \tag{13}$$

In Eq. (13), $z(j)$ is a discrete signal sequence. k is the delay generated by the equalizer. λ represents a complex constant. If the signal passed through the equalizer does not match the actual situation, it will be improved. The improvement operation is shown in Eq. (14).

$$J(g) = E[|(\rho(h)|a(j) + a(j-1)|^2 - 1)^2] \tag{14}$$

Each factor in Eq. (14) is shown in Eq. (15).

$$\begin{cases} \rho(h) = [\sin(\frac{\pi h}{2})\sin(\pi h)]^2 \\ E[|(a(j)|^2 - 1)^2] = 0 \\ E[(\rho(h)|a(j) + a(j-1)|^2 - 1)^2] = 0 \end{cases} \tag{15}$$

In Eq. (15), $a(j)$ is the signal output by the equalizer. In order to improve the accuracy and efficiency of the DTMF signal detection algorithm, this study utilizes the high-precision performance of the DSP algorithm to improve the DTMF signal detection algorithm. The flowchart of the improved DTMF signal detection algorithm is shown in Fig. 3.

From Fig. 3, the improved DTMF signal detection algorithm is divided into a DTMF module and a DSP module. In the DTMF module, the input signal is generated into low-frequency and high-frequency signals through an oscillator. Then, the two signals are respectively fed into the counter for signal inversion and sine processing. Finally, the two signals are mixed through the mixer. The mixed signal is input into the DSP module. The signal is extracted, detected, and reconstructed through the equalizer in this module to eliminate other factors and improve detection accuracy. Finally, the signal is output. The fast dialing speed of DTMF is utilized for dialing operation through signal judgment. The DSP algorithm is used in DTMF signal detection. When the two signals are fused, the signal needs to be resampled before the DSP module. The update iteration is shown in Eq. (16).

$$l(k+1) = l(k+1) - J(g) \cdot \mu_g \nabla_g \tag{16}$$

In Eq. (16), μ_g represents the iteration step size. $l(k)$ represents the tap coefficient vector. At this point, $y_a(i)$ represents the signal received from the DTMF mixer.

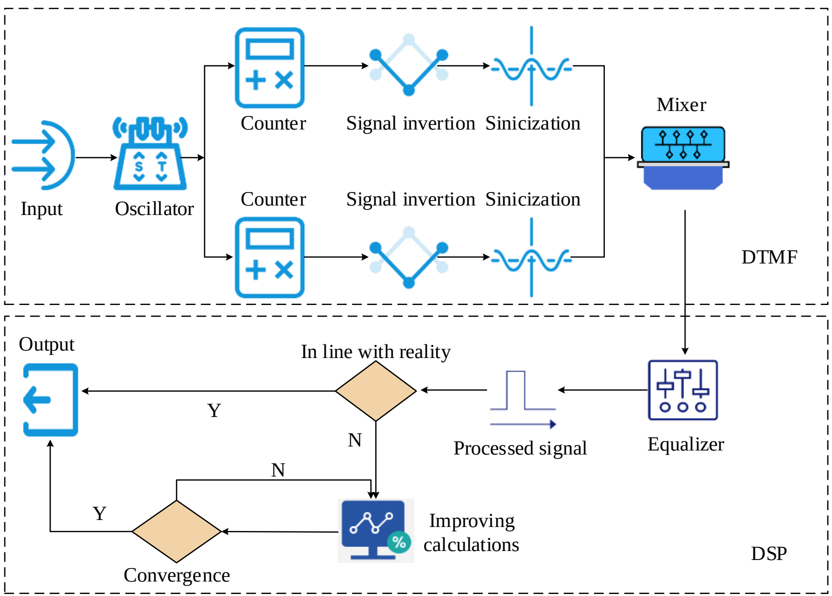


Fig. 3. Improved DTMF signal detection algorithm.

B. Construction of Improved Autonomous Call Model Based on DSP-DTMF Algorithm

In emergency command scenarios, constructing a multi-scenario autonomous call rule pattern model is crucial. This model needs to comprehensively consider multiple factors such as the urgency of the event, resource types, geographical location, etc. to better improve the effectiveness of emergency command. Firstly, the multi-scenario autonomous call rule model can set call priority based on the urgency of the event, ensuring timely response to important events. Secondly, the model needs to intelligently identify and allocate relevant emergency resources, such as personnel and materials, to achieve efficient disposal. In addition, the model can automatically select the nearest emergency team and resources to call based on the event location. When constructing this model, holographic and analogical modeling methods can be used to clarify user, usage scenario, and entity features, simplifying unnecessary dimensions and attributes. At the same time, it is necessary to achieve autonomous calling in multiple scenarios by setting flexible call rules and algorithms. This study takes fire emergency command as an example to construct a multi-scenario autonomous call rule model. The basic framework of the constructed model is shown in Fig. 4.

In Fig. 4, the fire emergency command multi-scenario autonomous call model is divided into signal perception layer, signal transmission layer, and signal receiving layer. The signal perception layer mainly includes smoke detectors and temperature detectors, which are used to detect smoke concentration and temperature in fires. When the detection result meets the alarm conditions of the detector, the signal will be sent to the alarm in the signal transmission layer. The alarm sends the next command to the signal receiving layer based on the smoke concentration and temperature. The signal receiving layer receives the sent reminder signal or alarm signal. If a reminder signal is received that there is someone inside the room, it indicates that the indoor fire is not serious, and can be dealt with without calling the alarm. If the signal received by the receiving end is an alarm signal, it indicates that the fire is serious or not serious, but there is no one indoors. The model can automatically call the alarm number. Although the fire emergency command multi-scenario autonomous call model can predict and call fires autonomously, it has a series of problems such as slow detection speed, low accuracy, weak anti-interference ability, and slow call transmission speed. The DSP-DTMF algorithm can improve the accuracy and speed of signal detection, enhance the anti-interference ability, and reduce the response time [17]. Therefore, this study uses the DSP-DTMF algorithm to optimize the traditional fire emergency command multi-scenario autonomous call model, in order to improve the overall performance of the model. The basic structure diagram of the autonomous call mode model that integrates the DSP-DTMF algorithm is shown in Fig. 5.

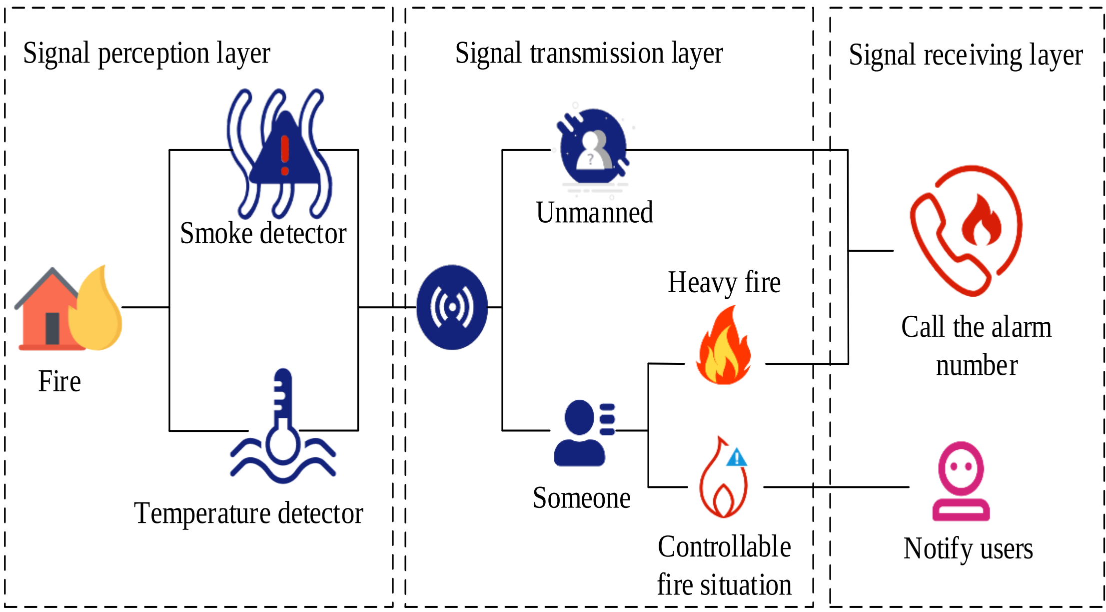


Fig. 4. Basic framework of autonomous call rule model.

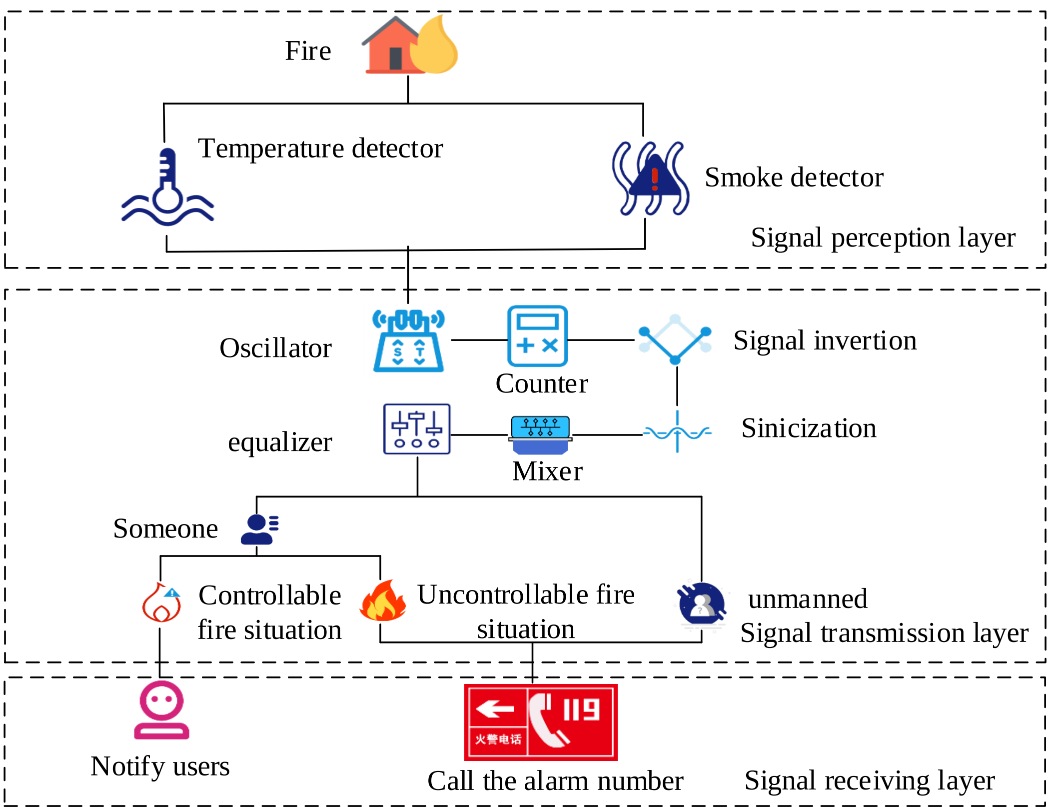


Fig. 5. Improved autonomous call model.

In Fig. 5, the improved autonomous call model is also divided into three layers: signal perception layer, signal transmission layer, and signal receiving layer. The signal perception layer and signal receiving layer have not changed, but only the signal transmission layer has changed. In the signal perception layer, after detecting relevant signals through temperature detectors and smoke concentration detectors, the signals are sent to the signal transmission layer. In the signal transmission layer, the signal is detected by the oscillator, counter, and mixer of the DTMF module. Then, the detected signal is sent to the DSP module, which extracts and re-detects the signal through the equalizer in the module. If the detected signal shows that there is no one present at the fire scenario, an alarm will be triggered. DTMF will call the alarm number. If someone is trapped on site and the fire is controllable, the model will notify rescue personnel. If the fire is uncontrollable, an alarm will be triggered. The operation instructions for fire alarm notification to users are transmitted to the signal receiving layer through dial-up processing. The comprehensive performance score of the improved autonomous call model is shown in Eq. (17).

$$W_k = \sum_{k=1}^{n} x_k * y_k \tag{17}$$

In Eq. (17), W_k represents the comprehensive score of the k-th indicator. x_k represents the weight of the k-th indicator. y_k represents the rating of the k-th indicator. This calculation method can be used to compare the comprehensive performance of different models.

III. Results

A. Performance Analysis of DTMF Signal Detection Algorithm Based on DSP

MIMO-OTFS algorithm is a signal detection technology based on Multi-Input Multi-Output (MIMO) and Orthogonal Time-Frequency Space (OTFS), which performs well in dealing with complex signal environments [18]. SDNSR-Net is a deep learning network specifically designed for signal detection and noise suppression [19]. In order to verify the superiority of the improved DTMF signal detection algorithm, DSP-DTMF algorithm (Algorithm 1) is compared with MIMO-OTFS (Algorithm 2) and SDNSR-Net (Algorithm 3) in experiments. Signal detection accuracy, error rate, transmission speed, and minimum detectable signal are used as comparison indicators. The specific environment of the comparative experiment is shown in Table I. The experiment is repeated 10 times, and T-test is used for statistical verification.

The parameter settings during the experiment are as follows. The sampling frequency of each algorithm for the signal is set to 8000HZ, the duration of each digital signal is set to 50ms to ensure the accuracy of the digital information, and the output frequency is set to 100Hz. Comparative experiments are conducted on three algorithms under the same environmental configuration in Table I. The dataset used is the radar radiation source recognition signal dataset, which is sourced from the measured data of AD9910 and USRP hardware. The dataset mainly consists of 6 individuals, each with 6 modulation types and 5000 pulses per modulation type, totaling 180000 samples [20]. The waveform comparison results of the detection accuracy of three algorithms on the radar radiation source recognition signal dataset are shown in Fig. 6.

TABLE I. Experimental Environment Configuration

System modules	Parts	Type
Single chip	Storage	8KB Flash storage
	RAM	256 bit
	I/0 line	32 programmable I/O lines
	Interface type	Serial interface
	Oscillator	Clock oscillator
Number receiving circuit	Chip type	MT8870
	Type of micro-controller	89C52
Signal circuit	Chip type	UM91513
Main engine	Winds system	Wind11-64
	CPU model	i7-12700KF

As shown in Fig. 6 (a), the average accuracy of the DSP-DTMF algorithm reached 0.91, which fluctuated between 0.8 and 1.0, indicating good stability. In Fig. 6 (b), the average accuracy of Algorithm 2 was 0.62, which fluctuated greatly when the sample size was less than 60, resulting in unstable accuracy. After the sample size exceeded 60, the accuracy of the algorithm fluctuated between 0.57 and 0.64, which was relatively stable. According to Fig. 6 (c), the average accuracy of Algorithm 3 was 0.46. When the sample size was less than 100, the accuracy fluctuated greatly, with poor stability. When the sample size reached 100, the accuracy gradually stabilized. The error rate and recall rate of the three algorithms are shown in Fig. 7.

As shown in Fig. 7 (a), the error rates of Algorithm 1, Algorithm 2, and Algorithm 3 stabilized at 0.05, 0.10, and 0.13, respectively. Algorithm 1 reached a maximum of 0.15 when the sample size was 40. When the sample size exceeded 40, the error rate gradually decreased and stabilized at 0.05. Algorithm 2 and Algorithm 3 were 0.21 and 0.22, respectively when the sample size was 60. When the sample size was greater than 80, the error rates of the two algorithms decreased and eventually stabilized at 0.15 and 0.13, respectively. As shown in Fig. 7 (b), the recall rates of Algorithm 1, Algorithm 2, and Algorithm 3 ultimately stabilized at 0.90, 0.79, and 0.68, respectively. The recall rate of Algorithm 1 gradually increased with the increase of sample size. The overall recall rate of Algorithm 2 increased. When the sample size was less than 100, the fluctuation range of error rate was large, with poor stability. The overall recall rate of Algorithm 3 also increased. When the sample size was less than 100, the recall rate was extremely unstable, with a large fluctuation range and frequency. After the sample size exceeded 100, the recall rate gradually stabilized. The signal detection transmission speed and minimum detectable signal are experimentally analyzed. The experimental results are shown in Fig. 8.

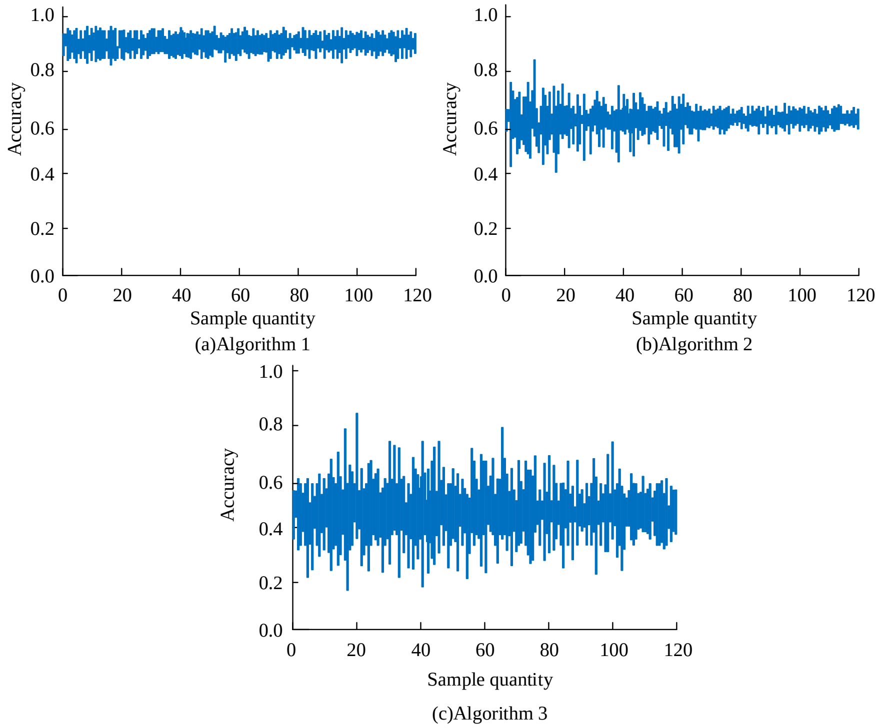


Fig. 6. Comparison of accuracy among three algorithms.

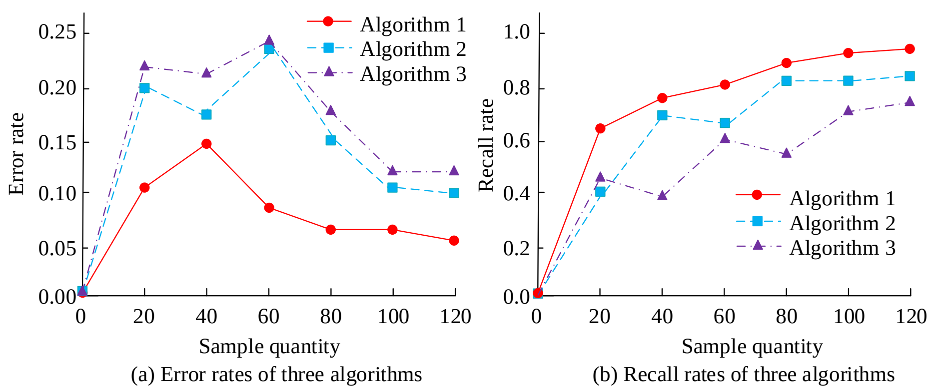


Fig. 7. Comparison of error rate and recall rate of three algorithms.

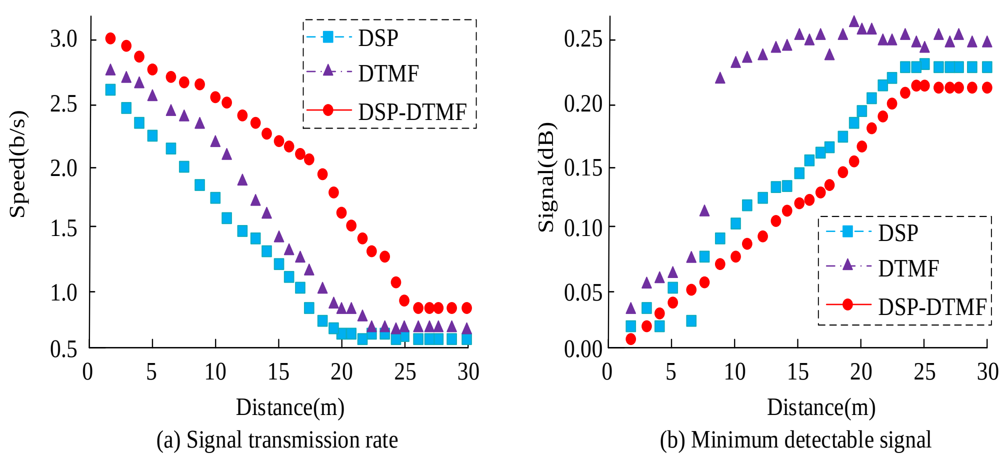


Fig. 8. Signal transmission rates and minimum detectable signals of three algorithms.

From Fig. 8 (a), the signal transmission rates of Algorithm 1, Algorithm 2, and Algorithm 3 all decreased with increasing distance. Among them, the signal transmission rate of Algorithm 1 slowed down and tended to increase when the distance reached 15m. When the distance reached 25m, the signal transmission rate reached its lowest value, at 0.8b/s, and then fluctuated around 0.8b/s. Algorithm 2 and Algorithm 3 reached the minimum transmission rate at 25m, which was 0.53b/s and 0.67b/s, respectively. As shown in Fig. 8 (b), as the distance increased, the minimum detectable signal values of all three algorithms increased. At 25m, Algorithm 1 and Algorithm 2 had minimum detectable signals of 0.19dB and 0.21dB, respectively. At 10m, the minimum detection signal of Algorithm 3 skyrocketed to 0.23. Subsequently, it fluctuated between 0.22 and 0.24. In summary, the DSP-DTMF algorithm proposed in the study has the best overall performance among the three algorithms. In order to more comprehensively verify the effectiveness and scalability of DSP-DTMF algorithm and its autonomous call model, it is tested with the model proposed in literature [13] and the model proposed in literature [14] in a variety of data sets. In addition to the radar radiation source identification signal dataset, several other key datasets were introduced to evaluate the algorithm's performance in different scenarios. The radar radiation source identification signal dataset comes from the measured data of AD9910 and USRP hardware, which contains 6 individuals, each individual has 6 modulation types, each modulation type contains 5000 pulses, a total of 180,000 samples; Fire simulation data set is a data set generated by simulating fire scenarios, which contains fire data under different temperature and smoke concentration conditions. The multi-source information fusion dataset synthesizes data from video, audio, sensor and other sources, and contains multi-modal data under various emergency scenarios. The performance of the three models on different data sets is shown in Table II.

TABLE II. THE PERFORMANCE OF THE THREE MODELS ON DIFFERENT DATA SETS

Model type	Data set	Signal detection accuracy	Error rate	Transmission speed (b/s)	Minimum detectable signal (dB)
DSP-DTMF	Radar radiation source identification signal dataset	0.91	0.05	0.81	0.19
	Fire simulation data set	0.93	0.04	0.77	0.18
	Multi-source information fusion dataset	0.89	0.06	0.66	0.22
Literature [13]	Radar radiation source identification signal dataset	0.72	0.10	0.53	0.21
	Fire simulation data set	0.71	0.12	0.48	0.23
	Multi-source information fusion dataset	0.69	0.13	0.45	0.26
Literature [14]	Radar radiation source identification signal dataset	0.77	0.13	0.67	0.23
	Fire simulation data set	0.68	0.15	0.61	0.25
	Multi-source information fusion dataset	0.73	0.17	0.56	0.24

As can be seen from Table II, the model proposed in this study has high signal inspection accuracy in the three data sets, which are 0.91, 0.93 and 0.89 respectively. Through testing on different data sets, the research proves that DSP-DTMF algorithm and its autonomous call model have good scalability. In addition, this result also proves that the proposed model has better performance than other studies. The above results show that the algorithm and model can adapt to various emergency scenarios and have wide application potential.

B. Performance Analysis of the Optimized Autonomous Call Rule Model

After verifying the superiority of the DSP-DTMF algorithm, in order to analyze the application effect of the proposed multi-scenario autonomous call rule model based on the DSP-DTMF algorithm, the DSP-DTMF algorithm, MIMO-OTFS algorithm, and SDNSR-Net algorithm are used in the autonomous call rule model for comparison. Taking the fire emergency scenario as an example, different models are used in the fire simulation environment to compare the comprehensive performance of the three models and the model without using the proposed algorithm. The accuracy and response comparison of the four models are shown in Fig. 9.

According to Fig. 9 (a), the average accuracy of the DSP-DTMF model, MIMO-OTFS model, SDNSR-Net model, and original model were 0.93, 0.79, 0.68, and 0.61, respectively. When the temperature was 200°C and the smoke concentration was 0.5dB/ppm, the accuracy of the DSP-DTMF, MIMO-OTFS, SDNSR-Net, and original model were 0.97, 0.90, 0.81, and 0.72, respectively. When the temperature and smoke concentration increased, the accuracy of all four models decreased. The DSP-DTMF model had an accuracy of 0.94 at 400°C and 2dB/ppm smoke concentration, while the accuracy of the MIMO-OTFS, SDNSR-Net, and original model under these conditions were 0.76, 0.65, and 0.58, respectively. According to Fig. 9 (b), the average response time of the four models was 0.08s, 0.12s, 0.23s, and 0.31s, respectively. The DSP-DTMF, MIMO-OTFS, SDNSR-Net, and original model had response time of 0.05s, 0.08s, 0.14s, and 0.20s, respectively at 200°C and 0.5dB/ppm. As the temperature and smoke concentration increased, the response time of the four models also gradually increased. Moreover, when the temperature was 400°C and the smoke concentration was 2dB/ppm, the response time of four models was 0.10s, 0.34s, 0.40s, and 0.42s, respectively. Fig. 10 shows the stability and loss function curves of four models.

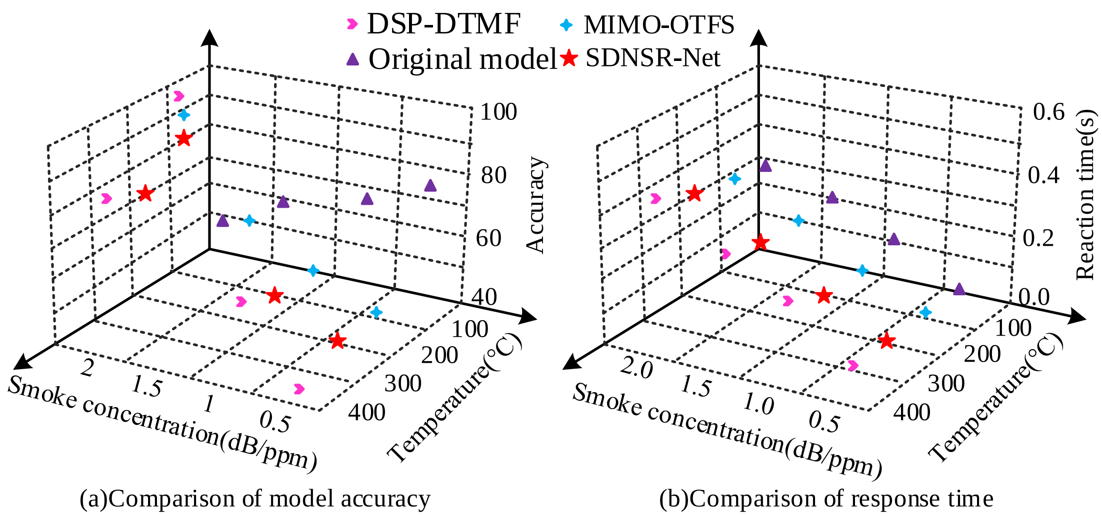


Fig. 9. Comparison of accuracy and response time of four models.

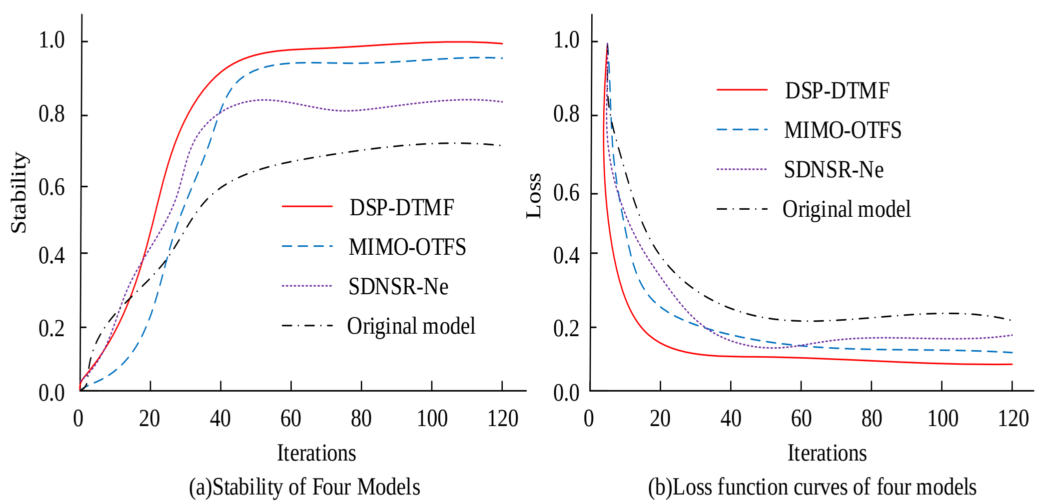
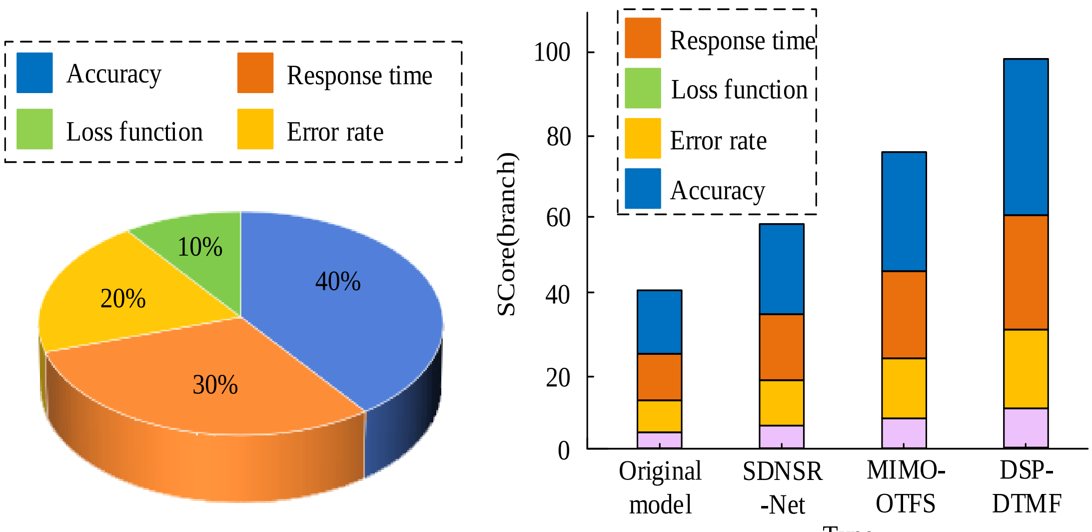


Fig. 10. Comparison of stability and loss function curves for four models.

From Fig. 10 (a), the stability increased with increasing iterations. The final stability of the DSP-DTMF model, MIMO-OTFS model, SDNSR-Net model, and original model was 0.93, 0.91, 0.87, and 0.63, respectively. The stability of all four models reached its maximum at an iteration of 40. From Fig. 10 (b), the loss values of all four models decreased with increasing iterations. Among them, the DSP-DTMF model, MIMO-OTFS model, SDNSR-Net model, and original model had final loss values of 0.07, 0.10, 0.16, and 0.21, respectively. Moreover, the loss values of all four models reached the lowest value at 20 iterations. Fig. 11 shows the comprehensive performance score of the four models.

From Fig. 11 (a), the comprehensive performance score is composed of the accuracy, response time, loss function, and error rate of the model. In the comprehensive performance score, the accuracy of the model accounts for the largest proportion of 40%, the loss function accounts for the smallest proportion, at 10%, and the proportion of response time and error rate is 30% and 20%, respectively. The comprehensive performance score of the model can be calculated from the proportion in Fig. 11 (a) to obtain Fig. 11 (b). The comprehensive score consisted of four parts, among which the DSP-DTMF model had the highest comprehensive score of 97 points, MIMO-OTFS model and SDNSR-Net model had a comprehensive score of 69 points and 60 points, respectively, and the original model had the lowest comprehensive score of 40 points. In summary, the comprehensive performance of the DSP-DTMF autonomous call model proposed in this study is the best. In order to more comprehensively verify the effect of the autonomous call rule model based on DSP-DTMF algorithm, this model and the novel multi-source information autonomous call rule model, swarm intelligence autonomous call rule model and adaptive autonomous call model are tested in five actual fire scenarios. This comparison is to further verify the performance of the optimization algorithm and ensure the effectiveness and reliability of the model in emergency scenarios. The test results are shown in Table III.



(a)The comprehensive performance score of the model and the proportion of each function

(b)Comprehensive performance evaluation of the model

Fig. 11. Comparison of comprehensive performance scores of four models.

TABLE III. PERFORMANCE OF DIFFERENT MODELS IN REAL FIRE SCENARIOS

Index	DSP-DTMF autonomous call rule model	Multi-source information autonomous call rule model	Swarm intelligence autonomous call rule model	Adaptive autonomous call model
Accuracy rate (%)	95.2%	90.1	89.6	88.1
Reaction time (s)	2.1	3.3	3.1	4.5
Number of scenarios	5	5	5	5
Total test duration (h)	100.1	98.8	98.9	95.6
Average frames per second (FPS)	30.1	24.2	25.1	20.6

From Table III, the autonomous call rule model based on DSP-DTMF algorithm performed well in the simulated fire scenario, with an accuracy of 95.2% and a reaction time of only 2.1s, which was far better than comparison models. It was tested in five different real scenarios, and the total test time reached 100.1h, showing the stability and durability of the model. In addition, from Table III, the average FPS of the autonomous call rule model based on DSP-DTMF algorithm was 30.1, which was better than 24.2, 25.1, and 20.6 of comparison models, indicating that the algorithm had higher processing speed. Finally, the paper also considers the scalability and robustness of the autonomous call rule model based on DSP-DTMF algorithm in many different scenarios. The robustness of the model is analyzed by comparing the accuracy and response time of the model in five specific scenarios. The specific results are shown in Table IV.

From Table IV, under different actual scenarios, DSP-DTMF algorithm maintained a high accuracy rate, and its mean value was 94.9%. In addition, the response time of the model fluctuated slightly in different environments, but the overall level was also kept low, with a mean response time of 2.2s. The above results show that the autonomous call rule model based on DSP-DTMF algorithm has scalability and robustness. The performance of the DSP-STMF autonomous call model is compared with the widely used disaster autonomous call model based on GA-SVM algorithm, as shown in Table V.

TABLE IV. ACCURACY AND RESPONSE TIME OF THE AUTONOMOUS CALL RULE MODEL BASED ON DSP-DTMF ALGORITHM IN DIFFERENT SCENARIOS

/	Accuracy rate	Response time (s)
Residential area fire	96.1%	1.9
Industrial area fire	94.5%	2.2
Forest fire	93.8%	2.4
Commercial fire	95.2%	2.0
Mountain fire	94.8%	2.3
Mean value	94.9%	2.2

TABLE V. MODEL PERFORMANCE COMPARISON

Model	DSP-DTMF model	GA-SVM model
Precision	95.2%	87.6%
Reaction time	2.1s	3.5s
Monitoring accuracy	97.5%	82.1%
False negative rate	1.1%	8.3%
False report rate	1.4%	9.6%
Fraction of coverage	98.9%	89.7%

According to Table V, the proposed DSP-STMF model outperformed the current GA-SVM autonomous call model in all aspects of performance. The monitoring accuracy, precision, and coverage of the DSP-DTMF autonomous call model were all above 95%, while the monitoring accuracy, precision, and coverage of the GA-SVM model were all below 90%. The false negative rate, false alarm rate, and response time of the DSP-DTMF model were lower than those of the GA-SVM model. From the above results, it can be concluded that the DSP-DTMF autonomous call model proposed in the study outperforms current autonomous call models in all aspects of performance.

IV. Discussion

This study designed a comparative experimental analysis on the performance of the DSP-DTMF algorithm. Then, comparative experiments are conducted on autonomous call models based on DSP-DTMF algorithm, MIMO-OTFS algorithm, and SDNSR-Net algorithm. The results showed that the DSP-DTMF algorithm outperformed the other two algorithms in accuracy, stability, error rate, and signal transmission speed. In the accuracy waveform, the average accuracy of the DSP-DTMF algorithm was the highest at 0.9, with small fluctuation in accuracy and strong stability. This result was similar to the experimental results of Schaumont using the DSP-DTMF algorithm to process remote course selection for courses [21]. This result indicates that in practical applications, the DSP-DTMF algorithm can make more accurate judgments on emergency scenarios. In the recall and error rate curves of the algorithm, the DSP-DTMF algorithm had the lowest error rate of 0.05 and the highest recall rate of 0.9, further verifying the superiority of the algorithm. In terms of the signal transmission rate and minimum detectable signal, the DSP-DTMF algorithm outperformed the other two algorithms. Wibowo et al. also had similar conclusions [22]. This result indicates that the DSP-DTMF algorithm can more quickly and accurately determine emergency scenarios in practical applications.

Secondly, all three algorithms were applied to the autonomous call model. Through comparative experimental analysis between the three models and the original model, it was found that the autonomous call model based on the DSP-DTMF algorithm had strong advantages in accuracy, response time, stability, loss function, and comprehensive performance evaluation. In terms of accuracy and response speed in emergency scenario assessment, this model accurately assessed the emergency scenarios under high temperature and high concentration smoke, and made timely next steps. In the comparison of model stability and loss function curve, it was found that the DSP-DTMF model had the strongest stability of 0.93 and the smallest loss function. This result indicates that the model has strong anti-interference ability, which is not easily affected by other external factors in emergency scenarios. This model is relatively accurate in predicting emergency scenarios. Perng also conducted similar conclusions in the research on DSP digital filters [23]. In the comprehensive performance evaluation of the model, the DSP-DTMF model had the highest comprehensive score of 97 points, which was much higher than other models. This coincided with the conclusion on an automatic unlocking system based on improved DTMF proposed by Iwuji [24].

This result fully demonstrates that the autonomous call model based on DSP-DTMF algorithm can effectively predict emergency scenarios and respond quickly to them, meeting sudden emergency needs. The DSP-DTME autonomous call model is used to test the performance of the model in different fire actual scenario environments. The test results show that the DSP-DTMF autonomous call model maintains a high accuracy rate in different fire scenarios, and its average accuracy rate reaches 94.9%, and the average response time is only 2.2s. It can be concluded that the disaster autonomous call model based on DSP-STME algorithm can improve the speed of disaster emergency rescue, reduce the economic and property losses caused by disasters, and protect the safety of people's lives and properties.

V. Conclusion

Aiming at the problems of slow processing speed, weak anti-interference and low accuracy of autonomous call model in emergency command scenario, this paper innovatively integrates DSP and DTMF to construct an efficient hybrid algorithm, and designs a new autonomous call model based on this algorithm. Through a series of comparative experiments, the superiority and practical application value of DSP-DTMF algorithm and its autonomous call model are verified. The main contribution of the research is to propose a new DSP-DTMF hybrid algorithm, which is successfully applied to the autonomous call model in the emergency command scenario. The algorithm not only significantly improves the accuracy and efficiency of signal detection, but also enhances the anti-interference ability of the model, so that it can maintain stability and accuracy in complex and changeable emergency scenarios. In addition, the experimental results of the autonomous call model designed based on the algorithm in the fire simulation scene show that its comprehensive performance score is much higher than other comparison models, which proves the effectiveness and practicability of the model in emergency command.

In practical applications, the autonomous call model based on DSP-DTMF algorithm has significant advantages. First of all, the model can judge the situation in the emergency scenario more quickly and accurately, so as to start rescue operations in time and reduce disaster losses. Secondly, the model has strong anti-interference ability, can maintain stable operation in complex and changeable emergency environment, and improve the reliability and stability of emergency command. In addition, the model has good scalability and robustness, can adapt to the emergency needs in different scenarios, and provide comprehensive technical support for emergency command.

Although this study has achieved certain results, there are still some limitations. First of all, the current research mainly focuses on the optimization of autonomous call model in fire scenarios, and its applicability to other disaster types (such as earthquake, flood, etc.) needs to be further verified. Second, although the performance of the model has been improved, there may still be some limitations in extremely complex or specific emergency scenarios. In addition, due to the limitations of experimental conditions, some data in the study may have certain biases, which may affect the accuracy of the results.

In view of the above limitations, future research can be expanded and deepened from the following aspects. Firstly, the applicability of DSP-DTMF algorithm under different disaster types is further verified, and the model is optimized and improved according to the characteristics of different disaster types. Second, explore fusing multimodal data into the model to achieve more comprehensive emergency scenario perception and more accurate call decisions. In addition, the real-time and robustness of the model can be enhanced to improve its response ability in complex emergency scenarios. Finally, the possibility of cross-domain application of the model in intelligent transportation, security monitoring and other fields can be explored to further expand its practical application value. Through these efforts, it is expected to further improve the efficiency and accuracy of emergency command, and provide more powerful technical support for disaster relief work.

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