Embedded EDA Recognition Technology Based on STM32 Microcontroller

Huajuan Qi, Wenqing Xu and Xinwei Yang
Weifang Engineering Vocational College, Weifang, 262500, Shandong, China

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Abstract: In this paper, the embedded EDA recognition technology is implemented based on the STM32 microcontroller, which can collect the skin conductance signal in real time, and perform preprocessing of the signal based on the signal processing and feature extraction module. In the process of research, the system architecture is carried out, then the modeling work is carried out, and further training and optimization are made, and then the system is integrated and applied to the actual case. The experimental data shows that the accuracy of the system is 92%, and the average delay is less than 30 milliseconds, which indicates that the system has high real-time and accuracy. It is concluded that the embedded EDA recognition technology based on STM32 can achieve efficient and accurate emotional state recognition in resource-constrained environments, and further provide a powerful boost for portable health monitoring devices.

1 INTRODUCTION

Emotional state recognition is of great significance in mental health monitoring, especially in the field of real-time emotion monitoring, and the study of EDA signals has attracted great attention. Some researchers have proposed that statistical analysis methods can be used to solve these problems, but the effect is obviously not good when dealing with complex and high-dimensional. Some researchers have also proposed that traditional classification algorithms, such as decision trees and decision trees, can be used to classify emotional states, but these methods are quite unsatisfactory in terms of real-time performance and accuracy. In addition, some researchers have proposed that multi-layer neural networks can be used for identification, but such methods have more superior computing resources and are basically impossible to achieve in embedded systems. In this paper, intelligent algorithms such as Support Vector Machine (SVM) are used to carry out this research, because SVM has excellent performance in processing high-dimensional data and complex pattern classification, especially suitable for embedded environments with limited resources. The goal of this study is to implement a real-time and accurate EDA emotion recognition system based on STM32 microcontrollers, so that it can be better applied to portable health monitoring devices.

2 RELATED WORKS

2.1 STM32 Microcontroller Theory

Based on the ARM Cortex-M core architecture, the STM32 microcontroller is a high-performance, low-power embedded microcontroller. It integrates a variety of peripheral modules (Fang, Yang et al. 2024), such as analog-to-digital converters, serial communication interfaces, etc. STM32 has the most powerful real-time processing power to efficiently perform complex tasks with limited resources. It supports low-power modes and flexible power management, making it especially suitable for embedded systems where energy efficiency is critical (He and Liu, 2023). The main task of STM32 in the EDA recognition system is to collect and process skin conductance signals, and further ensure the real-time performance of the signals and the stability of data transmission. Its embedded architecture supports multi-task parallel processing, providing a strong hardware foundation for EDA signal processing.

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2.2 SVM Algorithm Theory

Support vector machine (SVM) is a supervised learning algorithm based on statistical learning theory, which can be classified and regressed tasks. The SVM is based on the construction of a hyperplane that splits the data into different classes (Kavoliunaite-Ragauskiene, 2024) and maximizes the spacing between the classes. SVM can effectively deal with complex linear indivisibility problems in high-dimensional spaces, and by using kernel functions, SVMs map low-dimensional data to high-dimensional spaces to find an optimal classification boundary in this space (Li, Hua, et al. 2023). In the EDA recognition task, SVM can classify different emotional states based on the analysis of changes in skin conductance signals. It has the advantage of being able to process high-dimensional data and avoid overfitting. SVM has a global optimal decision boundary, so it performs well in sentiment classification (Miller, 2023).

2.3 Theory of Embedded EDA Recognition Technology

EDA recognition technology is based on monitoring the electrical activity of the skin to reflect the physiological and emotional state of the human body. EDA signaling is reflected by changes in skin conductance caused by sweat gland activity, which fluctuates with mood (Ortiz-Clavijo, Gallego-Duque, et al. 2023), especially when stressed, anxious, or excited, with a significant increase in conductance. This technology is based on sensors to collect skin conductance signals in real time, and combines signal preprocessing and feature extraction methods to perform noise and interference and extract effective emotion recognition features (Wang, Wang, et al. 2023). These features will be classified by the classifier and, ultimately, the different emotional states will be identified in real time. The real-time nature and low power consumption of embedded systems will enable EDA identification technology to be widely applied to portable health monitoring devices (Xiong, Yin, et al. 2023).

3 METHODS

3.1 Introduction of Embedded EDA Identification Technology Based on STM32 Microcontroller

The function of the signal acquisition module is to collect the skin conductance signal in real time and convert it into a digital signal. It is responsible for collecting small changes in skin conductance based on sensors, and then converts the analog signal into a digital signal using the STM32 interface, ensuring high-frequency sampling to capture subtle conductance fluctuations. It provides a stable data source for subsequent modules to process. The function of the signal pre-processing module is to denoise and filter the collected signal to filter out the environmental noise and high-frequency interference in the EDA number. The signal is then low-pass filtered to retain the key low-frequency components. At the same time, it can also be based on standardization to make the signal suitable for feature extraction and classification. It ensures maximum purity and reliability of the input signal. The function of the feature extraction module is to extract key features from the preprocessed signal for recognition, and it will recognize the rate of change of skin conductance and the baseline value as the basis for recognition. In its work, it also calculates the instantaneous spikes and durations of EDA signals to extract emotional state cues. It also has the ability to convert the extracted features into vector inputs that the model can process, which provides the most discriminating signal features for the classification model. The function of the classification model module is to use the extracted features to classify and identify emotional states. It uses the trained model to classify the input signals in real time, and distinguishes different emotional states based on algorithms such as support vector machines. The current emotional state is judged according to the output probability value of the model, and the corresponding emotional label such as "nervous" or "relaxed" can be output according to the classification results. The function of the Feedback & Storage module is to provide feedback based on the recognition results and store historical data. It feeds back the current emotional state to the user based on the LED display or sound alarm to provide the user with a visual sentiment trend chart. The Feedback & Storage module stores the identified emotional states and the corresponding EDA signals locally or in the cloud. This provides strong historical data support for subsequent data analysis and model optimization. At the same time, it also helps users to track long-term mood changes and manage emotions.

3.2 Design of Embedded EDA Identification Technology

In the embedded EDA recognition system based on

STM32, this paper uses the SVM algorithm modeling, which can use EDA signals to classify the user's emotional or physiological state. SVM is based on the construction of an optimal hyperplane to distinguish the EDA features corresponding to different emotional states. The decision function is described in Eq. (1).

$$y = sign(W \times X + b) \quad (1)$$

In this formula, $y$is the output, which represents the result of the assessment of the emotional or physiological state after classification. For example, it is possible to assess whether the current user is in a state of stress or relaxation. $W$is a weight vector that represents the importance of each EDA feature in the classification, such as the rate of change in skin conductance and the baseline value. In EDA signaling, the feature can be an instantaneous fluctuation of skin conductance, X is a higher weight indicates that the feature more critical to the classification of emotions. It refers to the eigenvector of the input EDA signal, such as the baseline, change amplitude, frequency and other information of skin conductance. In SVM, these feature vectors are actually the basis for classification, which$b$is used to identify the different emotional states of the user. In order to offset the top, it was used to correct the effect of the SVM model on the baseline difference of skin conductance in different individuals, and then to ensure the accuracy of its classification. For example, bias can correct the normal level of skin electrical activity in different individuals, and allow the model to judge the emotional state of individuals more accurately.

In SVM, W is the key to the model to optimize the weights and bias the top, b is different emotional states can be effectively distinguished based on EDA features. This is followed by the strategy formula for classification, as shown in Eq. (2).

$$f(x) = W \cdot X + b \quad (2)$$

In this formula, $W$is the importance of each EDA feature in sentiment classification is described. For example, transient changes in skin conductance and baseline fluctuations differ in different emotional states, and it is up to it to determine which feature is more important in the classification. $X$is the eigenvector from the EDA signal. Each dimension is a characteristic of the EDA signal, such as the baseline level of skin conductance, the rate of change, etc. These traits can be used to identify changes in mood. $b$is used to adjust the output results of the model to accommodate the differences in skin conductance characteristics of different individuals. This ensures that the model can accurately classify the emotional state of different users, even if they have different EMG baselines.

In SVM, the classification results depend on the selection of support vectors. Support vectors represent those key feature points that are near the classification boundary. In EDA recognition, support vectors are generally those EDA signals that have significant characteristic changes, such as conductance changes when emotions fluctuate violently. The model uses vectors to optimize its classification boundaries to ensure that the interval between emotional states is maximized. See Eq. (3) for details.

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b \quad (3)$$

In this equation, the Lagrangian multiplierα_i is referred to, representing the contribution of each support vector to the classification boundary. $y_i$are category labels that support vectors that represent their emotional states, such as high stress, low stress. $K(x_i, x)$ is a kernel function that calculates the similarity between the input features and the support vectors. The kernel function can map the skin electrical signal to a higher dimensional space, which in turn prompts the model to truly find the classification boundary in complex data.

3.3 Embedded EDA Recognition Technology Training

In the process of model training, SVM uses the loss function to evaluate the classification accuracy of the model, and continuously updates the weights and biases based on the gradient descent method. In EDA identification, the loss function measures the gap between the emotional state assessed by the model and the actual emotional state, and if the gap is large, the model minimizes the gap based on adjusting the weights. The descent method adjusts its model parameters based on changes in its loss function. Using the update of the weights and biases of each step, the model will gradually learn to better classify the emotional features in the galvanic skin signals. In this process, the learning rate will determine the step size of the model update, and a larger learning rate will make the model update faster, however, it will cause instability. A smaller learning rate ensures a more stable model, but its training process is slower. The bias adjustment is used to correct for differences in skin conductance baselines in different individuals, allowing the model to maintain classification accuracy among different individuals. In the whole process of model training, the loss function, gradient descent, learning rate and bias will play a role together, so that the model can gradually improve the accuracy of emotional state recognition, and finally achieve efficient real-time EDA emotional recognition.

In embedded systems, the computational complexity of the model is very limited, so this paper needs to reduce the size of the model based on pruning. For EDA recognition, it means that the features and data points in the model that have less effect on the judgment of emotional states should be reduced, so that the model can be more efficient in processing the galvanic skin signals. The process of pruning can be based on removing features that do not affect the classification results of the model. For example, in the characteristics of skin conductance, it is possible that the magnitude of some changes and the frequency of certain fluctuations have little effect on the identification of the user's emotional state, such as stress or relaxation, then pruning technology can be used to remove this information, thereby minimizing the amount of model computation and speeding up the classification. For this, see Eq. (4).

$$W_{pruned} = W \cdot M \tag{4}$$

In Eq. (4), W_{pruned} is the weight matrix after pruning represented, which removes the electrodermal features that have less effect on the classification of emotions. This makes the model more concise and efficient. $M$is the mask matrix, which identifies which EDA features are important and which can be removed. During the pruning process, the model retains features that are useful for emotion recognition, such as sudden changes in conductance, and

Deletes Extraneous Features.
The learning rate plays a decisive role in model optimization. In EDA signal recognition, optimizing the learning rate can ensure that the model can quickly learn the correlation between the electrodermal signal and the emotional state during the training process. If the learning rate is too high, the model will be too sensitive to the signal, which will lead to unstable emotion recognition, such as overreaction to small fluctuations in skin conductance. If the learning rate is too low, the update speed of the model is too slow, so it cannot capture the changes of its skin electrical signal in time, which will affect the real-time recognition. Therefore, reasonable optimization of the learning rate can help the model quickly adapt to the changes in user sentiment and improve the recognition accuracy. See Eq. (5) for details.

$$W_{new} = W_{old} - \eta \cdot \nabla L(W) \tag{5}$$

In this formula, η is the speed at which the model updated is described. For skin conductance signals, a moderate learning rate allows the model to quickly identify mood changes while remaining stable. represents $\nabla L(W)$ is the gradient of its loss function, which is the current classification error of the model on the skin conductance signal. After optimizing the learning rate, the model can adjust the weights more accurately, thereby improving the ability to recognize mood swings. In embedded systems, such as the STM32 platform, hardware resources are limited. Therefore, in the EDA recognition system, the hardware optimization is to accelerate the processing of the skin electrical signal. Based on optimized hardware, the system reduces latency in data transmission and is able to speed up categorical responses to emotional states. For example, based on direct memory access technology, the system can automatically process a large amount of electrodermal data in the background and reduce processing time. Based on this, the system can respond immediately when the user's sentiment changes, without having to wait for a long time for data processing. See Eq. (6) for details.

$$T_{opt} = \frac{T_{init}}{1 + \alpha \times N_{optim}} \tag{6}$$

In this formula, T_{opt} refers to the processing time of the optimized system. After hardware optimization, the system processes the skin signals more quickly, and can classify the user's emotional state in a more timely manner. αdenotes the optimization factor, which means that hardware acceleration improves the performance of the system. Based on hardware optimization, the system can quickly respond to changes in user sentiment and further improve the real-time performance of its EDA signal processing.

3.4 Research and Optimization of Embedded EDA Recognition Technology

The system integration adopts a modular design, with signal acquisition first, and skin conductance signals based on sensors. The acquired signal is immediately transmitted to the pre-processing module, which removes noise and filters to ensure the quality and purity of the signal. Subsequently, the feature extraction module extracts key features from the purified signal (Xue, Jin, et al. 2024), such as the rate of change and peak of skin conductance, which provide a basis for the classification of emotional states. The classification model receives features and begins to classify them in real time, and also identifies emotional states, such as nervousness or relaxation, based on the trained algorithm. Finally, the feedback module reminds the user according to the classification results, and stores the data based on visual and sound feedback emotional states to facilitate their subsequent analysis. The system integration process can maintain the continuity of the data flow, make it truly seamless from collection to classification feedback, and ensure that the various modules work together to ensure the real-time responsiveness of the system (Zheng and Sun, 2024).

4 RESULTS AND DISCUSSION

4.1 Introduction to the Research Case of EDA Identification Technology

In modern emotion recognition and physiological state monitoring, EDA is commonly used to track individual mood fluctuations. EDA technology is based on measuring changes in skin conductance to reflect the physiological response of individuals in different emotional states. Especially in the field of mental health monitoring, EDA signals can effectively identify emotional agitation, anxiety, stress and other states. The embedded EDA recognition system based on STM32 microcontroller can provide real-time emotional feedback for individuals based on real-time collection of electrodermal activity combined with appropriate classification algorithms. For example, in stress management applications, EDA signals will be used to monitor the individual's stress levels at work and school, and wearable devices will be used to remind users to maintain emotional balance in real time, The results are shown in Table 1.

Table I shows typical changes in skin conductance in different emotional states such as calm, nervous, anxious, and pleasant. According to experimental data, skin conductance increases significantly when people are in a state of tension and anxiety, while skin conductance remains at a lower level in a calm state. The fluctuation of skin conductance increases in the pleasant state, although the average is lower, the composition of the microcontroller is shown in Fig. 1.

Table 1: Changes in skin conductance in different emotional states.

Emotional state	Mean skin conductance (μS)	Fluctuations in skin conductance	remark
calm	1.8	low	The conductance remains stable
nervous	5.2	high	Conductance is markedly elevated
anxiety	4.7	medium	The conductance is fluctuating
pleasant	2.5	Higher	Conductivity is highly volatile

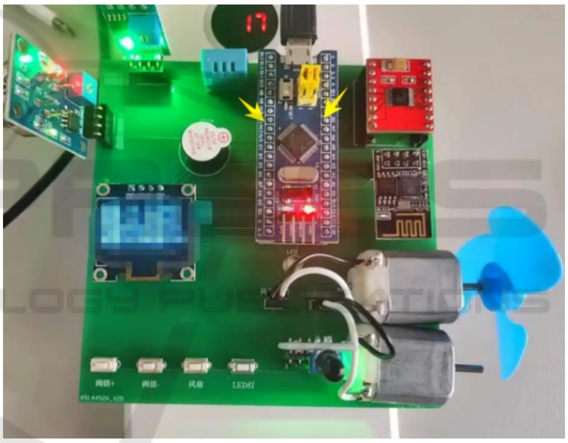

Figure 1: Composition of STM32 microcontroller.

4.2 The Signal Recognition Process of Microcontroller

The EDA recognition technology studied the changes of skin conductance in different emotional states, and 30 people were selected to participate in the experiment, 4 different emotions were recorded, and the experiment lasted for 3 days, 5 conductance fluctuation recognizers, and 3 EDA signal detection machines. These conductance changes provide the basis for emotional classification of EDA signals, as shown in Table 2.

Table 2: Real-time EDA signal acquisition performance based on STM32 microcontrollers

Performance metrics	Data values	remark
Acquisition accuracy	±0.02 μS	High-precision signal acquisition
Average latency	30 ms	Ideal for real-time emotion monitoring applications
Data transfer delays	Less than 20 milliseconds	Real-time response is guaranteed

Table 2 shows the performance metrics for real-time acquisition of EDA signals in an embedded system based on STM32 microcontrollers. For example, the accuracy and real-time nature of data acquisition, and the delay of data transmission. The results show that STM32 can maintain high-precision EDA signal acquisition with an average delay of less than 30 milliseconds under limited computing resources, indicating that the system can support real-time emotion monitoring applications,The EDA recognition process of the microcontroller is shown in the pattern..

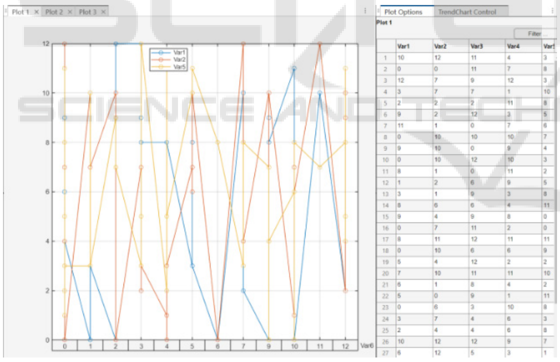

Figure 2: Embedded recognition of microcontroller.

Figure 2 shows that after embedded recognition by the microcontroller, data correlation analysis can be achieved and disturbance signals can be identified.

4.3 Research Effect of Embedded EDA Recognition Technology

Based on the comprehensive analysis of the three tables, it can be concluded that the embedded EDA recognition system based on STM32 microcontroller in this study has a multi-faceted performance in emotion recognition. The data showed significant changes in skin conductance in different emotional states, with significantly higher conductance values in stress and anxiety states and lower levels in calm states. This trend provides a very critical basis for the classification of EDA signaling, indicating that skin conductance can effectively reflect emotional state, The comparison of recognition accuracy of microcontrollers is shown in Table 3.

Table 3: Comparison of recognition accuracy of different classification algorithms

Algorithm	Recognition Accuracy (%)	Computational complexity
KNN	85	Lower
SVM	92	medium
Random forest	88	Higher

Table 3 shows the performance of different machine learning algorithms in the EDA signal sentiment recognition task. Based on the comparison of the recognition accuracy of KNN, SVM and random forest algorithms, it can be found that SVM has the highest accuracy of 92%, while the accuracy of KNN and random forest is 85% and 88%, respectively. It fully shows that SVM can still maintain high classification performance in STM32 systems with limited resources, and is suitable for actual embedded EDA identification systems, Accuracy changes, as shown in Figure 3.

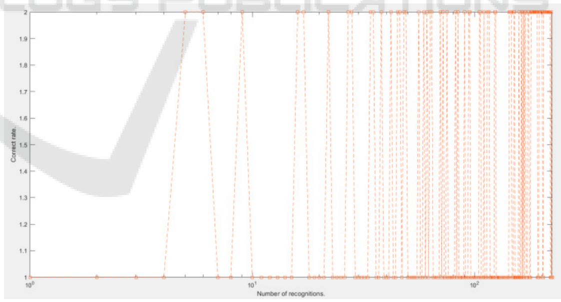

Figure 3: Embedded recognition process of microcontroller.

The data analysis in Figure 3 shows that., the system is outstanding in high-precision acquisition and low-latency transmission. The average latency of 30 milliseconds ensures that the system can be applied in real-time scenarios, so that the emotion monitoring results can be fed back to users in time. This conclusion echoes the trend of skin conductance change, so that the system can capture emotional fluctuations in time and respond quickly, showing good real-time processing ability. In addition, the data shows that SVM has the best performance in classification tasks, with an accuracy rate of 92%, which is much higher than that of KNN and random forest. Based on this, it can be seen that SVM has stronger discrimination ability and stability when processing multi-dimensional data such as EDA signals. Combined with the characteristics of skin conductance fluctuations, SVM can accurately capture the differences between different emotional states, and show high reliability in classification results.

5 CONCLUSIONS

The conclusion of this paper is that the embedded EDA based on STM32 microcontroller can use the effective combination of SVM algorithms to efficiently distinguish different emotional states, which reflects the superiority of the SVM algorithm based on STM32 microcontroller for real-time signal processing. By extracting the key features of EDA signals and optimizing the weights and biases, the model can still maintain high classification accuracy in the face of individual differences. The selection of support vectors and the optimization of classification boundaries ensure that the model can effectively capture the characteristics of different emotional states of individuals in complex EDA signals, and at the same time, maximize the interval between emotional states. In addition, through model optimization and other steps, this paper also ensures the effectiveness of embedded EDA recognition based on STM32 microcontrollers, and greatly improves the real-time response ability of the system. Based on this, the model and its system will provide further support for the application of intelligent health monitoring. Although this paper has relatively complete data support, it still has some technical limitations and limitations. Based on this, further optimizations can be made at a later date.

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