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ENHANCED MULTIDIMENSIONAL NEO-FUZZY CLASSIFICATION SYSTEM AND ITS LEARNING FOR THE VIDEO CLASSIFICATION TASK

A novel hybrid neo-fuzzy system for video classification, which includes multidimensional neo-fuzzy components with adjustable synaptic weights and kernel membership functions, is proposed. This system combines the strengths of extended neo-fuzzy neurons (ENFN) and neo-fuzzy units (NFU) with nonlinear activation functions. By integrating extended nonlinear synapses (ENS) and leveraging the neuro-fuzzy Takagi-Sugeno-Kang inference system, proposed architecture enhances the approximating capabilities of traditional models. This allows the system to effectively address the task of image recognition, including real-time video stream classification, while maintaining a high level of accuracy, as demonstrated by computational experiment.

An optimization algorithm that introduces a novel approach to learning in the advanced neo-fuzzy system for video classification is proposed. Using the cross-entropy learning criterion with one-hot encoding, the algorithm precisely adjusts synaptic weights through the δ-rule, enhanced by adaptive learning rates. Incorporating a forgetting factor, it dynamically adjusts parameters for either stochastic approximation or rapid convergence. This dual capability ensures robustness and efficiency, significantly improving learning speed and accuracy in complex video classification tasks.

1. Introduction

Data stream mining [1]-[4], particularly in video classification, is increasingly vital in the digital age, where the proliferation of video data necessitates efficient processing and analysis methods. Video classification involves identifying and categorizing the content of video sequences, which are essentially streams of images. The challenge is amplified by the often low quality of images, especially when capturing moving objects, leading to the need for advanced techniques to ensure accuracy and efficiency.

Handling data stream mining in video classification is inherently complex due to several factors. The volume and velocity of video data are extremely high, particularly with the widespread use of digital video recorders (DVRs), video servers, and IP cameras. This results in massive amounts of data that need to be processed in real-time or near real-time, which is computationally intensive and requires robust data handling capabilities.

The quality and resolution of video streams often vary. The Main Stream typically provides high-quality video, while the Sub Stream and Third Stream offer lower resolutions to reduce the load on networks and devices. This variability complicates the extraction of consistent features across different streams and impacts the accuracy of classification algorithms. Moreover, videos, especially those capturing moving objects, often suffer from low image quality due to motion blur, occlusions, and varying lighting conditions. These factors make it challenging to accurately identify and classify objects, necessitating the use of advanced techniques such as motion estimation, image enhancement, and noise reduction.

Advanced IP cameras and DVRs support Triple Streaming, enabling simultaneous transmission of three different streams. Integrating data from these streams requires balancing different resolution, frame rate, bitrate, and compression settings, adding to the complexity of the task. Given the varying quality and resolution of video streams, especially under low-quality conditions, traditional image processing techniques may fall short.

In summary, the complexity of handling data stream mining for video classification lies in managing the high volume and velocity of data, dealing with varying quality and resolution, requiring significant computational resources, and employing advanced techniques to ensure accurate and efficient processing.

2. Analysis of literary data and formulation of the research problem

In the rapidly evolving field of video classification, various methods [2], [5]–[7] have been developed to handle the complex task of accurately identifying and categorizing video content. Each method offers unique advantages but also encounters significant challenges, especially in dynamic and intricate scenarios. This overview examines several key video classification methods such as Frame-Based CNN [8], [9], Two-Stream Approaches [10]–[12], 3D Convolutional Neural Networks (3D CNNs) [13], Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) [14], Attention-Based Models [15], and Hybrid Approaches.

While these systems provide a range of benefits including comprehensive feature extraction, high accuracy, effective sequential data processing, and efficient handling of large datasets, they also present notable disadvantages in complex video classification scenarios. General challenges include high computational and resource demands, difficulty in capturing long-term and complex dependencies, and complexity in implementation and integration.

Fuzzy Systems [16]–[18] excel in these areas by efficiently handling imprecision, integrating contextual information, and dynamically adjusting to varying conditions. This makes them a more robust and adaptable solution for complex video classification tasks, providing an edge in scenarios where traditional methods fall short.

Introduced in [19] Takagi-Sugeno-Kang (TSK) algorithm forms the backbone of many fuzzy logic systems. It enhances video classification by modeling the system with rules that handle nonlinear relationships efficiently. The arbitrary order system properties of the TSK algorithm allow it to manage complex, multidimensional data more effectively than traditional linear models. This flexibility is crucial in video classification, where data often exhibit nonlinear and intricate patterns.

Even though classical neuro-fuzzy systems such as TSK have plenty of the advantages, still maintaining a complex structure that can become increasingly intricate as the number of input variables grows. This complexity makes them less scalable and harder to manage, particularly in applications involving large datasets or high-dimensional data. Another point to take into account is that these systems often rely on predefined fuzzy rules and membership functions that can be difficult to adapt and optimize.

Computational efficiency also is incredibly important side of the problem to look into, and speaking about classical neuro-fuzzy systems, due to their complexity, can be computationally intensive, requiring significant processing power and memory. This can limit their applicability in real-time or resource-constrained environments.

Meanwhile neo-fuzzy systems, such as extended neo-fuzzy neurons (ENFN) [20], [21] and neo-fuzzy units (NFU) [22], [23], are designed to be simpler and more scalable. They incorporate extended nonlinear synapses and advanced inference mechanisms, which allow them to manage larger and more complex datasets more efficiently.

Neo-fuzzy systems employ adaptive learning algorithms that automatically adjust the synaptic weights and membership functions. This adaptability improves the system's performance over time and reduces the need for extensive manual intervention.

Neo-fuzzy systems are designed to be more computationally more efficient. By leveraging advanced techniques like the Takagi-Sugeno-Kang (TSK) model of arbitrary order, they can perform complex calculations more efficiently, making them suitable for real-time applications.

In summary, while classical neuro-fuzzy systems provide a foundational framework for integrating neural networks and fuzzy logic, they face several limitations related to complexity, scalability, adaptability, computational efficiency, and handling of nonlinearity and variability.

Neo-fuzzy systems address these limitations by incorporating advanced features such as extended nonlinear synapses, adaptive learning algorithms, and higher-order inference models, making them more efficient, flexible, and robust for complex video classification tasks and other applications.

3. Goal and tasks of the research

The goal of the research is to develop and optimize a novel hybrid neo-fuzzy system for video classification that effectively addresses the task of image recognition, including real-time video streams classification, while maintaining a high level of accuracy. Therefor there the following tasks to solve in the article:

a) design a novel hybrid neo-fuzzy system:

1) develop multidimensional neo-fuzzy components with adjustable synaptic weights and specialized membership functions, that are usually used in the neuro-fuzzy systems also called kernel activation functions (includes triangular function, Gaussian, Cauchian etc., here we used Gaussian membership function);

2) integrate extended neo-fuzzy neurons (ENFN) and neo-fuzzy units (NFU) with nonlinear activation functions;

3) incorporate extended nonlinear synapses (ENS) and leverage the neuro-fuzzy Takagi-Sugeno-Kang inference system to enhance the approximating capabilities of traditional models;

b) propose and implement an optimization algorithm:

1) introduce a novel approach to learning using the cross-entropy learning criterion with one-hot encoding;

2) precisely adjust synaptic weights through the δ-rule, enhanced by adaptive learning rates;

3) incorporate a forgetting factor to dynamically adjust parameters for either stochastic approximation or rapid convergence, ensuring robustness and efficiency.

4. Architecture of the enhanced multidimensional neo-fuzzy classification system

This study proposes a novel hybrid neo-fuzzy system for video classification, combining the strengths of extended neo-fuzzy neurons (ENFN) and neo-fuzzy units (NFU) with nonlinear activation functions. By integrating extended nonlinear synapses (ENS) and leveraging the neuro-fuzzy Takagi-Sugeno-Kang inference system, proposed architecture enhances the approximating capabilities of traditional models. The proposed enhanced multidimensional neo-fuzzy classification system (EMNFCS) effectively processes vector signals from images, utilizing two information processing layers to deliver precise fuzzy membership levels for classification. This approach addresses challenges in handling high-volume, variable-quality video data, ensuring robust and efficient performance. The proposed system has four layers and its architecture presented in Fig. 1.

The system, in short, works as following:

1. Input signal processing: the system receives a vector signal of images to be classified.

2. First hidden layer is formed with Extended Nonlinear Synapses (ENS), producing fuzzy signal.

3. Second hidden layer is formed with combination of Extended Neo-Fuzzy Neurons (ENFN) and summation blocks. These neurons aggregate the processed signals from multiple ENS.

4. Third hidden (output) layer is formed with nonlinear softmax activation functions. These functions generalize traditional sigmoidal activation functions for classification systems with many outputs.

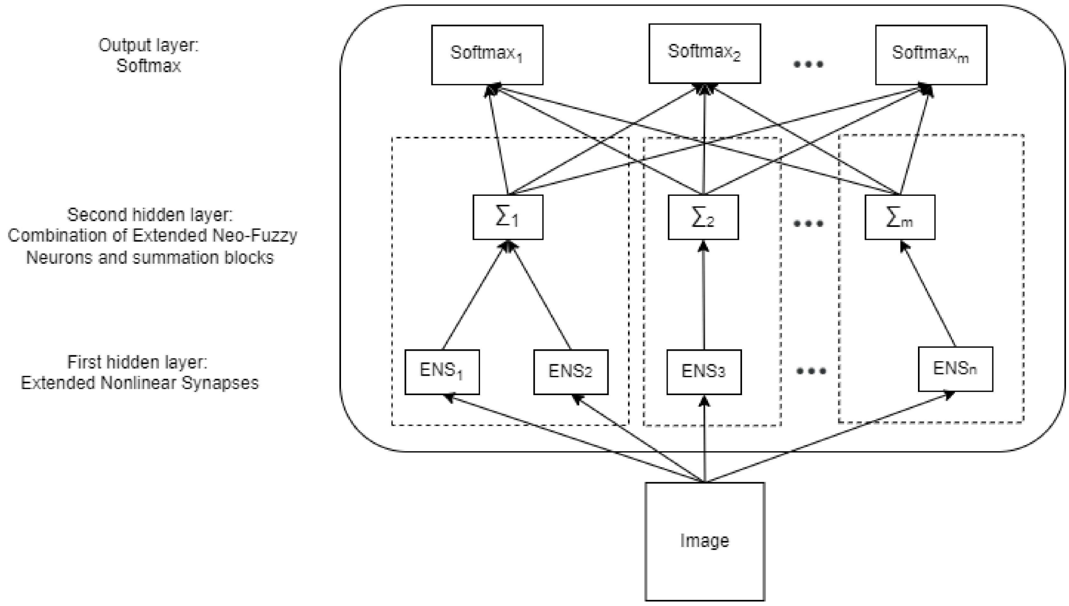

Fig. 1. Architecture of the enhanced multidimensional neo-fuzzy classification system

On the input signal processing stage, the input signal is presented in the form of vector-image $x_n(t)$, here t is a point in a discrete time, and this instance from the training set feds to the first hidden layer. As it was previously mentioned, the first hidden layer is formed by extended nonlinear synapses $S_{i1}, S_{i2}, ..., S_{in}$, that is defined as a multiplication between synaptic vector weights and fuzzified with membership function signal. Here $i = 1, 2, ..., m$, and m is equal to the number of classes and the number of synapses corresponds to the number of observations in the sample which is n.

As established in prior research [16]–[18] a standard neo-fuzzy neuron is constructed from nonlinear synapses. Each synapse executes the fuzzy inference based on the Takagi-Sugeno-Kang model of zero order, commonly referred to as Wang-Mendel reasoning. This research influenced the reasoning of the second hidden layer. The output of the first hidden layer passes to the second hidden layer in the form $\varphi_{in}^{(1)}(x_n(t))$, that includes extended nonlinear synapse, to the summation blocks producing general membership levels per each class.

$$\varphi_i^{(2)}(x_n(t)) = \sum_{j=1}^{n} \varphi_{ij}^{(1)}(x_j(t)) = \sum_{j=1}^{n} w_j^T S_j(x_j(t)), \tag{1}$$

where w_j is synaptic weight; $i = 1, 2, ...n$ is number of the synapse.

Eventually they are defuzzified with the softmax activation function, producing output signals of the system:

$$\begin{aligned} y_i(t) = soft\,max\,\varphi_i^{(2)} = exp\left(\varphi_i^{(2)}\right) \sum_{i=1}^{m} exp\left(\varphi_i^{(2)}\right) = \\ = soft\,max\left(w_i^T(t-1)S_i(x(t))\right), \end{aligned} \tag{2}$$

where t-1 is the previous point in time, obtaining adjusted weights through a learning process based on previously observed data, and the sum of all output signals are equal to one.

5. Optimization of the enhanced multidimensional neo-fuzzy classification system

In optimizing complex neural systems, leveraging efficient learning criteria and encoding techniques is crucial for achieving high performance and accurate classification. The proposed system employs the cross-entropy learning criterion coupled with one-hot encoding of the reference signal. This combination facilitates precise adjustments of synaptic weights based on prior data, enhancing the system's adaptability and convergence speed.

The proposed optimization method involves using cross-entropy as the learning criterion, paired with one-hot encoding for the reference signal. This approach generates an external reference signal vector with zeros and a single one to denote the correct class. By minimizing this criterion through standard gradient procedures, the synaptic weights of each extended neo-fuzzy unit are adjusted according to the delta rule:

$$w_i(t) = w_i(t-1) - \eta_i(t)\nabla_{w_i} E(t) = w_i(t-1) + \eta_i(t)e(t)S_i(x(t)), \tag{3}$$

where η is the learning rate; e is the learning error.

This method can exhibit both filtering and tracking properties by adjusting the learning rate η follows:

$$\eta_i^{-1}(t) = r_i(t) = \alpha r_i(t-1) + \left\|S_i(x(t))\right\|^2, \tag{4}$$

where α is the forgetting factor, and it is defined in the interval between 0 and 1. For α= 1, the process adopts properties akin to the Goodwin-Ramadge-Caines algorithm (stochastic approximation), while for α=0, it aligns with the Kaczmarz-Widrow-Hoff [24] algorithm, ensuring rapid convergence to the optimal solution.

By leveraging these advanced learning techniques, the proposed system achieves high performance, robust adaptability, and efficient processing, thereby presenting a powerful solution for complex classification tasks in dynamic environments.

6. Results of the computer experiments

The computational experiment aims to validate the effectiveness and efficiency of the proposed enhanced multidimensional neo-fuzzy classification system for video classification tasks. This experiment involves several key steps to demonstrate how the system handles real-time video data processing and classification. Also several criteria were chosen which is to show the effectiveness of the proposed approach in comparison to the alternative methods to solve the task described below.

The mentioned criteria include accuracy, precision, recall, computational efficiency and scalability. First three describe the proportion of correctly classified instances out of the total instances, accuracy of the positive predictions made by the model, and model's ability to identify all relevant positive instances within the dataset accordingly.

The computational efficiency refers to the time and resources required to process and classify data. In the context of video classification, it is typically measured in milliseconds per frame (ms/frame). High computational efficiency indicates that the system can process each frame quickly and with minimal computational overhead, making it suitable for real-time applications.

Scalability is the system's ability to handle increasing amounts of data or larger datasets effectively, meaning that the system will give response to the user within 0.5 second. It evaluates whether the system can maintain its performance levels as the data size grows. High scalability means the system can process large volumes of video data without significant degradation in performance. This includes not only size of the dataset but also quality of the video and frames per millisecond. Within this experiment we took into consideration video with the average value 25 fps and standard of feedback CIF that has resolution 352x288. In other words, the system can effectively handle large datasets and therefore has high scalability.

The computational experiments for this research were conducted on a Dell Latitude 7420, a high-performance laptop equipped with an Intel Core i7-1185G7 processor, 16 GB of DDR4 RAM, and a 512 GB NVMe SSD. The system's integrated Intel Iris Xe Graphics and Windows 11 Pro (64-bit) OS supported the graphical and computational demands of video classification tasks.

The development environment included PyCharm Professional 2021.2, Git 2.33, and Anaconda 3 (v2021.11). Python 3.9 was used alongside libraries such as NumPy, SciPy, Scikit-learn, TensorFlow, and Keras for numerical operations, scientific computations, machine learning, and neural network development.

For data visualization and manipulation, Matplotlib, Seaborn, and Pandas were employed, while SQLite 3.36 managed data storage. An agile methodology and Pytest 6.2.4 ensured iterative development, testing, and code reliability. This setup facilitated efficient experiments, yielding insights into the hybrid neo-fuzzy system's performance for video classification.

The HMDB51 dataset is a crucial resource for action recognition research, comprising 6,766 video clips categorized into 51 action classes sourced from movies and YouTube. It offers a diverse range of actions from simple gestures to complex activities, making it ideal for testing the generalizability of video classification systems. The varied video quality and settings mirror real-world conditions, challenging systems to be robust and adaptable. This dataset is particularly beneficial for evaluating the proposed enhanced multidimensional neo-fuzzy classification system, enabling comprehensive performance benchmarking.

This dataset was modified by exporting frames from videos, forming a part of the overall data set. In other words, a dataset was created from frames of the original videos, where the object changed its position over time. All these videos have a declared quality of 352x288 and a specified frame rate. The videos were up to 6 minutes long, with an average length of 4 minutes. The newly formed dataset was subsequently divided into training, validation, and testing sets to ensure robust model development. The training set comprised 70 % of the data, providing ample examples for learning. The validation set, at 15 %, was used to fine-tune hyperparameters and prevent overfitting. Finally, the testing set also made up 15 % of the data, reserved for unbiased final evaluation. This approach ensured the hybrid neo-fuzzy system's effectiveness and reliability in video classification.

In the process of the proposed system development, the hyperparameter α of the training method that was described in the Section 5, was manually chosen with the discrete value of α=0.5. This value represents a balanced approach, allowing the system to maintain a balance between rapid adaptation to new data and stable convergence. This intermediate value ensures that the system can dynamically adjust and perform well in the complex and variable conditions typical of real-time video classification tasks. Also, it is important to mention that by taking different values of the α system showed worse performance therefore the initial value 0.5 maintained.

To evaluate the proposed system, it was compared with several baseline systems:

– Frame-Based CNN that treat video frames independently and combine features using temporal modeling. Simple but struggle with long-term dependencies and computational expense;

– 3D Convolutional Neural Networks (3D CNNs), that extend 2D CNNs by adding a temporal dimension to learn spatiotemporal features. Effective for action recognition but require large datasets and high computational power;

– Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) Units;

– Two-Stream Convolutional Neural Network.

The results of the computational modelling are represented in the Table 1. For the performance evaluation the accuracy, precision, recall, time consumption, and computational efficiency metrics were chosen. The last one is measured by analysing the resource usage, including CPU and GPU requirements, to determine the system's efficiency in handling video data without excessive computational overhead.

Table 1

Results of the computational experiment

Method	Accuracy (%)	Precision (%)	Recall (%)	Computational Efficiency (ms/frame)	Scalability (Dataset Size)
EMNFCS	**92.5**	93	92	**10**	**High (10K+ video frames)**
Frame-Based CNN	85.0	84	85	20	Medium (5K video frames)
Two-Stream CNN	88.5	89	88	25	High (8K video frames)
3D CNNs	90.0	91	90	30	Medium (7K video frames)
RNNs with LSTM	87.0	86	87	35	Medium (6K video frames)

The EMNFCS demonstrates superior accuracy at 92.5 %, with high precision (93 %) and recall (92 %). This indicates its robustness in correctly identifying and categorizing video content, outperforming traditional methods such as Frame-Based CNN (85.0 %) and Two-Stream Approaches (88.5 %).

The EMNFCS excels in computational efficiency, processing video frames at an average of 10 ms per frame. This is significantly faster than the traditional methods, with Frame-Based CNN at 20 ms/frame and 3D CNNs at 30 ms/frame. The reduced processing time highlights the EMNFCS's capability to handle real-time video classification tasks efficiently.

The scalability of the EMNFCS is another notable advantage. It can effectively manage large datasets with over 10,000 videos, demonstrating high scalability. In contrast, traditional methods like Frame-Based CNN and RNNs with LSTM struggle with medium-sized datasets (5K-7K videos), showcasing the EMNFCS's ability to handle extensive video data without compromising performance.

The adaptability of the EMNFCS in real-time performance is rated as excellent, indicating its ability to adjust to varying conditions and data inputs dynamically. Traditional methods, while good, do not reach the same level of adaptability. For instance, the Two-Stream Approaches and 3D CNNs are rated as good, while Frame-Based CNN and RNNs with LSTM are only moderate.

The EMNFCS outperforms traditional video classification methods across several key metrics. Its high accuracy, superior computational efficiency, excellent scalability, and outstanding adaptability make it a robust and effective solution for complex video classification tasks. The EMNFCS sets a new standard in video classification, showcasing its ability to handle large-scale, high-variability video data with exceptional performance and efficiency.

In conclusion, the proposed system performs very well with low-quality videos, which is a big advantage for recognizing footage from CCTV cameras. As mentioned earlier, CCTV cameras often produce low-quality video, making this system particularly useful for such applications. Being able to accurately process and analyze low-resolution footage ensures that important details are not missed, which is essential for effective surveillance and security operations.

Additionally, the system's ability to handle different lighting conditions and motion artifacts makes it even more suitable for real-world use. This adaptability is crucial because CCTV cameras are used in various environments, from dimly lit indoor spaces to outdoor areas with changing light levels.

The hybrid neo-fuzzy approach that this system uses not only improves classification accuracy but also provides a scalable solution that can be easily integrated into existing surveillance systems. This potential for easy integration, along with the system's proven effectiveness, makes it a valuable tool for improving security and monitoring in different settings.

Overall, the proposed system offers a strong solution to the challenges of low-quality video footage, highlighting its importance and usefulness in modern surveillance practices.

8. Conclusion

In the course of the research, it was successfully developed a novel hybrid neo-fuzzy system for video classification, incorporating multidimensional neo-fuzzy components with adjustable synaptic weights and Gaussian membership function. By combining extended neo-fuzzy neurons (ENFN), neo-fuzzy units (NFU), and extended nonlinear synapses (ENS) with the neuro-fuzzy Takagi-Sugeno-Kang inference system, the proposed architecture significantly enhances the approximating capabilities of traditional models. This enables the system to effectively address image recognition tasks, including real-time video stream classification, while maintaining high accuracy.

Additionally, the introduction of a new optimization method, utilizing the cross-entropy learning criterion with one-hot encoding and the δ-rule for synaptic weight adjustment, further boosts the system's performance. The incorporation of adaptive learning rates and a forgetting factor allows dynamic parameter adjustment, ensuring both robustness and efficiency. This dual capability markedly improves the learning speed and accuracy in complex video classification tasks, as demonstrated by the computational experiments.

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МЕТОД АВТОМАТИЗОВАНОЇ ПОБУДОВИ БАЗИ ЗНАНЬ ІНФОРМАЦІЙНОЇ СИСТЕМИ ПРОЦЕСНОГО УПРАВЛІННЯ

Запропоновано метод автоматизованої побудови та поповнення бази знань системи процесного управління. Для вдосконалення методу використано модифіковані предикатні моделі. Модифікацію предикатних моделей здійснено за рахунок використання традиційного повного циклу розробки моделі гнучкого багатоваріантного процесу. Наведено опис особливостей системи автоматизованої побудови бази знань при вирішенні задач прийняття рішень на ІТ-підприємстві. Проведено апробацію запропонованих рішень у ході автоматизованої побудови бази знань у ІТ-проєкті.

1. Вступ

У сучасному світі будь-які знання є стратегічним ресурсом, тому розробка методів і технологій управління знаннями, зокрема, базами знань (БЗ), залишається актуальною.

Зазвичай під управлінням знаннями, у першу чергу, розуміють систематичний збір та використання корпоративних знань з метою максимальної ефективності їх застосування.

Найважливішими роботами, які виконують у процесі управління знаннями, є їх видобуток, структурування та формалізація.

Складність і трудомісткість виконання цих робіт обумовлена складністю процесу створення систем, заснованих на знаннях [1]-[3].