Analysis of the Hungarian Unaccented Dactylic Finger-Spelling Alphabet Using an Adaptive Neuro-Fuzzy Inference System (ANFIS)

A magyar ékezet nélküli daktil ujjábécé elemzése egy adaptív neuro-fuzzy következtetési rendszerben (ANFIS)

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Abstract — **This study presents the principles of fuzzy logic and the operation of the Adaptive Neuro-Fuzzy Inference System (ANFIS). It then focuses on the analysis of the Hungarian, unaccented finger-spelling alphabet using the ANFIS approach. In the course of the research, a specific finger-spelling gesture was selected, through which the application of image processing techniques and the results obtained are demonstrated.**

Keywords: hearing impairments, sign language, finger-spelling alphabet, fuzzy logic, ANFIS, image processing techniques, edge detection, image denoising, image enhancement, fuzzy clustering

Összefoglaló — **A tanulmány a fuzzy logika alapelveit és az adaptív neuro-fuzzy következtetési rendszer (ANFIS) működését mutatja be. Ezt követően a magyar, ékezet nélküli ujj-betűző ábécé ANFIS-modell segítségével történő elemzésére összpontosít. A kutatás során egy konkrét ujj-betűző gesztus került kiválasztásra, amelyen keresztül bemutatásra kerülnek a képfeldolgozási technikák alkalmazása és az ezekből levezetett eredmények.**

Kulcsszavak: hallássérült, jelnyelv, ujj-betűző ábécé, fuzzy logika, ANFIS, képfeldolgozási technikák, élérzékelés, képzajmentesítés, képjavítás, fuzzy klaszterezés

1 INTRODUCTION

According to the World Health Organization (WHO), more than 1.5 billion people worldwide live with hearing impairments, which accounts for approximately 20% of the global population. Among them, nearly 35 million children are affected. Projections suggest that by 2050, this number is expected to rise to 2.5 billion, with about 766 million individuals requiring hearing rehabilitation. From a medical perspective, hearing loss is defined as a hearing threshold of 35 decibels (dB) or higher, as indicated by an audiogram. Around 80% of people with hearing loss live in low- and middle-income countries, and the prevalence increases with age. For instance, over 25% of people aged 60 and above suffer from hearing loss. The severity of hearing loss can vary (mild, moderate, severe, or profound) and may affect one or both ears, hindering the ability to perceive conversational speech, or even loud sounds [1].

Hearing impairment significantly affects the ability to communicate verbally, making interaction between hearing and hearing-impaired individuals difficult. In this context, sign language becomes the primary means of communication for individuals with hearing impairments. However, for hearing individuals, understanding sign language poses a considerable challenge since they are typically unfamiliar with the meanings of gestures and signs. Effective communication requires individuals to either learn a common language or rely on the assistance of interpreters. However, the use of sign language interpreters can be time-consuming and resource-intensive, which may limit the privacy of individuals with hearing impairments.

Sign language is one of the most advanced visual communication systems used as a first language by deaf and hard-of-hearing individuals. Each country has its own sign language and grammatical structure. For example, there are British, American, Spanish, Japanese, Chinese, and Arabic Sign Languages. Sign language enables deaf individuals to express their thoughts and reach their full potential. Linguistic research indicates that sign language meets all the criteria for natural languages, as it developed through the interactions of deaf communities [2].

Sign language has a unique "alphabet", known as finger-spelling or dactylology. In Hungary, two types of sign language finger-spelling are used: the Hungarian accented dactylic alphabet and the Hungarian phonemic finger-spelling alphabet. Finger-spelling represents the letters of the alphabet through the shape of the hand and fingers as well as the hand's position. It is an integral part of Hungarian Sign Language and the signed Hungarian. The phonemic finger-spelling alphabet is primarily used to spell out foreign words, technical terms, and concepts for which there are no corresponding signs in Hungarian Sign Language [3].

The paper is organized as follows: Section 2 provides an overview of hearing impairments and the importance of sign language as a means of communication. It also introduces the Hungarian unaccent dactylic alphabet and highlights the challenges of learning and recognizing sign language gestures. Section 3 discusses the theoretical background of fuzzy logic and the the Adaptive Neuro-Fuzzy Inference System (ANFIS), while Section 4 focuses on the experimental setup and image processing techniques used. Section 5 presents the results and analysis of the Hungarian unaccented dactylic alphabet recognition, and Section 6 concludes with a summary of findings and future research directions.

2 INTERNATIONAL AND NATIONAL EXPERIENCES

In [4], the authors focused on the analysis of spatial features in sign language gestures. In their research, they utilized data derived from the spatial recognition of hand skeletons and musculature, and concluded that these features play a crucial role in addressing the similarity issues among sign language words. They also highlighted that the diversity and complexity of movement features pose significant challenges in accurate recognition of spatial characteristics.

To solve these issues, the researchers suggested the use of spatial cubes, which are capable of handling continuously varying features. The input data were transformed using 3D wavelet transformation (3D-WT), which were then fuzzified and used as input vectors for the ANFIS. This method was able to adaptively learn the 3D spatial features of the hand joints, which were integrated through an iterative learning process to provide rich contextual information for accurate recognition of dynamic sign language words.

The success of the method was partly attributed to the application of fuzzy logic, which more closely resembles human thought processes and natural language compared to traditional logical systems. One of the major advantages of fuzzy logic is the simplicity with which its mathematical principles can be applied. ANFIS combines the strengths of artificial neural networks (ANN) and fuzzy logic (FL) systems, making it highly effective in modeling complex sign language systems.

The applied method achieved remarkable results, with recognition accuracy for one- and two-handed sign language words exceeding 90%, marking a significant advancement in the field of dynamic sign language systems.

3 THEORETICAL FOUNDATIONS OF THE RESEARCH

This section outlines the principles of fuzzy logic and the ANFIS, which serve as the foundation for this research. It emphasizes the advantages of fuzzy logic in handling imprecise data and modeling complex systems.

. A common challenge for learners of sign language is the interpretation of precise finger positioning when learning the alphabet's basic elements. For example, in the case of the "S" dactylic sign, recognizing and understanding the correct placement of the fingers can be difficult.

To address these challenges, the goal is to develop an image recognition system that can adaptively adjust to input data while effectively managing uncertainty factors. The ANFIS-based approach provides an opportunity to enhance the accuracy and reliability of the sign language learning process, particularly concerning the unique features of dactylic signs.

3.1 Fuzzy Logic

Fuzzy logic (FL) can be compared to the natural process of human thinking, as it is closely related to natural languages as well as traditional logical systems. One of the key advantages of FL is the simple and intuitive application of mathematical principles. The basis of designing fuzzy systems involves the development of fuzzy rules and membership functions (MFs).

ANFIS not only simplifies this process but also includes a learning mechanism that combines the applications of artificial neural networks (ANN) and fuzzy logic.

Fuzzy logic has several main advantages in various applications. In a narrower sense, it is considered an extension of multivalued logic, while in a broader sense, it is related to the theory of fuzzy sets. This theory examines objects whose boundaries are not sharp and allows the determination of the degree of membership in a given set. Fuzzy logic is especially useful because it can tolerate imprecise data and flexibly adapt to various problems. Additionally, it is capable of modeling a wide range of complex, nonlinear problems.

3.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is the result of a hybrid integration of two systems, where the fuzzy logic system is implemented within a neural network structure. Through the use of this hybrid approach, ANFIS is capable of approximating both linear and nonlinear functions using a five-layered network structure. [5]

It is specifically designed to model a first-order Takagi-Sugeno inference-based fuzzy system. This system combines fuzzy logic rules and the learning capabilities of neural networks, allowing for efficient adaptive inference in complex problems.

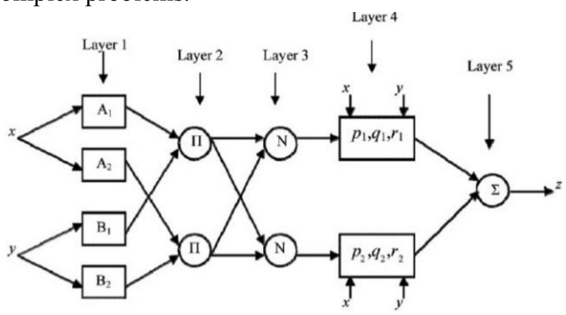

Figure 1. ANFIS Architecture [5]

Fig. 1 illustrates the structure of ANFIS, with two input variables (x, y) and one output variable (z). The rectangles represent nodes with adjustable parameters, while the circles represent nodes that operate without parameters. The Takagi-Sugeno type rules are located in the fourth layer of the system, and they are non-adjustable (fixed).

One characteristic of the system is that two rules are defined as follows [5]:

$$\text{if } x_1 = A_1 \text{ and } x_2 = B_1, \text{ then } z_1 = p_1 x + q_1 y + r_1, \quad (1)$$

$$\text{if } x_1 = A_2 \text{ and } x_2 = B_2, \text{ then } z_2 = p_2 x + q_2 y + r_2. \quad (2)$$

The ANFIS system is structured into five layers, each serving a different role in the operation of the system:

- **Layer 1:** This layer determines the values of membership functions. The nodes in this layer represent the linguistic terms of the input variables. Each neuron receives only one input, corresponding to the relevant input variable. The parameters of the membership functions are determined during the system's learning process.

- **Layer 2:** Each fuzzy rule corresponds to exactly one neuron, and this layer implements the antecedent part of the rules. The nodes here have no parameters and transform incoming signals into products that reflect the premise elements and/or relationships of the rules. The output represents the firing strength of the antecedent of the rule.
- **Layer 3:** The neurons here calculate the normalized firing strength for each rule. The number of nodes in this layer equals the number of rules. The normalization formula is given by in case of two rules:

$$\overline{w_i} = \frac{w_i}{\sum_{j=1}^{n} w_j} = \frac{w_i}{w_1+w_2}, \tag{3}$$

  where i is the rule index, and n is the number of rules.
- **Layer 4:** This layer determines the results of each rule. Each neuron is connected to a node in the previous layer and receives input values. The output is as follows:

$$\overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i), \tag{4}$$

  where $\overline{w_i}$ is the output of the third layer and $\{p_i, q_i, r_i\}$ are the consequent parameters.
- **Layer 5:** This layer contains a single neuron that generates the output of the system. Each node in Layer 4 is connected to the single node of Layer 5. The system's output is obtained through the normalized weighted sum:

$$f = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}. \tag{5}$$

3.3 The Learning Process of ANFIS

ANFIS employs a hybrid learning algorithm that combines the gradient method and the least squares method. The linear parameters are optimized using the least squares method, while the nonlinear parameters are optimized using the gradient method. The gradient method typically converges slowly and finds only a local minimum.

In the case of fixed input parameters, the final result can be expressed as:

$$f = \sum_i \overline{w_i} f_i = \sum_{\mathrm{i}} [\overline{w_i}(p_i x + q_i y + r_i)]. \tag{6}$$

The learning algorithm applies the hybrid method to optimize the parameters. The forward-propagated neuron outputs reach the fourth layer, where the consequent parameters (S_2) are optimized using the least squares method. In the second step, the gradient method is used to update the premise parameters (S_1) [6].

3.4 Applications

ANFIS is functionally equivalent to a Takagi–Sugeno-type inference system, and by modifying the fourth layer, Sugeno-type fuzzy control can also be implemented. Additionally, by using a discrete defuzzification method, Mamdani-type control can be replaced by the ANFIS structure. [7]

4 EXPERIMENT

This section details the experimental setup, including the image acquisition and processing techniques applied to the Hungarian unaccented dactylic finger-spelling alphabet. It highlights the use of MATLAB tools and fuzzy logic-based approaches for data analysis.

In this research, 92 images were captured of the Hungarian unaccented dactylic alphabet letters. Various technical tools were used for image acquisition, including a Xiaomi Redmi Note 12 mobile phone and a web camera. The technical specifications of the images were as follows: 72 dpi resolution, 24-bit color depth, sRGB color space, with a width of 3072 pixels and a height of 4080 pixels. Some images were also produced in grayscale versions.

The image processing was carried out in the MATLAB environment, where the necessary analyses were performed using the Neuro-Fuzzy Designer application. The ANFIS settings were employed to evaluate the image quality and processability.

The Fuzzy Logic Toolbox provided various functions during the image processing, including edge detection, noise reduction, and image enhancement. This toolbox enabled the design of fuzzy-based interfaces, the definition of membership functions, and the creation of system rules.

The Neuro-Fuzzy Design (NFD) application supported the analysis, design, and simulation of fuzzy logic-based systems. It allowed for modifications to the various elements and steps of the design process during the experiments. The application included procedures such as fuzzy clustering and adaptive neuro-fuzzy learning, making it possible to model the behavior of complex systems using simple logical rules.

Building on the experience of conventional control techniques, the NFD application could be expanded with the Fuzzy Inference System Modeling toolbox, which supports modeling Mamdani- and Sugeno-type fuzzy inference systems. The process begins by defining input and output variables, which were fine-tuned using the membership function editor. To assemble the rule sets, the rule editor was used, while the Rule Viewer provided visualization of the fuzzy inference process. The output dependence and surface mapping of the system were visualized using the Surface Viewer.

In the fuzzy-based image processing, the image features were treated as fuzzy sets. The process consisted of three main steps:

1. Fuzzification – converting grayscale values into membership functions,
2. Modification of membership values – for example, using fuzzy clustering, rule-based approaches, or fuzzy integration methods,
3. Defuzzification – if necessary, converting the modified values back into the grayscale range.

The key advantage of fuzzy image processing lies in the flexibility of modifying membership values, which allows for more precise determination of image features. The selected techniques and approaches were adapted to the specific characteristics of the problem under investigation.

5 Analysis of the Results

This section presents the findings from the analysis of the Hungarian unaccented dactylic finger-spelling sign for letter 'M'. It discusses the effectiveness of edge detection, noise reduction, and image enhancement techniques in improving image quality and accuracy.

In this research, letter 'M' from the Hungarian unaccented dactylic finger-spelling alphabet (Fig. 2) was selected for further analysis.

Figure 2: Hungarian unaccented dactylic finger-spelling sign for letter 'M'

The goal of the analysis was to apply four different image processing techniques and investigate the design possibilities of a fuzzy logic-based system, which were

- Edge detection,
- Noise reduction,
- Image enhancement,
- Image segmentation (which is also used in medical image processing, such as CT and MRI scans).

To implement the image processing techniques in MATLAB environment, the RGB image using the imread function was imported. The imported image was a 630×630 pixel, uint8 data type, three-dimensional array (I), where the third dimension represent the intensity value of the red, green, and blue channels.

To simplify image processing, the RGB image was converted to grayscale format. This transformation enabled the use of a two-dimensional array instead of a three-dimensional one, which made the analysis more efficient (Figs. 3 and 4).

Figure 3: The RGB image used in the research, showing the intensity values of the red, green, and blue channels

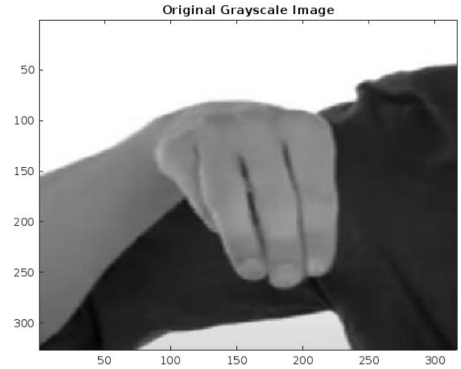

Figure 4: The grayscale version of the RGB image, represented as a two-dimensional array of image data

By converting to grayscale, the color of the image information was reduced to a single intensity channel, allowing for more efficient processing while maintaining the essential features of the image for further analysis.

5.1 Image Edge Detection

Edges are crucial features in images as they indicate significant local intensity variations and play a key role in information extraction. Edge points are the coordinates in the image where intensity changes occur. The fuzzy logic-based image processing enables the use of membership functions, which determine the degree to which a given pixel belongs to an edge or a homogeneous image region.

The edge detection process involved converting the RGB image to grayscale using the rgb2gray function in the MATLAB environment. The resulting image was then converted to double precision using the im2double function, enabling evaluation of the fuzzy inference system (FIS) with the evalfis function.

The edge detection algorithm is based on calculating the image gradient, which indicates the discontinuities in homogeneous image regions. To compute the gradient, filters were applied along the *x*- and *y*-axes (GImgx and GImgy, respectively). The gradient along the *x*-axis was obtained by convolving the image matrix *I* with the GImgx filter using the conv2 function. Similarly, the gradient along the *y*-axis was computed using the GImgy filter.

For the fuzzy inference system, Sugeno-type was chosen, and provided the gradient data (Imgx and Imgy) as input. For each input, I assigned a zero-mean Gaussian membership function, where zero gradient values corresponded to a uniform region. The sx and sy values controlled the spread of the membership function, and adjusting these parameters fine-tuned the sensitivity of the edge detection. Additionally, parameters of triangular membership functions (d_1, d_2, etc.) was set, which influenced the intensity of the detected edges.

When designing the fuzzy inference rules, I considered that pixels belonging to homogeneous regions are white, while those associated with edges are black. The detected edges were evaluated using the ANFIS model, as shown in Fig. 5.

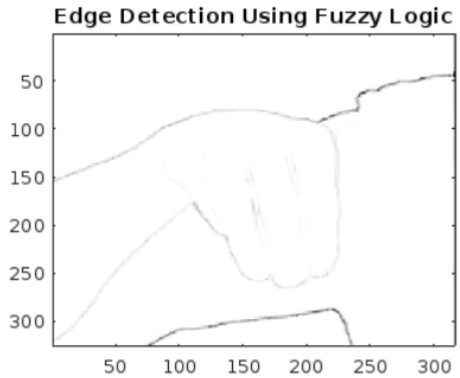

Figure 5: Clean edges of letter 'M', determined by the fuzzy logic-based edge detection algorithm

To design the fuzzy inference system, I used the MATLAB Fuzzy Logic Toolbox (FLT). The edge detection was applied to enhance the clarity of the images. The system inputs (Imgx and Imgy) were transformed based on fuzzy rules, and the output values (Iout) were obtained during defuzzification. According to the rules, if both input gradient values are zero, the output is homogeneous (white), while any non-zero gradient value results in an edge (black).

The fuzzy inference rules were visualized using the Rule Viewer (Fig. 6).

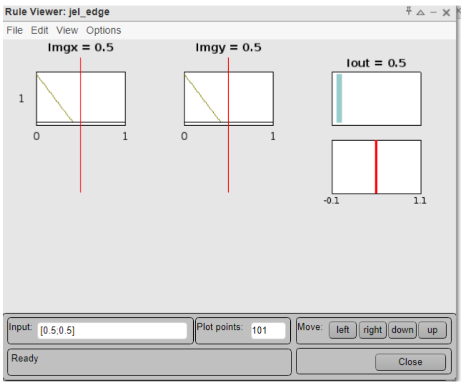

Figure 6: The fuzzy rule viewer illustrates the inference process applied to the image edge detection

The Surface Viewer allows the input variables (Imgx, Imgy) and the output (Iout) to be represented as a three-dimensional surface. The surface is automatically updated as the input variables are modified (Fig. 7).

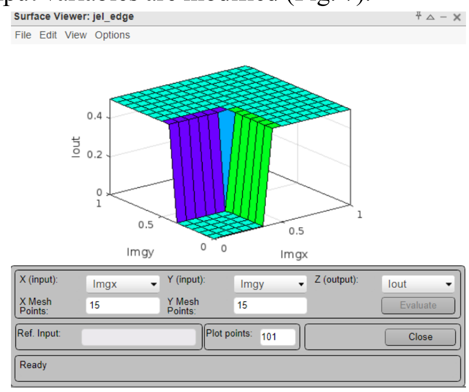

Figure 7: The top-down diagram of the fuzzy inference system during the image edge detection process

In conclusion, the fuzzy logic approach of edge detection provides a flexible tool for analyzing the local features of an image. The applied model allows fine-tuning system performance and effectively detects significant edges in the image, contributing to further image processing tasks.

5.2 *Application of Noise Reduction Techniques in Image Processing*

The goal of noise reduction in image processing is to remove or reduce noise while preserving the contrast edges and important details in the image. However, this process may lead to the concealment of some fine, low-contrast details.

For testing the noise reduction techniques, The rgb2gray function was used to convert the input image to grayscale. The image dimensions were determined using the size(Img2D) command. To add noise, the imnoise function was applied with a Gaussian noise level to 0.02. The noisy image was then refined using two types of filters: an averaging filter and a median filter.

The imnlmfilt function was used for averaging filtering, while the medfilt2 function was used for median filtering. The resulting images, including the original, noisy, average filtered, and median filtered versions, are shown in Fig. 8.

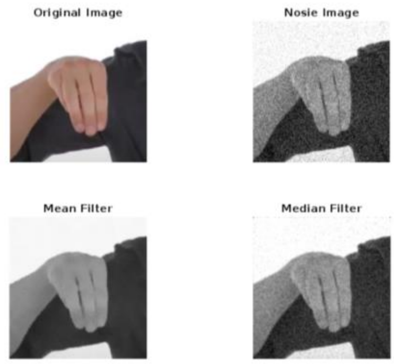

Figure 8: The results of noise reduction: original, noisy, average filtered, and median filtered images

5.3 *Fuzzy Inference System for Noise Reduction*

The noise reduction algorithm was based on a fuzzy inference system (FIS), for which the Sugeno model was chosen. The inputs were the average filtered and median filtered images, which were first converted to double precision using the im2double function. For each input, a zero-mean Gaussian membership function was assigned. In the fuzzy logic-based noise reduction, if a pixel value is homogeneous, meaning both the average and median values are zero, the output belongs to the "homogeneous" class. If neither value is zero, the output falls into the "details" class.

To fine-tune the noise reduction performance, the the membership functions of the noiseANFIS system were applied and visualized. The fuzzy rules were defined to refine the noise reduction process, and the results are illustrated in Fig. 9.

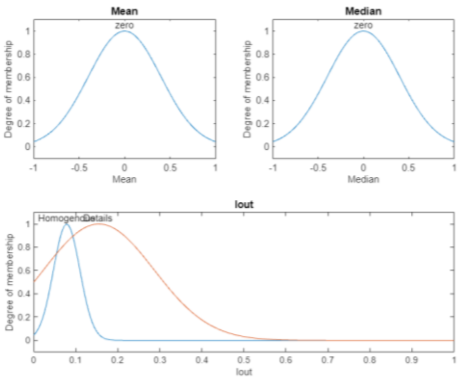

Figure 9: The results of the noise reduction technique: Mean, Median, and Iout representations

5.4 *Use of Neuro-Fuzzy Design Application*

For implementing the fuzzy logic system, the MATLAB Neuro-Fuzzy Design application was used. This tool enabled fine-tuning of the noise reduction process and record the results. The goal of the noise reduction technique is to improve image quality by eliminating intensity fluctuations that may arise from image acquisition or transmission errors.

The fuzzy rule viewer enabled visualization of the rules involved in the noise reduction process (Fig. 10).

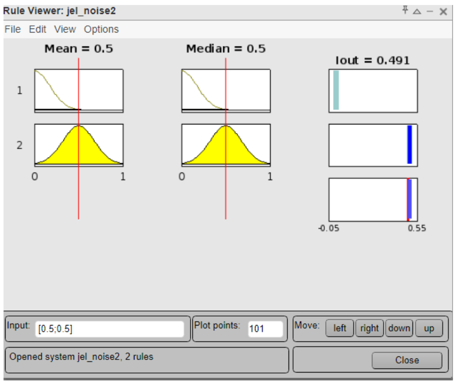

Figure 10: The fuzzy rule viewer for displaying the Iout output

The surface viewer diagram provided a three-dimensional representation of the noise reduction process output, which updated automatically when input variables were modified (Fig. 11).

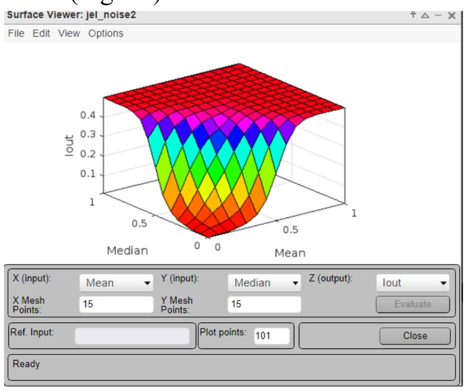

Figure 11: Surface viewer diagram of the noise reduction process result

In conclusion, fuzzy logic-based noise reduction techniques effectively reduce image noise while preserving important details and structures. The results demonstrate that combining average and median filtering with fuzzy logic rules provides a flexible tool for improving image quality.

5.5 *Image Enhancement in Image Processing*

The goal of image enhancement is to improve the quality of digital images, making them more suitable for display or further image analysis. This process may include noise removal, image sharpening, or brightening, making the most important features easier to identify.

The image enhancement process was initiated by using the rgb2gray function to convert the image to grayscale. The image dimensions were determined using $[y_1, x_1]$ = size(img2d) function. Gaussian noise (level 0.02) was added to the image using the imnoise function. Subsequently, the impixelinfo function was used retrieve the pixel values, allowing me to determine the minimum and maximum grayscale levels of the image. The corresponding minimum and maximum values were then subtracted from the image matrix.

The image was then converted to double precision using the im2double function, which was also applied to the noisy, average filtered, and median filtered images. For the enhancement task, the ANFIS was used with theSugeno-type model. The input variable was the Img image, to which triangular membership functions were assigned. The output variable, Iout, represented the enhanced image. According to the rule system, the following logical rules were applied:

- If the image is dark (r1), then Iout will be darker.
- If the image is gray (r2), then Iout will remain gray.
- If the image is bright (r3), then Iout will be brighter.

Fig. 12 demonstrates the result of the image enhancement. Through the application of ANFIS, the quality of the grayscale image significantly improved, as impulsive noise, which typically degrades image quality during capture or transmission, was removed.

Figure 12: Result of image enhancement

5.6 *Membership Functions in the Image Enhancement System*

In the image enhancement system, the membership functions are triangular functions assigned to the input values, determining the output grayscale levels. The different degrees of these membership functions ensure that the output is dark, gray, or bright, depending on the input values. This process is illustrated in Fig. 13.

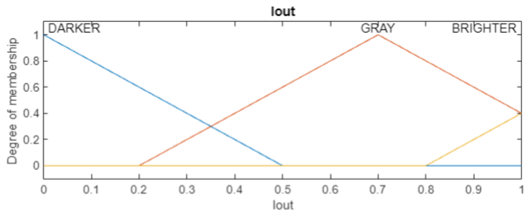

Figure 13: Membership functions of the Iout in the image enhancement system

5.7 *Rule Viewer in Image Enhancement*

The fuzzy logic rule system forms the core of the ANFIS system. Fig. 14 shows the rule viewer for image enhancement, illustrating how the system rules work between the input and output variables.

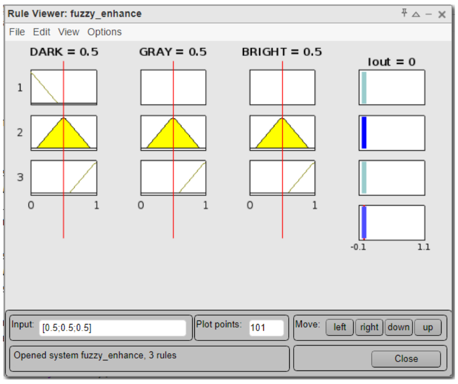

Figure 14: Rule viewer for image enhancement

Output Surface Representation

A three-dimensional representation of the output surface is shown in Fig 15. This surface demonstrates how the output changes as the input variables are modified, and how the results of the image enhancement process vary for different input images.

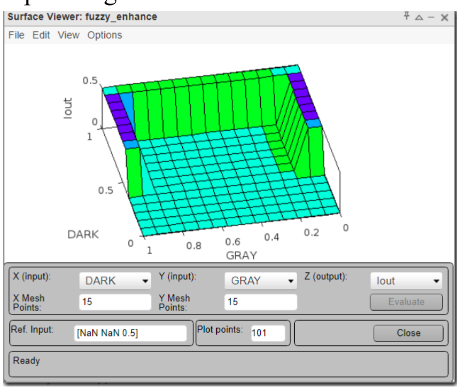

Figure 15: Surface viewer diagram for the results of the image enhancement process

In summary, the application of image enhancement techniques enables the improvement of image quality, particularly through noise removal, sharpening, and brightening. The use of fuzzy logic and ANFIS in this area helps enhance images while preserving important details and improving their recognizability.

5.8 *Fuzzy Clustering in Image Processing (Fuzzy C-means Clustering)*

One essential technique in image processing is image segmentation, which can be effectively implemented using the Fuzzy C-means Clustering (FCMC) algorithm. FCMC is sensitive to additive noise that affects pixel characteristics; therefore, particular attention must be paid to noise management during image processing. FCMC is a clustering method that allows a given data point to belong to two or more clusters (or "fuzzy sets"), in contrast to traditional hard clustering methods, in which each data point belongs to exactly one cluster.

Fuzzy C-means is a popular method for soft segmentation and is commonly used in medical image processing, such as modeling brain tissues. In MATLAB, the built-in FCMC function allows fuzzy clustering to be efficiently applied to image segmentation. Although fuzzy clustering is more computationally demanding than other segmentation methods, it yields significantly better results.

One advantage of FCMC is that there is no need for repeated segmentation of the images, which can be time-consuming. The segmentation results can be saved and reloaded when needed. The results of clustering performed by the FCMC algorithm are stored in the system, and the clustering results for the sets analyzed are easily accessible.

Based on the fuzzy clustering results, the clustered one-dimensional array is transformed into four two-dimensional arrays, as illustrated in Fig. 16.

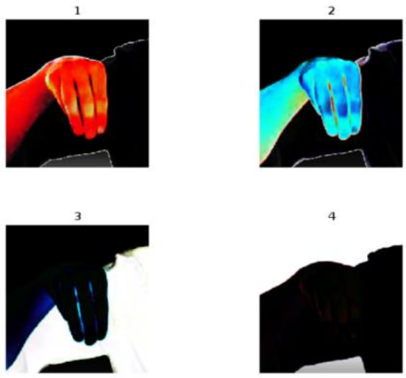

Figure 16: Fuzzy clustering result of the Hungarian "M" character.

Fuzzy clustering is a powerful and efficient method that plays a crucial role in image segmentation, especially in fields such as medical image processing. Its main advantage over classical segmentation is the ability to assign pixels to multiple clusters, thereby enhancing the detail and accuracy of the processed images.

6 Conclusion

Understanding and recognizing sign language communication can be achieved through various methods, including image recognition and the use of sensor gloves. Most research focuses on sign recognition, particularly those of the manual alphabet, since sign language is one of the most developed visual coding systems globally. However, learning sign language, which involves complex relationships among hand shapes and movements, facial expressions, and lip movements, remains a challenging task. Research on fuzzy methods applied to sign recognition has often been successful, enabling more accurate and efficient decoding of the signs.

Image processing extends beyond simple image manipulation; it is also applied in areas such as medical imaging, where uncertain, missing, or blurry information and data need to be handled. The theory of fuzzy sets plays a particularly important role in this field, as it provides a way to manage imprecise information and data processing challenges. The application of fuzzy logic in image processing and analysis has yielded successful results and may serve as a valuable tool for the processing of visual communication signals in the future.

The fuzzy logic approach to edge detection techniques offers a flexible tool for analyzing local features of images. The applied model allows for fine-tuning the system performance and can effectively detect significant edges, contributing to further image processing tasks. Furthermore, fuzzy-based noise reduction techniques effectively reduce noise levels while preserving important details and structures. The combination of average and median filtering with fuzzy logic rules provides a flexible tool for improving image quality.

Image enhancement techniques allow for improving image quality, particularly through noise removal, sharpening, and brightening. The use of fuzzy logic and ANFIS in this area promotes image improvement while preserving critical details and enhancing recognizability. Fuzzy clustering is also a powerful and efficient method that plays a key role in image segmentation, especially in fields such as medical image processing. Its main advantage over classical segmentation is that it allows pixels to be assigned to multiple clusters, increasing the detail and accuracy of the processed images.

The development and widespread application of artificial intelligence, along with its potential uses are expected to significantly contribute to the advancement of sign language communication and automatic translation of signs.

In summary, this section highlights the effectiveness of the Adaptive Neuro-Fuzzy Inference System in processing and analyzing the Hungarian unaccented dactylic alphabet. The findings demonstrate that fuzzy logic-based approaches can significantly enhance image recognition and processing in sign language applications.

For future research, several possibilities can be explored:

- Expanding the dataset: Increasing the variety and volume of training data, including additional dactylic signs and gestures, to improve the system robustness and adaptability.
- Real-time applications: Developing recognition systems that can be used in interactive applications for teaching and communication.
- Integration with other technologies: Combining ANFIS with advanced machine learning models, such as deep learning, to further improve accuracy and efficiency.
- Cross-language adaptations: Extending the model to other sign languages or dactylic alphabets, enabling broader applicability across diverse linguistic and cultural contexts.
- Sensor-based analysis: Incorporating sensor data, such as motion or muscle activity sensors, to enhance gesture recognition in dynamic settings.
- User-centric systems: Designing systems tailored for individuals with specific needs, such as children or elderly users, to increase accessibility and inclusivity.These directions could pave the way for significant advancements in the field of sign language recognition and foster the development of more comprehensive and user-friendly solutions for teaching.

7 References

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