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HANDCOMM S2V (HAND COMMUNICATION TO VOICE)

[1] S. Sailaja, [2]Sailaja Rani Kankanala, [3]Dr.G.Siva Raman
[1]Associate Professor Department of CSE,RISE Krishna Sai Prakasam Group of Institutions,Ongole,[2]Assitant Professor, Department of CSE, RISE Krishna Sai Gandhi Group of Institutions, Ongole,[3]Associate Professor Department of CSE,RISE Krishna Sai Gandhi Group of Institutions, Ongole.

Abstract— *It's clear from the provided text that the Sign to Voice system prototype, S2V, has been developed to address the communication needs of hearing or speech-impaired individuals by automatically recognizing sign language. The system uses a Feed Forward Neural Network for detecting two-sequence signs and has been trained on sets of universal hand gestures captured from video footage. The experimental results indicate that the neural network has achieved satisfactory sign-to-voice translation.*

The word "elevate" in the context you've provided seems to emphasize the positive impact and significance of this system in enhancing communication and bridging the gap between hearing/speech-impaired individuals and the general population. Here's a rephrased version of your text with "elevate" included:

"This paper introduces a groundbreaking system prototype known as the Sign to Voice system, or S2V, designed to address the communication challenges faced by individuals with hearing or speech impairments. Sign language, a vital method of non-verbal communication, is commonly used by this community to interact with both their peers and the general population. Existing sign language systems, while available, often lack flexibility and cost-effectiveness.

S2V leverages advanced technology, employing a Feed Forward Neural Network for the detection of two-sequence signs. To train the neural network for classification purposes, we collected data from various universal hand gestures captured through video cameras. Our experimental results are highly promising, demonstrating that the neural network has achieved satisfactory sign-to-voice translation.

In essence, S2V elevates the potential for meaningful communication between individuals with hearing or speech impairments and those without, fostering more effective and inclusive interactions."

Keywords—Hand gesture detection, sign language, sequence detection,neural network.

INTRODUCTION

The system described in this paper is a product of inspiration from individuals facing difficulties in verbal communication. It has been designed with the aim of creating an easy-to-use human-machine interface for the deaf and hearing-impaired population. The primary objective of this research is to develop a system prototype capable of automatically recognizing two-sequence sign languages and translating them into voice in real-time.

In general, there are two methods for collecting gesture data for recognition:

Device-Based Measurement: This method involves measuring hand gestures using equipment such as data gloves. Data gloves can accurately capture the positions of hand gestures as they are directly measured.

Vision-Based Technique: This technique encompasses both face and hand sign recognition without the need for the signer to wear data gloves. All processing tasks are achieved using computer vision techniques, which are considered more flexible and practical than the first method.

Sign languages have gained recognition as minority languages coexisting with majority languages, serving as native languages for many deaf individuals over the last half of the century. The proposed system prototype, Sign to Voice (S2V), has been designed to facilitate more effective communication between hearing individuals and those who are deaf or mute. S2V utilizes a Neural Network approach to recognize hand gestures and transform digitized images of sign language into voice.

The structure of the paper is as follows:

Section II provides a survey of previous work related to the recognition of hand gestures through image analysis.

Section III outlines the system architecture of the SV2 prototype (which may be a typographical error, as it was mentioned as S2V earlier).

Section IV discusses the experimental setup and presents the results obtained.

Finally, **Section V** concludes the paper and suggests directions for future work.

RELATED WORK

This research represents recent advancements in machine vision-based sign language recognition, addressing challenges and limitations prevalent in earlier studies. Sign language recognition from video data has historically encountered environmental constraints, such as reliance on skin color for hand detection. However, this method is not always reliable, particularly under varying lighting conditions and with non-standard skin-colored objects.

Another explored modality is motion flow information, which can be valuable under specific circumstances but becomes less reliable with non-stationary cameras.

Eng-Jon Ong and Bowden introduced an innovative unsupervised approach to overcome these challenges. Their method not only detects the presence of human hands in images but also classifies their shape. This is achieved through a boosted cascade of classifiers, primarily focusing on shape detection within grayscale images.

To create a robust hand detection system, a database of hand images underwent clustering using the k-medoid clustering algorithm. This process employed a distance metric based on shape context to group similar-looking hand images.

Subsequently, a two-layered tree structure of boosted hand detectors was developed. The top layer focused on general hand detection, acting as the initial filter. The second layer featured multiple specialized branches designed to classify sets of hand shapes derived from the unsupervised clustering method. This hierarchical approach significantly improved the system's ability to accurately and efficiently recognize and classify various hand shapes in images.

In summary, this research represents a significant advancement in machine vision-based sign language recognition. It addresses previous limitations and enhances

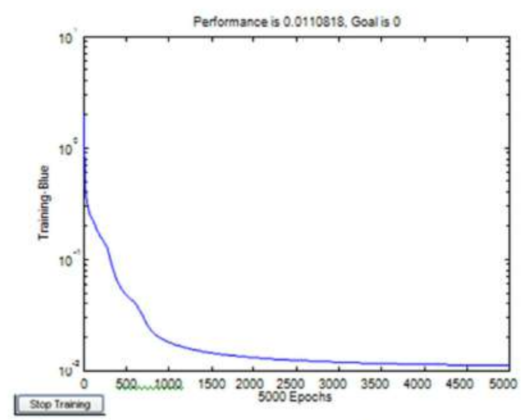

Fig. 5 FFNN Training with PCA

the accuracy and reliability of hand gesture and sign detection through a multi-layered approach that combines clustering, shape analysis, and specialized classifiers.

In MATLAB, an effective procedure for performing this operation is the principal component analysis (PCA). This technique has three effects: the first one is to orthogonalizes the components of the input vectors (so that they are uncorrelated with each other); second it orders the resulting orthogonal components (principal components) so that those with the largest variation come first; and finally it eliminates those components that contribute the least to the variation in the data set. By using this

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technique, the learning rate of training the neural network is increased.

As a result, the prototype has successfully detected the hand region as shown in Fig. 3.

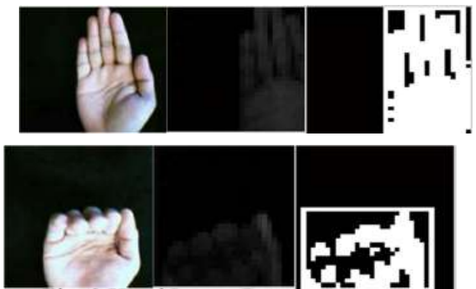

Fig. 3 Hand Image Detection

A. Neural Network Training Technique

Fig. 4 shows the comparisons of FFNN training without PCA and that of Fig. 5 FFNN training with PCA implemented.

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0 500 1000 1500 2000 2500 3000 3500 4000 4500 5000

5000 Epoch Stop Training

Fig. 4 FFNN Training without PCA

The parameter of neural network training are 0.01 in learning rate, epochs in 5000 and momentum coefficient is 0.8.

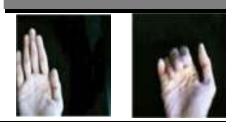
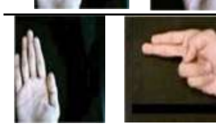
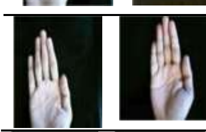
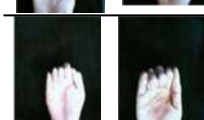
Fig. 4 shows the difference-curve of the error rate with difference technique before conduct the training to the neural network. It showed that principle component analysis will increase the learning rate of the neural network.

The result of the NN training without PCA is MSE 0.050038/0, Gradient 0.114071/1e-010 whereas NN training with PCA (Fig. 5) is MSE 0.0110818/0, Gradient 0.00490473/1e-010.

B.Sequence Detection Testing

Two types of testing were conducted i.e. positive testing and negative testing. The positive testing is to prove the sequence of sign language that can be recognized by the system. The negative testing is to prove that every time the sign language is not move, the systems will not response

TABLE I
RESULT OF SEQUENCE DETECTION TESTING

Sequence 1	Test (+)	(-)	Resu
	Yes		Tru
	Yes		Tru
	No		Fals
	No		Fals
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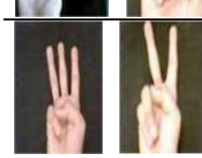	Yes		Tru

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The proposed solution is to implement S2V for real-time processing. The system is able to detect the sequence of sign symbols with additional functions that has to be automated to calculate the proportion of the black and white images and compare with threshold value specified by the program

. The difficulties that faced here were to recognize a little/small difference in portion of the images which were not detected by the threshold value (and even in recognition part). However, for this prototype, we manage to get the output by implementing the proposed technique to detect the sequence of sign symbols.

B. Recognition Rate

70 set of two-sequence hand gestures were captured in real- time from signers using video camera in which 20 were usedas training set and the remaining 10 were used as test set. The recognition rate of the sign languages is calculated as follows:

$$Recognitionrate = \frac{No.\ of\ correctly\ classifiedsigns}{Total\ No.\ of\ signs} \times 100\% \quad (2)$$

TABLE II
S2V SYSTEM RECOGNITION RATE

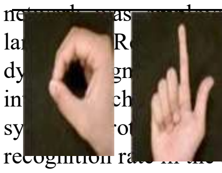
Data	No. of Samples	Recognized Samples	Recognition Rate (%)
Training	50	40	80.0
Testing	20	15	75.0
Total	70	55	78.6 (Average)

The overall results of the system prototype were tabulated in Table II below:

The results of segmentation and feature detection are performed as explained above. Experimental results of the 70 samples of hand images with different positions gave consistent outcomes.
Based on the above experiments, the two-sequence sign language or hand gestures have been tested with an average recognition rate of 78.6%.

CONCLUSION

Hand gestures detection and recognition technique for international sign language has been proposed and neural ne as d as a knowledge base for sign la R of the RGB image and longer dy gn s is one of the challenges to be look in ch e experimental results show that the sy ro 2V has produced satisfactory recognition ra automatic translation of sign language to voice. For future research, we propose Hidden Markov Model (HMM) to detect longer sequences in large sign vocabularies and shall integrate this technique into a sign-to-voice system, or vice-versa, to help normal people to communicate more effectively with mute or hearing impaired people.



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