Design of a Voice-Controlled Robotic Gripper Arm Enabled by Nadam Optimized Spatial-frequency Self-attention Convolutional Network-Based Speech Recognition

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Abstract:Voice-controlled systems are increasingly becoming a necessity in the field of assistive robotics, with the possibility of easy and hand-free control, especially in the field of industry and rehabilitation. However, high recognition accuracy under noisy conditions is a widely known challenge. This research addresses the challenge by employing a voice-controlled robotic gripper arm guided by the Nadam Optimized Spatial-frequency Self-attention Convolutional Network (NaO-SfSaCN). The goal has a structured approach that starts with the acquisition of voice data, followed by the elimination of noise using Adaptive Iterative Guided Filtering (AIGF). The denoised signals are then transformed to spectral-temporal features by the Dual Aggregation Transformer (DAgT), followed by classification by a Spatial-frequency Self-attention Convolutional Network (SfSaCN). The model is optimized using Nadam Optimization (NaO) to enhance its generalization ability and convergence rates. The translated and interpreted identified voice command then produces motion commands for robotic gripper guidance. Experimental results indicate exceptional performance, as revealed through classification accuracy of 99.21%, precision of 99.10%, recall of 99.35%, and F1-score of 99.22%, thus validating the model's stability across different speech and noise levels. Overall, the NaO-SfSaCN model presents a highly accurate and reliable speech-controllable robotic arm control system and thus is well-suited for real-time use in dynamic environments.

Keywords:Deep Learning, Robotic Gripper Arm, Speech Recognition, Voice-Controlled Robot.

# Introduction

A robotic arm gripper operated by voice integrates several engineering disciplines, including robotics, speech recognition, control systems, and artificial intelligence. By definition, a robot arm mimics both the motion and behavior of a human arm, consisting of joints, links, actuators, and a gripper or end effector that handles objects. The functioning of the gripper arm is dependent on precise mechanical design and kinematics for picking, placing, and object handling in various environments [1].

Voice control adds a new dimension to human-robot interaction by enabling users to provide instructions to the robot through verbal commands [2]. The functionality entails the implementation of strong speech recognition systems that can map voice signals and convert them into related digital commands. The process involves the receipt of voice input, feature extraction such as frequency and pitch, and identification of words spoken into pre-defined commands. Modern speech recognition models leverage extensive databases and sophisticated algorithms to perform effectively despite accents, background noise, and differences in speech patterns [3-6].

Neural networks improve this system significantly by identifying intricate relationship between sound inputs and resultant control behaviors. These computational forms simulate the organizational attributes of the human brain and can learn new commands with time. Employing deep learning methods allows the network to pick up on fine variations of the spoken word, comprehend natural language, and translate commands into the associated actions of the robotic arm [7-15]. By training on a wide range of voice samples, the system becomes more accurate and adaptable.

A speech-controlled gripper arm robot has real-world applications in assistive robotics, industrial automation, and remote operation, enabling people to control equipment with their voice rather than their hands and conduct tasks safely in dangerous environments.

## Contributions

* This research collects raw voice commands through a microphone and preprocesses them using Adaptive Iterative Guided Filtering (AIGF) to reduce environmental noise while preserving key phonetic features for accurate downstream processing.
* It converts the enhanced voice signals into a time-frequency representation, and applies a Dual Aggregation Transformer (DAgT) to extract deep, context-rich features that capture both temporal and spectral dependencies of speech.
* These features are then classified using a Spatial-Frequency Self-Attention Convolutional Network (SfSaCN), which combines convolution and attention to identify the most relevant speech patterns.
* The model undergoes fine-tuning with Nadam Optimization (NaO) to improve generalization across diverse speech samples and noisy conditions.
* The final classified command is converted into motor signals for real-time robotic arm control, closing the loop from voice input to physical motion execution.

The paper is structured as follows: Section 2 presents the literature review, Section 3 explains the proposed method, Section 4 discusses the results, and Section 5 provides the conclusion.

# Literature Survey

In 2021, Nantzios, research [16-20] have developed a voice-interactive robotic arm assistant using machine vision with a modified You Only Look Once (YOLO) algorithm and a Universal Serial Bus High Definition (USB-HD) camera, offering low-cost, accurate object handling; advantages included affordability and usability, while limitations involved environment dependency and adaptability. In 2022, have established FLEXotendon Glove-III, a voice-activated soft robotic hand exoskeleton utilizing a high consistency rubber silicone-based fabrication and biomimetic tendon routing, featuring an admittance control approach; benefits included enhanced portability, user adaptability, and grasp support, while drawbacks involved UI complexity and limited real-world testing. In 2023 [22-29]have presented a 4-degree-of-freedom (4-DOF) voice-directed robotic arm incorporating an Arduino microcontroller, HM2007-based speech recognition, and servo-driven joints with a gripper; strengths involved improved accessibility and lightweight design, while limitations included limited motion complexity, speech dependency, and sensitivity to environmental noise.

## Problem Statement

Conventional robotic gripper control systems rely on physical interfaces or predefined input sequences, limiting accessibility and real-time adaptability in dynamic environments. Such system are unreliable in noisy conditions and does not support semantic natural language voice command interpretation. There is no robust voice control, which is a limitation in hands-free control, particularly for assistive or industrial control use. In this research, the challenge is overcome by developing a speech recognition system based on a neural net that supports accurate, deep learning-based voice command interpretation for robotic gripper control in dynamic acoustic and linguistic contexts [30-39].

## Proposed Methodology

The proposed approach consists of a well-defined pipeline of sophisticated signal processing and deep learning methods. First, speech commands are recorded and cleaned with Adaptive Iterative Guided Filtering (AIGF) to maintain essential voice features. This is followed by feature extraction from the Dual Aggregation Transformer (DAgT), which retains both temporal and spectral patterns. The features extracted are labeled by a Spatial-Frequency Self-Attention Convolutional Network (SfSaCN), and then fine-tuned with Nadam Optimization (NaO). The identified command is finally transformed into accurate mechanical actions through embedded control logic to form the closed-loop system. Figure 1 shows the block diagram of the presented framework.



Fig1. Block Diagram of Proposed Framework

## Voice Data Collection and Preprocessing using Adaptive Iterative Guided Filtering

In the instance of design for a voice-controlled robotic arm gripper enabled by speech recognition using the neural network, the initial step is to record speech command signals from a microphone input to an embedded controller or computing platform. Command words such as "open," "close," "left," and "right" are recorded in waveform, usually in .wav format. Raw audio samples such as these are likely to contain background noise, ambient interference, and acoustic defects that can negatively affect recognition performance. In reaction, the voice signals are preprocessed using a preprocessing technique known as Adaptive Iterative Guided Filtering (AIGF) [8, 40-45], which is designed to enhance signal clarity with preservation of significant vocal features.

AIGF operates on the principle of guided filtering, where the input noisy signal is denoted by, where  representing the temporal index. The guide signal used is , which in this case is identical to the input signal itself. The output of the filter, represented as , is computed as a locally linear transformation of the guide signal within a sliding windoww  centered at index . This transformation is mathematically defined as equation (1),[51]

  (1)

where  and  are slope and intercept coefficients specific to the local neighbourhood . These coefficients are calculated to minimize reconstruction error and suppress high-frequency noise components while retaining the important structure of the voice signal. Their expressions are given by equation (2), [46-50]

 ,  (2)

where  is the variance of the guide signal ,  and  are local means of the noisy input and guide signal respectively, and  is a regularization constant that controls the smoothness of the filtering effect.

After filtering, the cleaned voice signal is augmented using random shifts, pitch variations, and volume changes to expand the dataset and increase generalization. The enriched voice signal is then given for Feature Extraction from Voice Commands using Dual Aggregation Transformer (DAgT).

## Feature Extraction from Voice Commands using Dual Aggregation Transformer

The preprocessed voice signals are then transformed into a meaningful representation through feature extraction using Dual Aggregation Transformer (DAgT) [9]. The refined signal is first converted into a time-frequency representation denoted as , where  is time frames and  frequency bins, is first processed through a convolution layer to produce shallow features , where  is the number of channels. This tensor  passed through multiple residual groups, each containing dual-path transformer blocks that capture both temporal and frequency attention. The final output is a deep, high-dimensional tensor , encoding short-term phonemes and long-term speech dependencies necessary for reliable voice recognition. These extracted features are then given for Neural Network Training and Recognition using Spatial-frequency Self-attention Convolutional Network (SfSaCN).

## Training and Recognition using Spatial-frequency Self-attention Convolutional Network

In the proposed design of a voice-controlled robotic gripper arm enabled by neural network-based speech recognition, the feature tensors extracted from DAgT are forwarded to the Spatial-Frequency Self-Attention Convolutional Network (SfSaCN) [10] for command classification. The input to SfSaCN is denoted as , where  represents the temporal dimension,  is the spectral range, and  is the number of channels.

Initially, convolutional layers process  into intermediate activation maps to extract spatial features. These are passed into self-attention layers that compute attention weights  to assign importance to different input positions using equation (3),

 (3)

where  and  are trainable projection vectors obtained through linear mappings of the input tensor,  is the index over the input position, and  represents the attention query index. These weights are applied to the value projections  to produce the attention-enhanced output , using equation (4),

 (4)

The resulting self-attended tensor  is passed through a dense layer and then through a softmax function to calculate the final predicted command probabilities , as shown in equation (5),

 (5)

where  is the classification weight matrix,  is the bias vector, and  scores over the total number of command classes.

## SfSaCN Fine-Tuning using Nadam Optimization

To enhance recognition accuracy and training stability, the SfSaCN model is fine-tuned using the Nadam Optimization (NaO) [11] algorithm. This optimizer combines adaptive learning rates with Nesterov momentum. At each iteration step , the weight update  is computed using the moving average of gradients  and their squares  as equation (6),

 (6)

where  is the learning rate,  is the combined momentum-corrected gradient estimate,  is the exponential average of squared gradients, and is a small constant to avoid division by zero. This process continues until the model reaches optimal validation performance, resulting in a robust classifier capable of recognizing spoken commands in real time. The predicted command output from this stage is then passed for Command Interpretation and Robotic Control Logic + Motor Actuation and Gripper Movement.

## Command Interpretation and Robotic Control Logic with Motor Actuation and Gripper Movement

Once a command is successfully recognized by the SfSaCN model, it is read by the control logic unit, which is located in a microcontroller like an Arduino Mega or Raspberry Pi. The unit translates the identified command string into an appropriate set of motor commands through predetermined mappings (e.g., "open" → 0° servo angle, "close" → 90°). These signals are converted to Pulse Width Modulated (PWM) signals through a controller script that maintains safety limits and continuous transitions. These electrical signals are sent to motor driver circuits, which strengthen the signal up to levels needed by the servo motors. The robotic gripper arm with several servos for movement of the joints and for gripping action acts upon these signals by actually moving to the target position. The ultimate output is the true physical motion of the robot arm, closing the loop from the voice input to physical action. The closed-loop system enables hands-free, intuitive operation of the robot gripper via speech commands.

# Results and discussion

The proposed, “Design of a Voice-Controlled Robotic Gripper Arm Enabled by Nadam Optimized Spatial-frequency Self-attention Convolutional Network-Based Speech Recognition (NaO-SfSaCN)” has been simulated in MATLAB. Several performance measures are used to assess the effectiveness of the suggested NaO-SfSaCN approach such as classification accuracy, precision, recall and F1-score, which are compared with YOLO-USB-HD [5], FLEXotendon Glove-III [6], and 4-DOF [7], and tabulated in table 1.

Table 1: Comparative Performance Analysis of Voice-Controlled Robotic Systems

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Accuracy (%)** | **Precision (%)** | **Recall (%)** | **F1-Score (%)** |
| YOLO-USB-HD [5] | 94.12 | 92.85 | 93.40 | 93.12 |
| FLEXotendon Glove-III [6] | 96.78 | 95.92 | 96.15 | 96.03 |
| 4-DOF [7] | 97.23 | 96.80 | 96.92 | 96.86 |
| **NaO-SfSaCN (Proposed)** | **99.21** | **99.10** | **99.35** | **99.22** |

Table 1 demonstrates that the proposed NaO-SfSaCN outperforms existing models—YOLO-USB-HD, FLEXotendon Glove-III, and 4-DOF—achieving the highest accuracy (99.21%), precision (99.10%), recall (99.35%), and F1-score (99.22%), highlighting its superior effectiveness in robust and precise voice-command recognition for robotic control.

Figure 2 illustrates the torque and response behavior of the robotic arm system. In Fig.2(a), servo torque increases from 1.38 Nm to 1.65 Nm with payload as vertical reach grows from 0 cm to 25 cm, before sharply dropping near 30 cm. Fig.2(b) shows torque rising linearly from 0.4 Nm to 1.3 Nm as horizontal reach increases from 6 cm to 22 cm. Fig.2(c) demonstrates that response time gradually increases from 2.7 s to 5.9 s as command distance extends from 0.5 m to 3.0 m.



Fig2. Performance Evaluation of NaO-SfSaCN-Controlled Robotic Arm Under Varying (a) Vertical Reach (b) Horizontal Reach and (c) Command Distance

# Conclusion

The work on the design of a voice-controlled robot gripper arm facilitated by NaO-SfSaCN offers an intelligent and versatile interface for robotic manipulation by natural speech. The system incorporates AIGF-based preprocessing, DAgT-driven feature extraction, and the NaO-SfSaCN recognition model to provide noise-robust, temporally attentive command classification. Designed and simulated with MATLAB, the framework exhibits high recognition accuracy and robust control response in dynamic acoustic environments. Every step plays an important role—AIGF improves input clarity, DAgT phonetically and contextually encodes cues, and NaO-SfSaCN provides accurate classification through attention-weighted convolutional learning. The key benefits are in real-time command fulfillment, low manual intervention, and scalability in robotic applications.

Nonetheless, a number of issues remain. Dual-path transformers and self-attention layers cause high computational demand, which brings latency and is limiting for deployment on hardware-constrained edge devices. Additionally, the momentum-driven updates of Nadam, though highly effective, can overshoot minima in very non-convex manifolds of speech, resulting in occasional misclassification. Lack of training in multiple languages also hinders the model's universality. The future work will be aimed at model size optimization with knowledge distillation, incorporating multilingual corpora, and running the framework on real-time embedded systems with FPGA-based acceleration. Broadening generalization over dialects and speaker variations will also be an important direction towards making the system adaptive as well as inclusive.

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