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A LLM-based voice user interface for voice dialogues between user and industrial machines

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Abstract

Recent advancements in Large Language Models (LLMs) have significantly expanded the role of Artificial Intelligence (AI) in manufacturing. One promising area for LLM integration is machine control, particularly for industrial equipment like milling, drilling, and turning machines. Despite their critical role, these machines often exhibit limitations in user-friendliness, operational flexibility, accessibility, and operator safety which are partially based on console-based interfaces. Voice user interfaces (VUIs) mitigate those limitations. The current literature on VUIs highlights challenges like constrained instruction sets, voice recognition, and reliance on physical machines for testing. The proposed approach addresses these challenges by using LLMs, and virtual prototypes of physical machines, for intensive training and testing of the VUI. The paper describes this approach, explores application challenges, identifies key implementation limitations. This article also provides a comparison of accuracies of 5 pre-trained transformer based language models for understanding a set of sample commands that can be issued to the milling machine providing idea on the usability of pre-trained transformer models as the core conversational-component of the conceptualised VUI.

Keywords: Artificial Intelligence; Large Language Models; Voice user interfaces; industrial machines, Virtual prototype; digital twin; virtual reality;

1. Introduction

Machine tools are fundamental to modern manufacturing, as they enable the precise shaping, cutting, and forming of materials into components that meet specifications, driving productivity, innovation, and quality across various industries. Numerical codes (NC) were first used to control machining operations in the 1940s which marked the phase of Industry 2.0. The first NC code machine for manual or fixed cycle operations was designed at MIT in the late 1940s [3]. These machines were limited by their memory and processing capabilities, which was rectified by the advent of Computer Numeric Code (CNC) machines. Advancements in pertinent research have added to the efficiency, operational flexibility, and reconfigurability of CNC machine tools. Technological advancements seen through artificial intelligence (AI) have widely reduced machine downtime, optimized CNC machine tools, and predicted surface quality [1]. AI can also be used to generate a more flexible, inclusive, safe, and efficient way of interacting with machine tools [2].

Human Machine Interfaces (HMIs) are composed of two parts the display and the control. The display is responsible for taking the information from and relaying the information to the user. The control is responsible for controlling the machine [5]. The display can also be replaced by other sensory methods like voice for providing information. HMIs for operating CNC machine tools have evolved alongside with them from straightforward displays consisting of dials to Command Line Interfaces (CLI), Text-Based Interfaces (TBI), to console-based and natural user interfaces. HMIs can now be classified based on the interaction with the user into gaze, voice, gesture, tactile, and haptic interactions [5]. Industry 4.0 and IoT-based advancements have paved way for techniques like Augmented Reality. However, this development is also marred by certain challenges. Touch-based or console-based interfaces limit the mobility of the operator due to their stationary positioning. Ad-

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ditionally, such interfaces are limited in the aspects of inclusivity. The newly emerging field of Generative AI (Gen. AI) can be used to build powerful HMIs, especially by taking advantage of voice interactions. This adds to the ease of communication with the machine by eradicating the need for stationary positioning of the operator. This also provides an advantage over touch-based interfaces as industrial settings often necessitate the use of protective covering like gloves.

This article discusses an approach where a Voice User Interface (VUI) is developed with the help of Large Language Models (LLMs) acting as a voice assistant and interface between the operator and the machine. The article starts by showing current advancements in the related fields, which is followed by the methodology, and then the implementation of the VUI on an application scenario of a 3-axis CNC machine. The application challenges and limitations are discussed in the last sections of this article.

2. State of the Art

2.1. LLMs in Manufacturing

LLMs are being widely researched in different production areas to increase efficiency and reduce the manual intervention on machines. They form the core component of the intelligent manufacturing paradigm as described in [6]. They streamline various operations in computer-aided design and manufacturing, consequently reducing the manual intervention in the different phases for the same [7].[8] discusses a similar approach where they can be used for devising a methodology for color-matching design. Another application area can be as knowledge experts in computer-aided process planning (CAPP) systems [9][10]. They are also researched in manufacturing to enhance the decision-making of assembly robots. Approaches like [11] propose their use in industrial robot control. [12] proposes an LLM-based manufacturing execution system (MES) for human-robot collaboration. Other researched areas regarding the use of LLMs include quality control, intelligent process planning, and predictive maintenance [6]. All these approaches use the conversational prowess and solvability of LLMs regarding various natural language processing (NLP) tasks to advantage. The conversational ability of the LLMs can also be used to design a machine control interface that interacts with the operator in natural language. The advanced NLP abilities of LLMs, such as text generation, intent classification, and function calling, can be used to create more powerful declarative VUIs, rather than the fixed vocabulary-based VUIs currently being developed and studied [20].

2.2. Virtual Reality in Industrial Applications

An important aspect of Industry 4.0 is facilitating product development and improving collaboration in every production stage. This, among other emerging technologies, is also achieved by the increasing use of Virtual Reality (VR) techniques. VR techniques can reduce the cost associated with design and production, maintain production quality, and reduce the duration between conception and production [13]. Virtual commissioning (VC) is another important application area of VR in manufacturing. VC can mainly be broken down into three main categories: reality-in-loop commissioning, hardware-in-loop commissioning, and software-in-loop commissioning [17]. Real commissioning is the practice of testing the real automation or control loop in the real machine. VC is mainly identified with factory design, especially concerning machine controllers. As identified in [18], up to 15% of plant engineering time is expended on solving the programming errors in the control logic. This can be eradicated by using simulation strategies. Such strategies are rapidly used in plant design [17]. [19] shows an application scenario where VC is used to integrate digital twins into manufacturing execution systems. Another interesting application area that can benefit from the use of VR and VC methods is the design of alternate interfaces for communication between humans and machines. The usage of virtual prototypes and digital twins (DT) that can emulate the underlying physics of the machine operations in a VR environment can act as an immersive software in loop (SIL) environment for training and testing of the HMI [30]. This reduces the time and performance costs associated with the testing of the HMI on the physical machine and improves safety and quality.

2.3. VUIs in Industry

Throughout the past, VUIs have been extensively used in the areas of consumer electronics in the form of voice assistants (VA). Some examples of such interfaces are the VA available in the form of Alexa and Google VA. VUIs have also been used in a limited sense for other micro-controller-based applications in home appliances. [20] finds research regarding the application of VUIs in an industrial setting scarce. Most studies focus on the future development of voice controls for smart factory setups. The above study tests the feasibility, and speed of a VUI as compared to a conventional HMI when controlling a CNC milling machine using voice commands. The issue of background noise has also been addressed. It has been claimed that the power of modern automatic speech recognition (ASR) systems helps in attenuating background voices to create a signal of high fidelity. It reports an efficiency advantage of 67% when comparing different control hierarchies of a conventional HMI. Another such approach found in the literature focuses on implementing a simple prototypic VA for a CNC milling machine, that explains operators and maintenance personnel mainly by assisting in alarm situations [21]. This study also creates a framework for measuring the quality of any VA that can be implemented for an industrial machine. Other relevant studies can be found in [22] for using VUI in production logistics, [23] uses a conventional VUI as a digital assistant to a digital twin and notices the barriers and forthcoming in the approach.

The described approaches are mostly limited in their functionalities related to the control of industrial machines. VUIs aimed at machine control work on a very restricted set of

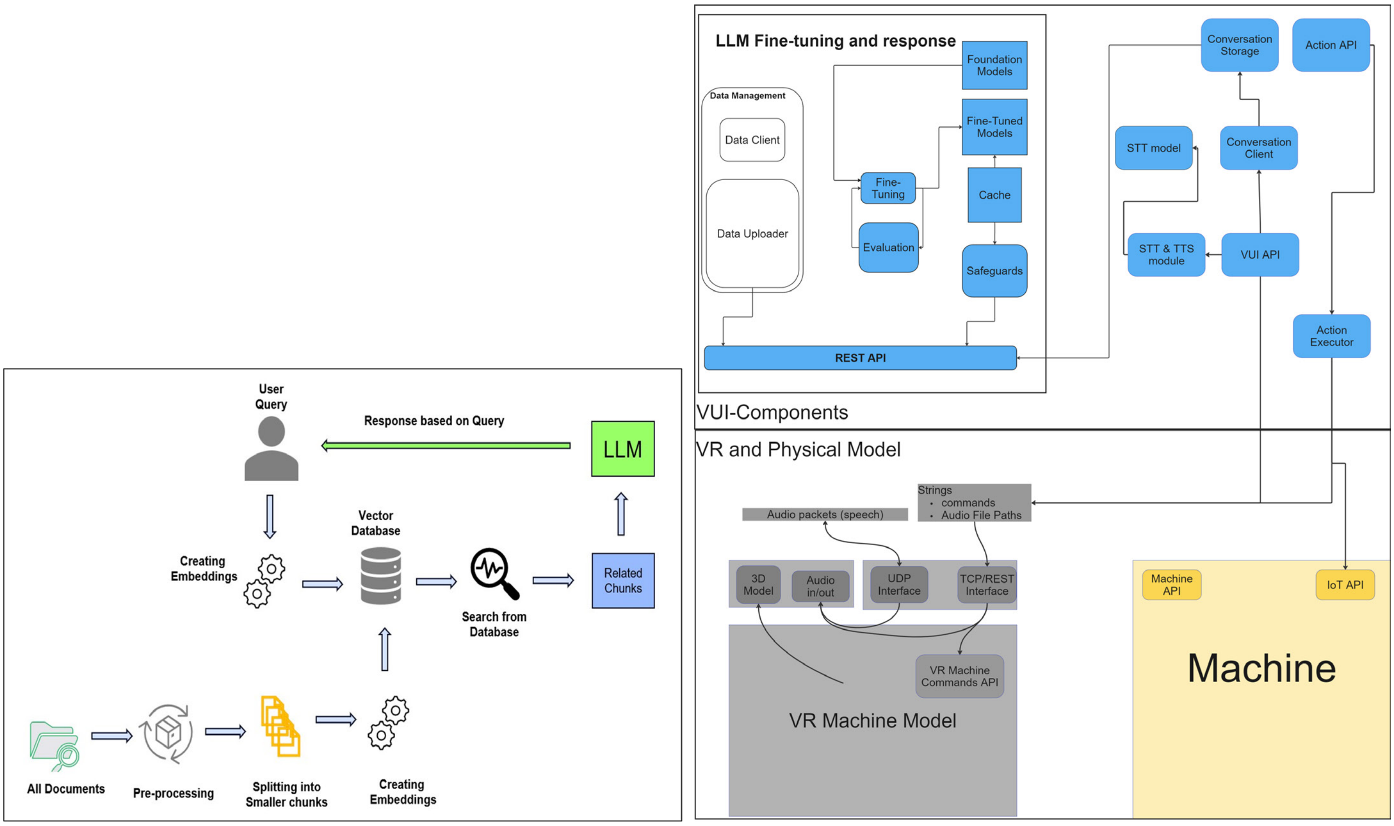

Fig. 1. (a) Pipeline for implementing information extraction; (b) Conceptual Architecture of entire VUI solution.

commands. Additionally, currently available VUIs are also restricted in their approach to validation where use of machines for validation of various scenarios proves ineffective. The state of the art also points out a gap in the use of conversational ability of the LLMs, and testing mediums like VC in the context of VUIs. LLMs and VC can be used for generating VUIs that can act as an alternative to conventional HMIs This article proposes to explore the research gap by proposing an approach with the capabilities brought forward by the advances in Gen AI. This article focuses on developing an LLM-based VUI and explains in detail the conceptual blocks needed for such an implementation. An exemplary application scenario of a 3-axis CNC milling machine with corresponding use cases pertinent to start, stop, and pause milling and general command utterances for starting and stopping the voice bot is discussed. The performance of different open-source LLMs is compared according to datasets pertaining to three different NLP tasks needed by the VUI, and an analysis is provided along with the further direction of implementation and challenges faced. The next section discusses the overall concept highlighting the main components and the flow of data.

3. Methodology

This section describes the conceptual architecture of a VUI implementation for communicating with industrial machines. The architecture proposed in this section is divided into two major sub-parts: the VR component, and the VUI component. The VR components provide the SIL implementation for training and testing of the VUI. The DT simulation is built using the machine computer-aided design (MCAD) models, and the control logic to mimic the behavior of the physical machine.

The virtual twin simulation is created by using a PolyVR virtual engineering software [24]. The application logic and features provided in the virtual twin simulation are established using requirements engineering. The VR communicates with the VUI using the Unified Datagram Protocol (UDP) [25] interface, as shown in Fig. 1. The VR interface accepts the processed commands in .json format, which are then mapped to application logic simulations via the Representational State Transfer (REST) interface. The VR components play a crucial role in generating training data sets for fine training of the underlying LLM architectures. Training data is recorded by combining the wizard-of-oz testing methodology [26] with a virtual prototype. VR also plays a major role in the validation and testing of the trained VUI. The responses generated from the LLMs are executed in the SIL pipeline and the deviations from the real machine movements are recorded to train the LLMs.

The VUI components form the backbone of the entire software as they include the components for speech-to-text and text-to-speech, interpretation of the transcribed text, conversion of the text into suitable data formats for interpreting the command, deriving the appropriate action from the commands, relaying the actions in a suitable format to the VR components for testing of the solution. The overall conceptual depiction of the components can be found in Fig. 1(b) The VUI module can be broken down into the following components: the interface components that interact with the other modules, the conversation module, the speech processing module, the action executor module.

The interface component of the VUI takes in the voice commands provided by the VR module. The speech processing module uses conventional speech-to-text/ text-to-speech (STT/TTS) service from Microsoft Azure for transcribing the input speech to text. The text is then passed on over to the conversation-handling module. This module considers the transcribed text and creates the command data structure for communicating with the other sub-components. The .json [27] data format is used for communication between the individual subcomponents. The data format mainly comprises the transcribed message, the machine identifier for the VUI to understand the machine that the request is directed to, and the time stamp for the request generation. The .json data is used as input to generate responses from the LLMs.

In this approach, LLMs are used for text generation, intent classification, and multilingual comprehension. Text generation is used to answer queries of the user to machine commands in natural language imitating a conversation between two humans. This is facilitated by the use of an information extraction pipeline as detailed in Fig. 1(a). A data-processing pipeline is used which takes into consideration, the functional requirements, manuals, and other explanatory documents focusing on industrial machines, extracts the text from these documents, chunks them into fixed-size byte-sequences [28], generates embeddings [29] for these chunks, and store them in a vector database as per the pipeline shown in Fig. 1(a). The collection of the documents should be exhaustive resulting in semantically similar chunks to the user queries. The input text transcribed in the speech processing modules is similarly embedded and checked for similarity in the vector database. The most similar embeddings are then extracted and sent to the LLM for generating the responses.

Intent classification identifies the command from the user to the machine. This component also recognizes the general emotion of the user which can also be used to identify any malintent meant by the user. Such an approach also improves the safety and security of the VUI. Consequently, intent classification forms a critical component of the application. The data for the intent classification is developed by studying the use cases and the functional requirements in detail which are then used for generating a set of intents and their respective utterances. The intents are divided depending on different user categories, and the commands they can utter. The intents can be classified broadly into general and machine-specific, depending on the type of command being initiated by the user. This dataset is then used for fine-tuning the underlying LLM architecture using prompt-engineering. The implementation scenario can be considered as the voice utterance from the user being transferred to the transcribed text, passing through the pipeline for generating the command data structure and generating two responses, a text generated as the response for the user and a function call generated for the machine. The next section describes the theoretical validation scenario of the above concept in a three axis CNC Milling machine.

4. Implementation and experiments on a CNC Machine

Commands are generated depending on the use cases developed after expert reviews and requirement analysis. The commands can be machine-specific commands like ”start milling operation” or general commands like ”activate voice user interface”. These commands are then divided into intents, and utterances are developed for each of these intents. The individual components have been developed only for the four milling operations, the start, stop, pause, and resume milling operations.

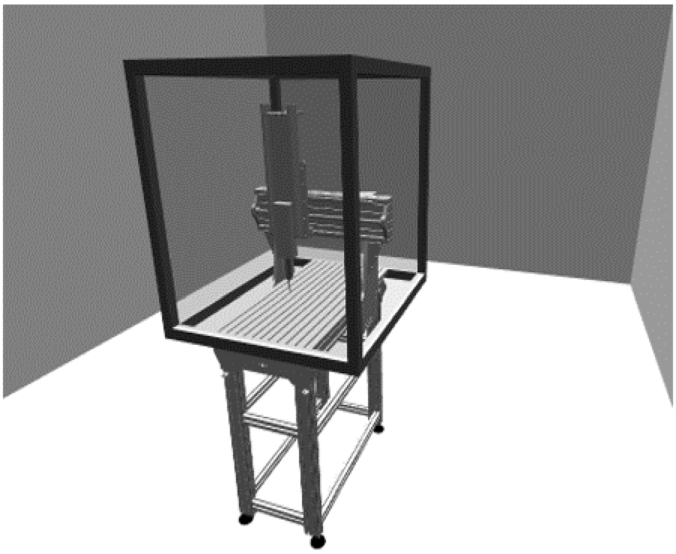

Fig. 2. Implemented virtual twin of 3-Axis CNC Milling machine.

The virtual twin of the CNC machine is composed of the simulation components that contain logic for importing the CNC code, accepting the commands over the REST interface, and converting them to the functions for start, stop, and pause milling. The MCAD data of the physical CNC machine are carefully inspected and optimized to meet specific requirements to develop the virtual twin of the CNC machine as shown in Fig. 2 [24]. To further enhance simulation precision, 3D models of the machining tool are created, and the components are restructured to seamlessly emulate Cartesian kinematics of the tool’s movements along the X, Y, and Z axes. The VUI module takes the sound signals as input through the UDP interface, the UDP packets are then sent to the STT/TTS component to convert them to transcribed text. A wake word ”Hey CNC” is used for activating the STT service as implemented in popular voice assistants in mobile phones. The STT/TTS service runs asynchronously, consequently, necessitating the breakout time normally associated with such services. The transcribed text is then transformed to the conversation API. The conversation API is responsible for creating the command data structure.

Table 1. The classification score using cosine similarity of a list of pre-trained LLMs

Model	Dimension	Average score	Translation	Binary classification	Intent classification
openai/text-embedding-3-small	1536	0.938	0.940	0.960	0.914
BAAI/bge-small-en-v1.5	384	0.670	0.25	0.9605	0.8
BAAI/bge-small-en	384	0.694	0.222	0.973	0.885
sentence-transformers/all-MiniLM-L6-v2	384	0.620	0.244	0.960	0.657
BAAI/bge-base-en	768	0.707	0.320	0.973	0.828

The command data structure is then passed on to the information extraction module which extracts relevant chunks from the vector database created by using CNC operation manual and linux-cnc command manuals. The command data structure is also used to extract the intent associated with the user's speech. The response generated is passed on to the STT/TTS API which converts the response to natural language and relays it to the user. Another output of the AI language model is the intent identified from the user conversations.

An example can be considered when the user as per the present command set speaks the command "Please load the NC code file named test .ngc in the current folder and start the milling operation using the tool - 1", should be identified as the intent for start milling and the parameters should be noted and formulated in the .json command structure. The missing parameters determined by the LLMs are then asked as machine feedback. This .json data is passed on to the action executor that transforms the .json command into a format that is identified by the VR module, the JSON commands are then passed on to the VR module where they are passed through the series of layers as discussed for the final machine movements. A set of pre-trained and fine-tuned LLMs are evaluated as per the implementation of the four milling operations mentioned above as a screening process for selecting a suitable LLM and the results of the analysis are published in this article.

4.1. Dataset Generation

The intents described above are then converted into sample utterances: possible ways a person can express the same intents. A proper mapping of the utterances to their respective intents is extremely important. A set of 10 utterances are considered each for German and English. Similar datasets are created for language translation, and sentence rephrasing binary classification. A set of 96 sentences is considered for evaluating the performance of the machine translation. The translation was intended from German to English. The sentence rephrasing dataset contains 77 sentences in English.

4.2. Results

The information extraction component is implemented using the Llama 3.0,8-billion parameter model. Documents like the CNC operation manual,linux-cnc documentation were used for implementing the information extraction pipeline as described in Fig. 1 (a). A total of 5 pre-trained AI language models were tested in this section to investigate the accuracies related to intent recognition, machine translation, and sentence rephrasing tasks. All listed models, except openai/text-embedding-3-small are accessible from hugging face hub: *https://huggingface.co/*. The cosine similarity score is used to determine the different evaluators accuracy. The evaluator scores achieved on the different datasets are listed in Table.1. The BAAI/bge-base-en model can be chosen as one of the most optimum model as per performance is considered, as the openai model, which has a higher accuracy, is limited by online API calls. The lower scores in machine translation necessitate the use of separate models when considering a multi-lingual VUI. The results as shown above, give a hint of the efficiency of pre-trained transformer based large language models in NLP tasks.

5. Discussion

An advantage of this solution is the application of virtual commissioning with the help of immersive digital twins. Immersive digital twins of machines are used for validation and training of the VUI solution. The advantages of such an approach are mainly two-fold: it helps to collect realistic training data sets for the LLM with potential users and validation of the voice user interface without the interference of the physical machine. One of the major challenges is achieving real-time responsiveness in the specific modules of VUI. The real-time latency of the immersive digital twin, the LLM response, and the internal VUI operations including the STT/TTS, are bottlenecks that can prove critical in industrial application scenarios. One possible method for eradicating such problems can be caching the most frequently used commands and their kinematics. Additionally, the kinematics accuracy of the virtual twins proves to be a general challenge as it plays a crucial role in collecting training data, and also in testing the solution. The scalability of the solution proves to be another critical aspect for the deployment of the VUI in real-time scenarios. The solution should be in a cost-efficient way, and be scalable beyond the proof-of-concept phase where the complex user interactions can also be implemented with high fidelity and low latency. The future work aims to address the above-mentioned challenges and create a generalizable platform for implementing a VUI-based solution for multiple application scenarios. The noisy environment of the factory is also considered among one of the principal challenges of implementing the VUI. Special noise-attenuating headgear should be used that provide propüer speech clarity in highly noisy settings to alleviate this issue.

6. Summary and Outlook

This article discusses an approach for implementing a declarative VUI with the help of LLMs for a three axis CNC milling machine. The conceptual architecture provided in Section. 3 is then exemplified with a theoretical application scenario shown in Section. 4. The implementation of an end-to end VUI solution undergoing SIL testing and integration into a physical CNC machine can be considered as the final outcome of the above defined approach. The challenges discussed in Section. 5 will be addressed when considering the final implementation.

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