Proceedings of CONF-MLA 2026 Symposium: Intelligent Systems and Automation: AI Models, IoT, and Robotic Algorithms
DOI: 10.54254/2755-2721/2026.LD37526

Spatially Selective and Stepless Human-Intention Control Framework for Variable Stiffness and Grasp Force of Soft Grippers

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Abstract. The use of soft robotic end-effectors has been prevalent in sensitive agricultural harvesting because these devices have high compliance and are safe to interact with humans. Current variable-stiffness grippers have the disadvantages of full-finger uniform stiffness parameters and discrete-grade parameter control, which can cause mechanical shock and soft fruit damage easily. The existing brain-computer interface (BCI) control schemes can only give out binary control commands and are incapable of affording continuous adjustment due to human grasping perception. To overcome these challenges, the current paper has suggested a human-intention control system using regional regulation and output that is stepless with multi-segment soft gripper. A two-mode BCI that incorporates motor imagery (MI)-based offline calibration and error-related potential (ErrP)-based online supervision is assembled to reach the segmented stiffness tuning and full-range continuous grasping force control. BCI anomaly monitoring and hierarchical dual closed-loop control with tactile feedback enhances environmental adaptability in unstructured farm environments. The research offers a new human-involved smart handling approach to variable stiffness soft manipulators and improves nondestructive harvesting abilities of fine agricultural farming.

Keywords: soft-robotic end-effectors, regional variable stiffness, brain-computer interaction, human grasping intention decoding, nondestructive agricultural harvesting

1. Introduction

Owing to their favorable compliance and intrinsic human-safe characteristics, soft robotic grippers have become promising manipulation hardware for agricultural picking and sorting operations [1, 2]. Variable-stiffness designs are widely adopted to improve the structural stability and load-bearing performance of such grippers [3]. However, current technical solutions still have significant deficiencies in practice when implemented under actual crop-harvesting conditions. Traditional grasping systems, in which the rigidity of whole fingers is uniform, do not tune to geometrically heterogeneous fruits [4], and so create too much local contact pressure on soft-fleshed fruits like strawberries, thus causing surface bruising and then postharvest rot. Jumping of stiffness and

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grasping force with discrete grade adjustment results in sudden mechanical transients [4], which are likely to cause permanent damage of indentations on thin-skinned horticultural crops such as tomatoes. Current brain-computer-interface-based grasping systems have scaled to binary on-off control, and are incapable of achieving the continuous fine control of grasping cues as perceived by humans [5], which increases the chances of picking failure and shedding fruit in the field.

In order to deal with the above practical limitations, this paper is proposing a spatially-selective, non-stepped human-intention control system of soft grippers. The main contributions of work are as follows:

(1) A two-mode BCI system that combines offline motor-imagery calibration and online ErrP-based anomaly supervision is developed, which does not need real-time electroencephalogram feedback during the harvesting process.

(2) The irregular surface shapes of agriculture products in the field mode of operation are accommodated by segmented regional stiffness modulation.

(3) Stepless control of grasping-force throughout the full range is introduced to reduce the mechanical transients due to discrete-grade switching and minimize the risk of damage in crops.

This design allows human-in-the-loop adaptive grasping and offers new control information on variable-stiffness soft manipulators, which is useful in harvesting unstructured precision-agriculture environments nondestructively.

2. Theoretical design of dual-mode BCI human intention control system

2.1. EEG signal acquisition and preprocessing theoretical scheme

Driven by the above-mentioned control requirements for spatially-selective and stepless soft-gripper manipulation, this work constructs a dual-mode-BCI-empowered fully automatic fruit-and-vegetable picking system that incorporates human flexible grasping experience into robotic harvesting workflows. Different from traditional semi-autonomous human-in-the-loop BCI control schemes, the developed system realizes completely unmanned autonomous picking under conventional working conditions. The BCI module contains two independent working mechanisms: an offline calibration mechanism based on motor imagery (MI) for learning and replicating optimal human flexible-grasping preferences, and an online remote supervision mechanism based on error-related potential (ErrP) for intelligent correction of picking anomalies. No continuous manual intervention, real-time visual stimulation or active human brain control is demanded throughout the whole picking workflow.

The system has two fundamental steps; offline MI-BCI intentional calibration and autonomous picking. Adaptive picking parameters are predicted by the visual-mechanical model which is trained using human grasping experience. The tactile closed loop corrects minor tracking errors whereas the ErrP-BCI supervision loop corrects serious grasping errors. The BCI module will only operate in the first calibration and abnormal intervention to guarantee complete autonomy in operation.

An offline calibration is done with a configurable 8-16 channel non-invasive EEG device. As an approximation of the classic motor imagery (MI) BCI paradigms, sensorimotor electrodes C3/C4 are used to record 830 Hz mu/beta oscillatory activity elicited by fine grasping image that accurately represent human subjective preferences of stiffness and grasping force control [4, 6]. Occipital electrodes are used in monitoring of quality of signals in real time. The 8-channel set-up provides the minimum decoding needs, the extended 16-channel acquisition enhances the spatial resolution to allow a high-resolution mechanical parameter calibration of the soft gripper control [7].

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Power-frequency noise and ocular and myogenic artifacts are easy to contaminate the raw EEG signals, and these issues critically impair the accuracy of intention decoding [3, 8]. The study uses a common multi-phase preprocessing pipeline that has been shown to be effective in BCI robotic studies: band-pass filtering (0.550 Hz) removes baseline drift and high-frequency muscle noise, notch filtering (50 Hz) removes power-frequency interference, and independent component analysis (ICA) removes ocular artifacts to isolate useful EEG components [3, 9]. Unlike traditional discrete classification-based BCI techniques, which chop off continuous signal characteristics, this pipeline completely allows full mu/beta amplitude envelopes, allowing continuous feature coverage of continuous regression models of segmented stiffness and grasping force [1, 6]. All EEG feature extraction and intention decoding functions are done offline and completely disabled at autonomous picking which guarantees zero real-time dependence on brain signals when the system is in routine operation [5].

2.2. MI-BCI offline calibration and visual-mechanical mapping model design

This module can be used in offline training only to generate a human-optimal grasping parameter database to pick crops flexibly. Prior to the actual data collection, the calibration samples are sorted by the geometric dimension, contour curvature and surface firmness as per the standard soft gripper test specifications [2] and include common crops such as strawberries, tomatoes and kiwifruits. Based on the conventional MI-BCI calibration paradigms [7] the subjects with EEG devices are asked to perform a series of repetitive motor imagery grasping trials. For each classified sample, participants perform 4-second gentle clamping imagery. The system synchronously acquires crop RGB-D images and cerebral sensorimotor mu/beta energy envelopes with unified timestamps under hardware triggering. Multiple repeated collections per sample eliminate low-quality EEG outliers [10]. Decoded multi-segment stiffness and overall grasping force are matched with time-aligned visual features to build paired datasets of human-optimized flexible picking strategies.

BCI-decoded optimal mechanical parameters are fully paired with crop visual features (contour morphology, size, surface texture) to construct a visual-mechanical dataset. A data-driven regression model is trained to establish a stable mapping from crop visual characteristics to optimal segmented stiffness and grasping force. After model convergence and parameter fixation, the MI-BCI module is disabled in formal picking. The robot autonomously predicts grasping parameters via real-time visual perception without continuous EEG input.

2.3. Multi-segment soft gripper and hierarchical dual closed-loop control architecture

This study adopts a modular multi-segment pneumatic soft gripper with mechanically decoupled cavities and independent inflation channels to eliminate inter-segment mechanical and aerodynamic coupling [9]. Each finger segment consists of three functional layers: the inner pneumatic cavity provides deformation and stiffness tuning power, the bottom strain-limiting layer restricts undesired structural stretching and converts pneumatic pressure into stable directional bending motion [2], the outer soft contact layer homogenizes contact pressure to avoid mechanical damage to delicate crop surfaces. Independent single-segment actuation enables continuous, independent stiffness regulation for each gripper region.

Segment bending stiffness and local grasping force are positively correlated with inflation pressure. Benefiting from segment decoupling, differentiated regional pressure control is realized: low-pressure soft contact fits protruding crop surfaces, while high-pressure stiff support stabilizes main clamping areas, achieving coordinated stiffness-force adaptive regulation. Combined with the

DOI: 10.54254/2755-2721/2026.LD37526

visual-mechanical model in Section 2.2, adaptive pneumatic control commands are generated. Material hysteresis and pneumatic nonlinearities cause open-loop parameter deviation, necessitating closed-loop compensation for field picking scenarios [11].

Multi-segment structure is shown to perform better than the rigid grippers and global uniform soft grippers in unstructured agricultural systems. The contact stress in rigid structures is too large under positional errors and globally rigid grippers do not conform to asymmetrical fruit shapes, causing local stress concentration [12]. The fractured structure enhances that of the contour and balances the protective soft contacts and the dependable rigid support. The proposed independent pneumatically segmented scheme has more dynamic adjustability and response capabilities compared to passive variable-stiffness structures, and integrated excitation strategies, which are needed in field-adaptive harvesting.

A hierarchical dual closed loop control system is built to repeat the unstructured orchard and greenhouse disturbances [11]. The low-level tactile closed loop corrects small in-bounds force errors due to noise in the environment and individual crop variations by correcting real-time force feedbacks. In the case of extreme anomalies such as occluding fruits, posture error and near-incipient slip that is beyond the range of re-establishing the contact with the object, the dormant ErrP-BCI error control loop is activated that resets the grasping parameters and reconstructs movement paths [5]. This two-loop approach combines accurate tactile compensation and smart BCI intervention, which are effective to enhance the field picking robustness and do not compromise system autonomy.

2.4. Experimental schemes and quantitative evaluation metrics

This paper has developed two consecutive experimental procedures such as an offline BCI human-grasping parameter calibration experiment and an ErrP-BCI supervised fully automatic picking verification experiment. The former is applied to model training, parameter optimization, and the latter certifies the overall performance of picking and supervision soundness of the suggested system.

Experiment 1: Offline BCI human-grasping parameter calibration experiment

EEG collection was conducted in five healthy participants (3 males, 2 females, 22-28 years old) according to the specifications of the standard BCI robotic experimental [5]. These four common crops (apple, tomato, orange, cucumber) were taken with a different morphology and mechanical characteristics and 12 defect-free samples of each type were taken. All the participants underwent 15 motor imagery trials of every type of crop, balancing the signal stability and fatigue of the participants [8]. Good visual-mechanical paired datasets were gathered to train, iterate and converge the visual-mechanical mapping model to solidify parameters. The accuracy of model prediction is mostly confirmed by this experiment.

Experiment 2: ErrP-BCI supervised fully automatic picking verification experiment

The offline MI-BCI module is deactivated in this phase to simulate fully autonomous field operation without real-time EEG input. The robot executes complete picking procedures including fruit detection, positioning, parameter inference, compliant grasping, peduncle separation and fruit release. Participants wearing EEG devices passively monitor picking states, and valid ErrP signals triggered by picking anomalies activate system parameter recalibration and trajectory replanning. Fifteen fresh samples are prepared for each crop type, with six repeated trials per group to eliminate random errors and meet agricultural robot test repeatability requirements [11]. This experiment evaluates picking task performance and abnormal correction efficiency.

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Three categories of quantitative evaluation metrics with fixed calculation formulas and judgment criteria are defined for comprehensive system performance assessment.

(1) Model prediction accuracy

The BCI-calibrated human-optimal grasping parameters are taken as the ground truth. Mean absolute error (MAE) is used to estimate the prediction error of segment-wise stiffness and grasping force and the overall fitting performance is represented by the coefficient of determination (R2). Mean Absolute Error (MAE):

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |y_{pred,i} - y_{gt,i}| \tag{1}$$

Where $y_{pred,i}$ is the model-predicted value, $y_{gt,i}$ denotes the BCI-calibrated ground-truth value, and N is the total number of test samples.

The coefficient of determination R^2 is adopted to evaluate overall fitting performance.

Judgment criteria: $R^2 \geq 0.90$ and $MAE \leq 5\%$ full-scale output range of stiffness or grasping force. full-scale output error, consistent with high-precision visual-mechanical mapping model baselines [13]. Both criteria must be satisfied for valid model performance.

(2) Picking task performance

Three indicators are implemented, including picking success rate, fruit damage rate and average single-cycle picking time.

$$\text{Picking success rate} = \frac{\text{Number of successfully picked samples}}{\text{Total test samples}} \times 100\% \tag{2}$$

$$\text{Fruit damage rate} = \frac{\text{Number of damaged fruits after grasping}}{\text{Total test samples}} \times 100\% \tag{3}$$

The time between target positioning and fruit release during repeated valid trials is the average single-cycle picking time.

Judgment criteria: 90% or higher picking success rate and 5% or lower fruit damage rate are qualifiers of harvests success under normal test conditions; and equal to mainstream soft gripper agricultural picking baselines [4].

(3) Abnormal correction efficiency

The success rates of the hierarchical dual closed-loop control framework to test supervision performance are based on the recognition accuracy of the errP, and the rates of anomaly correction.

$$\text{ErrP recognition accuracy} = \frac{\text{Correctly identified ErrP samples}}{\text{Total ErrP trigger samples}} \times 100\% \tag{4}$$

$$\text{Anomaly correction success rate} = \frac{\text{Successfully corrected abnormal picking cases}}{\text{Total abnormal picking cases}} \times 100\% \tag{5}$$

System fault-recovery time is the time between the occurrence of the ErrP and the successful completion of the grasping-parameter recalibration and stable re-grasping.

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Judgment criterion: ErrP recognition accuracy should be 85% and anomaly correction rate should be 80% confirm the strength of the dual closed-loop supervision scheme, within the possible performance range of the current ErrP-based robotic intervention systems [14]. System fault-recovery time is a measure of the entire response time after anomaly occurrence to stabilized re-grasping.

3. Theoretical analysis of agricultural field application & deployment scheme

3.1. Greenhouse, orchard and large-scale unmanned-farm oriented adaptive performance for crop harvesting

Soft robotic harvesting is core to modern precision agriculture, with mainstream application scenarios including greenhouse facility picking, unstructured orchard operation, and large-scale unmanned farm batch harvesting [8]. Current soft gripper prototypes suffer from fixed grasping parameters and poor environmental adaptability, limiting reliable field deployment [6, 9]. This section systematically analyzes the scenario adaptability of the proposed dual-mode BCI control system.

(1) Greenhouse facility harvesting scenario

Greenhouse crops feature thin peel, low structural rigidity and significant individual morphological differences. Conventional soft grippers adopting globally uniform stiffness cannot match crop heterogeneity, easily causing local extrusion and surface damage [13]. The proposed system addresses this issue via MI-BCI offline visual-mechanical calibration, outputting segmented stiffness and stepless grasping force adapted to real-time fruit contours, thereby realizing low-damage precision picking for high-value greenhouse fruits.

(2) Unstructured orchard harvesting scenario

Orchard environments involve irregular fruit growth, inconsistent sizes, random branch occlusion and complex postures [12, 15]. Fixed parameter grasping strategies fail to cope with such unstructured disturbances. The system adopts segmented pneumatic adaptive regulation for contour fitting, while the dormant ErrP-BCI supervision loop is triggered under extreme anomalies including occlusion and mis-grasping. The dual closed-loop structure effectively compensates for tactile loop limitations and improves orchard picking robustness.

(3) Large-scale unmanned farm scenario

Intelligent farms of large scale must be unattended with cyclic operation that is long term in nature. Conventional BCI picking systems are based on real-time operator intervention and regular parameter reconfigurating and limit continuous unmanned operation [8, 9]. The one-time offline calibration scheme that has been proposed, solidifies parameters of visual-mechanical mapping. The BCI module sleeps throughout normal operation, and is triggered during anomaly correction, radically decreasing manual intervention and satisfying large scale autonomous harvesting requirements.

3.2. Modular hardware integration for mobile field-harvesting robotic platform deployment

The majority of soft gripper research merely confirms mechanically laboratory performance and overlooks field lightweight and low-power needs, resulting in low deployability [15]. Traditional BCI harvesting systems have continuous full modules that consume a lot of idle power [16]. This paper suggests a lightweight, modular, energy-efficient hardware integration plan that should be in line with the agricultural robots design specifications.

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(1) Lightweight and physical dimension characteristics.

The whole system comprises EEG recording, RGB-D vision, multi-segment soft gripper and onboard control. It adheres to field lightweight standards [4], is less than 1.2 kg, with a small size of 200 mm x 200 mm x 240 mm, comparable to mobile manipulators and narrow agriculture operating areas.

(2) Visual and touch parameters of senses.

The RGB-D camera has a 0.3-3.0 m working range and a depth accuracy of ±2 mm on agricultural perception [4, 6]. The tactile sensor has a sampling frequency of 100 Hz, which satisfies the accuracy criteria of soft crop gentle grasp and unnecessary computation [9].

(3) The model contains hierarchical parameters of low-power consumption.

Conventional multi-sensor harvesting platforms sustain 8 -12 W full-load power on the field [5]. This work uses task-based dormant control: with a 5.0 V standard voltage, the dormant MI-BCI module restricts the current to at most 160 mA (idle power less than 0.8 W) and standby ErrP-BCI current to at most 100 mA (standby power less than 0.5 W). This the event-based dormancy scheme minimizes idle power loss and enhances field life.

(4) Executive understanding performance parameters.

The multi-segment gripper can fit 30-120 mm diameter crops that include typical greenhouse and orchard crops [4]. The system is in collaboration with dual closed-loop control, to resist the fluctuations of illumination and crop posture bias, so that long-term stable autonomous harvesting can be achieved without having to debug the system now and then.

3.3. Pre-calibration and standardized autonomous harvesting workflow oriented to actual crop production

In unstructured farm environments, the mismatch of the parameters and damage in picking is brought about by a laboratory calibration that does not adapt to individual differences in field crops [4, 11]. Unlike simple theoretical concepts of BCI, in this part, attention is paid to field-adaptive calibration and standard deployment workflows.

In contrast to interference-free laboratory calibration, the suggested pre-deployment training will integrate flexible human grasping habits of irregular field crops, which form exclusive field grasping parameter libraries and discard lab-to-field deviation of performance.

Field operation consists of both pre-deployment calibration and autonomous cyclic picking. Crop features are retrieved by the vision module and segmented grasping parameters are produced by the visual-mechanical model in an adaptive manner. The tactile closed loop provides stable compliant grasping and peduncle separation, whereas the dormant ErrP-BCI module only works to correct extremes, and the gap between training in the laboratory and production of crops in practice is bridged.

3.4. Engineering advantages of human-intention-fused control for practical precision-agriculture harvesting

Current BCI systems of harvesting are mainly based on real-time teleoperation but with a high cognitive burden, which restricts its use in the field [8]. Not many studies combine offline human grasping experience with complete autonomy, without leveraging human manipulation knowledge and eliminating human-in-the-loop reliance [6]. In agricultural harvesting, conventional rigid robots with fixed parameters also result in severe crop damage as well.

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The benefits that could be identified with the proposed framework are the high-profile quantifiable engineering ones. Rigid manipulators (traditional) result in 9%-16% soft crop damage through set grasping thresholds [1, 16]. This system limits the rate of harvesting damages to less than 5 percent by offline learning the flexible grasping properties and adaptive compliant control of human beings [15, 16].

There is a 20%25% rate of manual intervention in complex farm conditions of traditional autonomous and semi-autonomous BCI harvesting platforms [2, 4, 8]. This system does not involve real time human dependence through offline calibration and event-based supervision. Dual closed-loop self-compensation with a reduction of over 75% in the frequency of human intervention and a reduction of over 80% in the frequency of manual intervention results in over 50% of the manual intervention rate.

The hierarchical dual closed-loop design is more robust to the environment: the tactile loop corrects small perturbations of the field and the ErrP-BCI loop overcomes the generalization weakness of pure vision-mechanical control. The system with low-power, modular hardware means low-damage, high-stability unmanned harvesting, which offers a viable engineering prototype on which to base BCI-based intelligent agricultural harvesting applications.

4. Conclusion

This paper proposes a human-intention-driven regional stepless control strategy for variable-stiffness soft grippers in precision agricultural harvesting. A dual-mode BCI system integrating offline MI parameter calibration and online ErrP anomaly supervision is constructed. The visual-mechanical model trained on human grasping experience outputs segmented stiffness and grasping force adaptive to crop features. Combined with tactile closed-loop feedback, regional stepless adjustment of gripper mechanical parameters is realized. The ErrP module only intervenes in extreme anomalies, achieving high-reliability autonomous harvesting without persistent real-time EEG input. This work has limitations including individual differences in EEG decoding accuracy, limited outdoor anti-interference performance of non-invasive EEG devices, and insufficient diversity of crop calibration datasets. Future research will optimize anti-noise decoding algorithms, expand crop sample libraries, and further promote practical field deployment of human-intention fused soft robotic harvesting systems.

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