Toward Human-in-the-Loop Shared Control for Upper-Limb Prostheses: A Systematic Analysis of State-of-the-Art Technologies

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***Abstract*—Dexterous prosthetic hand is an essential rehabilitation assistant device to improve the life quality of amputee patients. Despite the continuous emergence of commercial prostheses and laboratory prototypes, the rejection rate remains high caused by the poor neural interaction performance and excessive cognitive burden, especially for the usage of upper-arm prostheses controlled by above-the-elbow amputation stump. The progress in artificial perception, bidirectional neural interface and share control indicates a great potential to improve the manipulation efficiency of upper-limb prostheses. In this review, a comprehensive analysis of human-in-the-loop shared control studies is presented to provide researchers with a systematic technical route in upper-limb prostheses control. The latest avenues of research concerning myoelectric control, sensory feedback, perception, autonomous motion planning of multiple degree of freedom elbow-wrist, and share control are overviewed and discussed. The comprehensive assessments show that there remains inadequate technologies to achieve an anthropomorphic and efficient unified elbow-wrist-hand prostheses manipulation. By delineating the current shortcomings, the outcomes of this work highlight future investigation in the field of intuitive motion control, feedback of proprioception/touch and the natural interaction between human intent and machine autonomy.**

***Index Terms*—Myoelectric prostheses, share control, human-in-the-loop, sensory feedback, autonomous grasp planning.**

I. Introduction

There is a great significance to use bionics methods to create prosthetic hands to help amputee patients with capabilities replication of human hands. The myoelectric prosthesis first appeared in the middle of the 20*th* century [1], [2]. It records and translates the surface electromyography (sEMG) on the amputation stump into commands to realize the direct neural control on the mechanical body of the prosthesis. In recent years, with the development of engineering technologies, the dexterity of humanoid prosthetic hands and the performance of integrated sensors have been continuously improved [3], [4], [5], [6]. However, the neural control interface and human-machine interaction performance of prostheses are inadequate to match dexterous operation [7], [8]. The neural interface often cannot simultaneously achieve high bandwidth and long-term stability, let alone cope with various amputees [9], [10]. Particularly for the control of upper-arm prostheses with an elbow joint, there exists a contradiction between the multiple degrees of freedom (DoFs) including elbow-wrist-hand joints and the limited control signals due to high position amputation.

Specifically, there are two main restrictions in prostheses control. Firstly, the cognitive and manipulation burden for amputee patients is troublesome. The existing paradigm of prosthetic hand control usually involves switching between multiple states and complicated feedback patterns [11], [12], which causes heavy cognitive burthen to prosthesis users. During the process of prosthetic hand approaching and grasping, the amputee needs to pay close attention to finely adjust the elbow-wrist-hand pose and grasp gestures [13], [14]. Due to the functional degeneration of the patient's stump nervous system, limited control signal sources, time-shift characteristics of sEMG signals (such as electrode shift, muscle fatigue, contact impedance changes, etc.), interference caused by movement artifact, patients need frequently retrain the prostheses controller to maintain intention recognition accuracy [15], [16], [17], [18], [19]. Moreover, proprioception of touch and motion sensation of prosthetic hands are rarely provided to amputees, and the visual sense is thus occupied in the whole process of prosthetic operation [20], [21], [22]. The rapid response and reflex control commonly seen in human hands are hard to mimic without sensory information of the environment and low-level controllers, which makes the simple task of preventing objects from slipping a challenge to the existing prosthetic hands [23], [24]. Secondly, the grasping movement of prostheses is not consistent with the behavior of intact limb. The prosthetic hand generally adopts envelope grasping or a few fixed grasping gestures, which can only manipulate objects with simple geometric shapes, and it is difficult to form a natural envelope for objects with different shapes, stiffness and weights [25], [26]. Users have

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to actively adjust the orientation of the stump to increase the success grasp rate due to limited grasp gestures. Especially for patients with upper arm amputation, the elbow, wrist and hand grasping movements of prosthetic limbs are discrete with each other, and the requirement for natural and smooth anthropomorphic grasping trajectory is difficult to meet [21], [27].

The abovementioned problems are inherent defects of inadequate information transmission in the neural interaction system of artificial limbs, hence, we argue that combining the neural interface and machine intelligence to form a human-in-the-loop shared control provides a promising solution. The ideal dexterous prostheses should meet the requirement of patient's daily life, and two closed loops should be constructed. The first loop is a bidirectional human-machine interface (HMI) [28], which decodes the patient's motion intention through neural signals, and uses mechanical or electrical stimulation to feedback the status information of the prosthetic hand to the amputation stump in real time. The second is the closed-loop within prostheses. By integrating multi-modal perception of vision, touch and other sensors, the prostheses can autonomously realize the planning and control of part or all of the elbow/wrist/hand joints, reducing the cognitive and operational burden of patients. Previous studies show that the fusion of visual and tactile sensing is expected to be used for autonomous operation planning of humanoid robotic arm [29], [30]. Additionally, the tactile perception of prostheses can improve the interaction between the patient and the physical environment to improve the control ability [21], [25], [31], [32].

To achieve the dexterity of humanoid upper-limb prostheses through share control, the fusion of robot autonomous manipulation planning and bidirectional HMI technologies should be investigated. Furthermore, perception on the prostheses close-loop concerning operation environment, the physical properties of target objects, as well as the man-machine shared strategies are yet to be explored. The framework of human-in-the-loop shared control for upper-limb prostheses is illustrated as Fig. 1. There is a clear requirement for comprehensive approaches to bridge the sharing gap of human and machine. This review focuses on the following issues: 1) the motion intention-perception bidirectional neural pathway, 2) multi-modal vision/touch/proximity perception to realize the optimal autonomous grasp planning of elbow/wrist/hand joints, 3) the sharing and cooperation mechanism of human and machine. The purpose of this review is to shed light into the state of the art in human-in-the-loop shared control technologies, with implications for improved prostheses manipulation. We hope that this review provides a clear perspective and future prospects in the field of prosthetic hands research. The rest of this paper is organized as follows. The bidirectional neural pathway of prostheses including myoelectric control and sensory feedback are described in Section II, and multi-modal perception are systematically summarized in Section III. Subsequently, Section IV presents the automatic pre-grasp planning and share control of upper-limb prostheses. Finally, Section V concludes the paper by remarking on open challenges and future directions.

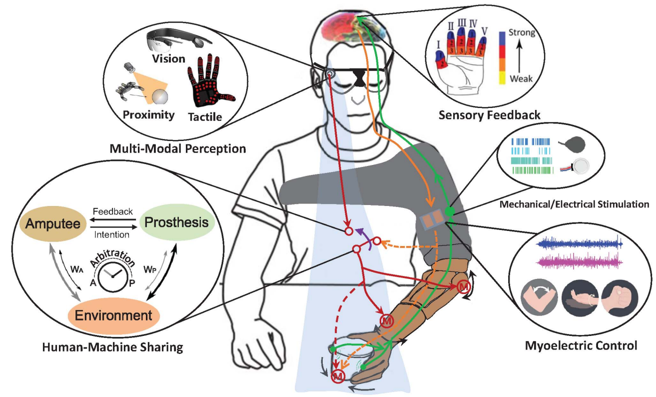

Fig. 1. General framework of the human-in-the-loop shared control for upper-limb prostheses. The motion intention is translated by sEMG signals detected with electrodes, subsequently, automatic or semi-automatic pre-grasp planning is performed through multi-modal vision/touch/proximity perception. The grasping can be controlled by sEMG signals or machine autonomy. The touch events are recognized by sensors integrated in prosthetic fingertip and are relayed to amputation stump via mechanical/electrical stimulation to activate neurally touch receptors. The sharing strategies between myoelectric control and prosthesis autonomy can be adjusted according to operating environment.

II. Bidirectional Neural Pathway

A. Myoelectric Control for Upper-Arm Prosthesis

The myoelectric prosthesis control technology has made great progress in the past 70 years, and a number of sEMG based control technologies have been introduced, including finite-state-machine (FSM) model, pattern recognition (PR) method, and simultaneous and proportional control (SPC) of multiple DoFs [33], [34]. These methods study how to extract features from sEMG signals and establish the matching relationship between signal features and kinematics of prosthesis through training with large samples and machine learning algorithms. Fig. 2 illustrates and compares the signal processing schema of the three myoelectric control paradigms for upper-arm prosthesis in a typical daily task (*i.e.*, grasping a mug from the table and transferring the mug to a higher position cabinet). The amputee performs the task by controlling the function of elbow, wrist and hand, *i.e.*, elbow flexion or extension, wrist rotation (pronation or supination), hand close or open, as shown in Fig. 2 (d).

The FSM control method (Fig. 2 (a)) uses two sEMG signals from two independent muscles, with each muscle controlling one direction of a certain DoF of prosthetic joints. The controlled DoF can be switched from one to another adjacent when the two muscles are activated simultaneously. Obviously, the limitation of FSM method is that when manipulating complex multi-DoFs operation tasks, the amputee needs a lot of forced training and the switching procedure of the prosthesis DoFs is time-consuming. Grounded on reproducible and discriminative sEMG signal patterns, the PR method (Fig. 2 (b)) is more intuitive than FSM and avoids switching between DoFs. The current most advanced sEMG PR based framework yields a recognition rate of more than 95% for 10 predefined motions under laboratory conditions [35]. However, PR technology can only identify preset discrete action pattern, which is inconsistent with the continuous and multi-DoFs

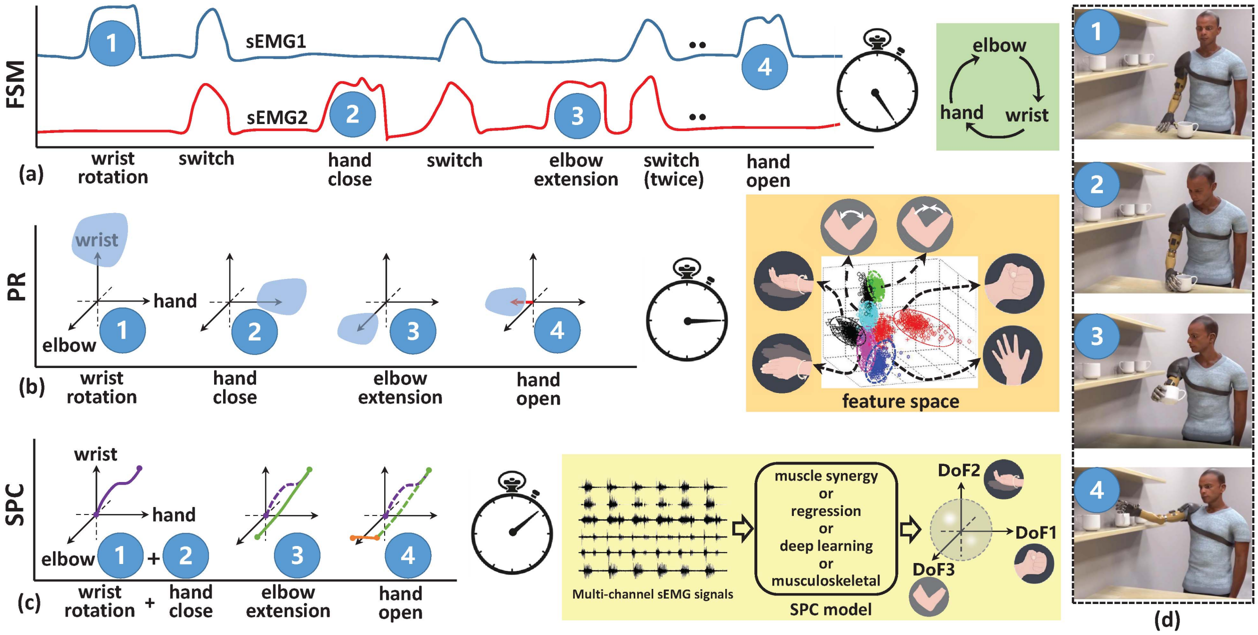

Fig. 2. Schematic diagrams of three myoelectric control technologies in typical daily manipulation scenarios using upper-arm prosthesis with elbow/wrist/hand joints: (a) finite-state-machine (FSM) based control; (b) pattern recognition (PR) method; (c) simultaneous and proportional control (SPC) for multiple DoFs; (d) the typical daily operation, *i.e.*, grasping a mug from the table and transferring the mug to a higher position cabinet [21]. From left to right in (a)-(c), they are the controlling process of multiple DoFs, the time required (the clock symbol) to complete the operation in (d), and an illustration of corresponding controller. In the FSM case, the three DoFs including elbow/wrist/hand joints are controlled by two-channel sEMG signals (sEMG1 and sEMG2), and the sequential switching between DoFs is performed by cocontraction. The feature space of predefined motions is illustrated in (b), and with PR approach, the same task is carried out through selecting discrete motions in sequence. More naturally and faster, the SPC allows the combination of multiple DoFs via a three-dimensional vector space.

cooperative motion control habits of human body. Therefore, the movement mode of PR control prosthesis is also unnatural and the operating efficiency is low [36].

Compared with FMS and discrete PR control, SPC (Fig. 2 (c)) allows to control the continuous movement for multiple DoFs of upper-arm prosthesis, which is closer to the natural operation of human beings. Jiang et al. made a pioneering work for SPC [37], seeking the synergistic factor of multi-channel sEMG signals through the non-negative matrix factorization (NMF) algorithm, and transforming the sEMG signals into the simultaneous and proportional torque prediction of three wrist DoFs. Subsequently, Farina et al. used regression analysis to achieve online simultaneous and proportional control of a two-DoF forearm prosthetic hand [17], and verified the manipulation performance by amputees in real life scenes, which promoted the clinical application of SPC method. To date, most of the myoelectric SPC researches are based on statistics, aiming to establish the mapping relationship between sEMG features and continuous kinematics parameters through deep learning [38], matrix factorization [39], regression model [40], musculoskeletal model [41], etc. Additionally, the feasibility of motor unit action potential trains (MUAPt) decomposed from high-density sEMG signals in the estimation of wrist/hand kinematics with multiple DoFs has been preliminarily validated [42], [43].

Despite the promising research results of myoelectric control, it is still a great challenge to operate multifunction prostheses. Due to the loss of stump muscle tissue and functional degeneration of the nervous system, there are few available sEMG signal sources, and the performance of myoelectric is limited [44]. In PR scenario, an error recognition would lead to unexpected motion and frequently adjustment for the movements of prosthesis maybe indispensable, the prosthetic users are thus frustrated. Furthermore, it is almost impossible to carry out SPC for high level limb deficiencies, since the nerves innervating the wrist and hand are missing, despite in the case of targeted muscle reinnervation (TMR) [45]. Therefore, how to improve the autonomous ability of upper-arm prosthesis and reduce the control burden of patients is crucial to ensure the dexterous and stable manipulation.

B. Sensory Feedback of Neural Prostheses

For amputees, the loss of tactile and proprioception makes it difficult to sense the interaction with the environment as well as to naturally control their artificial limbs. Sensory feedback is considered as an effective way to improve users' control capability over upper prostheses and provide amputees with a sense of body ownership [10]. Its essence is to transfer the somatosensory information of prosthetic hands to amputees through stimulation encoding. In the past ten years, to deliver modality-matched feedback like the natural perception path, developments in stimulation forms and information encoding have been made. Here, we mainly review three types of feedback techniques: vibro-tactile, electro-tactile as well as invasive nerve stimulation, as illustrated in Fig. 3.

Vibro-tactile feedback is produced by deploying a set of vibrators on the target skin and has been used to deliver information about contact event [12], grasp force [46], object stiffness [47], and surface texture [48], [49] via modulating

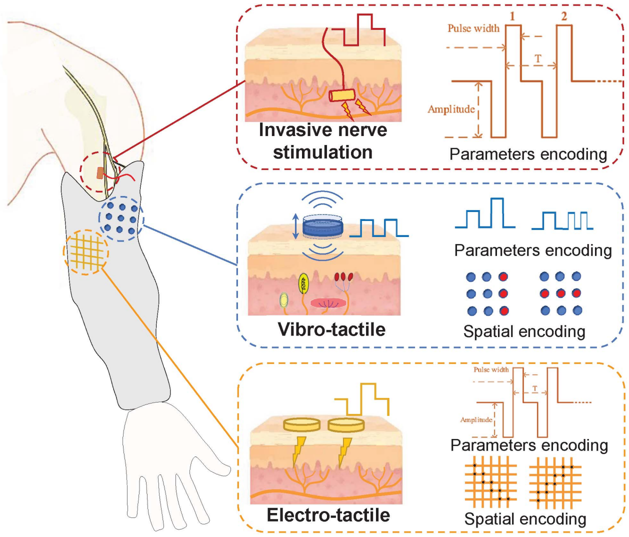

Fig. 3. Sensory feedback of somatosensory information of prosthetic hand to amputation stump via stimulation encoding including invasive nerve stimulation, vibro-tactile and electro-tactile.

the frequency and amplitude. Closed-loop force control can be implemented by modulating the amplitude and frequency of vibrations proportionally to the contact force [46]. Because of limited adjustable parameters, multi-channel vibro-tactile devices have been developed to increase the bandwidth of feedback. Distributed contact force and geometry can be conveyed via spatiotemporally programmable patterns of localized mechanical vibrations [50], [51]. The spatial and vibration parameters mixed encoding strategy has also been studied to achieve multiple information feedback [52]. Besides, the proprioception sensation regarding the joint position and movement of the finger can be successfully elicited via amplitude and position mixed modulation of a vibrator array [53]. However, vibro-tactile feedback still has some limitations. The stability of vibration stimulation is influenced by variations of stimulation location, ever-changing threshold, contact stress and cognitive ability across subjects. Additionally, the single modality of vibration and stimulation delay may not meet the requirements of modality-matching in continuous contact situations. Despite the abovementioned limiting factors, we still suggest that vibro-tactile feedback can enhance the grasping performance of prostheses.

The electro-tactile stimulation, also referred to transcutaneous electrical nerve stimulation (TENS), is considered as a plausible non-invasive way to restore somatosensory sensory feedback [54], [55], [56]. It uses surface electrodes to convey encoded electrical signals through the skin and indirectly activate underlying sensory nerves. TENS has been extensively adopted because of the advantages of fast response, low noise and multiple adjustable stimulation parameters (*e.g.*, pulse amplitude, pulse width and frequency). Multiple kinds of finger-specific tactile sensations (such as pressure and vibration) have been elicited via TENS [57], [58]. The features (*e.g.*, shape, size and stiffness) of a grasped object can be conveyed by encoding in both the TENS position and amplitude [59], [60]. Besides, evidence suggests that TENS can induce a sense of perceptual embodiment in amputation stump [61], and close-to-natural finger sensations can be elicited by stimulating the phantom finger map [62]. In addition, researches on multi-channel TENS have been performed to investigate how the induced sensation changes over the time interval between stimulation of two adjacent channels, the number of channels and pulses, and the position of electrodes, providing guidance for parameter and pattern selection of sensory feedback [63]. However, the implementation of closed-loop prosthesis equipping electro-tactile feedback still faces several unsolved issues, such as skin impedance fluctuations and the miniaturization of stimulation device [64]. Generally, electro-tactile feedback is a potential approach for the sensory restoration of neural prostheses.

Since the elicited sensations are delivered in the form of action potentials, it is possible to restore somatosensory feedback via directly stimulating the sensory afferent nerve of amputees. Recent representative progress has demonstrated that near-natural proprioception and tactile can be provided by invasive neural technologies at various peripheral levels [65], [66]. Raspopovic et al. [67] and Tan et al. [68] restored the sensory feedback by directly stimulating the peripheral nerves of amputation stump through implanted electrodes, respectively. They verified that peripheral nerve stimulation could provide effective sensory feedback to amputees during a variety of functional grasping tasks. Direct nerve stimulation could also induce close-to-natural tactile and slippage sensations, which are vital for significantly improving manipulative skills with the prosthesis [69]. It seems that the invasive approach can provide intuitive sensory feedback, which allows for finely tuning the applied stimulus in line with a lower cognitive load [70]. However, comparing to non-invasive approaches, the invasive way is still limited to case studies due to the risk of implantable surgery and electrical stimulation in the body. The implanted electrodes as foreign objects within the body would provoke an inflammatory response in the tissue. Possible tissue damage would be induced by electrical stimulation within the body, including hyperactivity of neurons depleting metabolic fuels, excessive formation of toxic electrochemical reaction products creating free radicals, and so on [71]. It is therefore difficult to apply to a large number of amputee users under the inextricable challenges (*e.g.*, surgical risk, biological compatibility and stability) [55].

III. Perception on Prosthetic Hand for Closed-Loop Control and Sensory Feedback

The perception of the hand is irreplaceable for humans to interact with the external environment. It synergistically perceives multi-modal information (*e.g.*, pressure, shape, temperature, etc.) to achieve precise control of interactive motion and a comprehensive understanding of manipulation objects. For the study of upper-limb prostheses or dexterous hands, reconstructing part of perception abilities has always been a hot pot of attention. In this section, we summarize the sensor work that has been achieved or is potentially available on prostheses, and mainly focus on the progress of necessary perception around the proposed human-in-the-loop framework, as shown in Fig. 4.

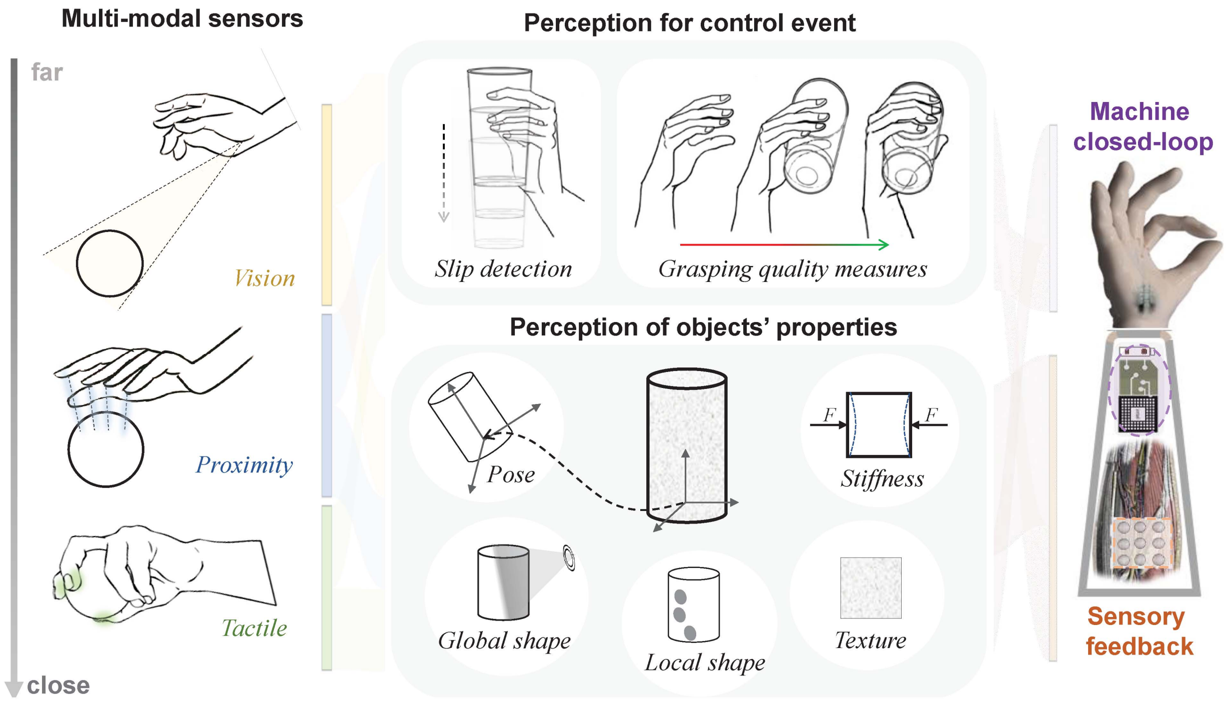

Fig. 4. Multi-modal perception of prosthetic hand for closed-loop control and sensory feedback. From the standard of distance between the prosthetic hand and the target object, perception is divided into vision, proximity and tactile sense. Furthermore, the output of multi-modal sensors can be used for the perception of control event such as slip detection and grasping quality measurement, as well as the perception of objects' properties including pose, stiffness, global shape, local shape and texture.

A. Multi-Modal Sensors on Prosthetic Hand

Various types of sensors (*i.e.*, vision, proximity and touch) have been attempted to integrate into prosthetic hands for multi-modal perception. In contrast to the dexterous hand, the usage of multi-modal sensors on prostheses has more wearable limitations, such as weight, wiring, outlook and comfort. Tactile sensing is an essential modality for acquiring physical information about surroundings (*i.e.*, pressure, shear force, temperature, contact geometry, etc.) and plays an important part in prosthetic grasping manipulation. To date, researchers have proposed diverse biomimetic structures and transduction mechanisms (*i.e.*, capacitive, resistive, barometric, optical, etc.) to obtain high-performance tactile perception similar to biological skin [72], [73]. Detailed sensing principles, fabrication methods and transduction design of flexible tactile sensor have been extensively reviewed in [74]. These contact data not only can directly assist to adjust the grasp force but also can be interpreted to extract contact events (*e.g.*, collision and slippage [75]) or material properties of interaction objects for sensory feedback [76]. For example, multi-dimensional force sensors [77] or high-density tactile arrays [78], are usually deployed at the fingertips to detect the closure of the grip [79] while some have been extended to the palm or whole hand of robotic hands to sense more complicated contact details [80], [81]. Although advanced tactile electronic skin has been able to meet needs of high-resolution and multi-modal sensing to some extent [82], the requirement of durability limits the use of these state-of-the-art electronic skins in prosthetics. To integrate into the prosthesis a necessary multi-modal tactile perception system is still an urgent need for future prosthetic systems [83]. In the future, with the development of array feedback technologies and semi-autonomous prosthetic control, the increased demand for information may further drive the integrated coordination design and application of tactile sensing.

Visual sensors have been widely used on prosthetic hand systems to achieve semi-autonomous control [84], [85]. Complementary vision can provide critical input for the perception of the object's location, size, and shape as well as the relative motion state [86]. It enables the prostheses controller to predict the grasped target, plan an appropriate reach and grasp strategy, select the appropriate gesture, and allow closed-loop corrections for better motion adaption [87], [88]. This would greatly reduce the amputee user's burden of gesture switching and grasping control. Researchers have tried to embed a small red-green-blue (RGB) camera in the palm [89], [90] or arrange commercial cameras such as Realsense or augmented reality (AR) glasses on the back of the hand [91], wrist [92], forehead [84], to achieve an eye-in-hand or global perspective [93]. The advantage of visual sensors is that they can obtain denser environmental scene information. Nevertheless, its application in prosthetic hands is mainly affected by obstacles such as integration, frame rate, occlusion and signal processing complexity.

Proximity sensors are considered to fill the gap between visual and tactile perception [94], [95]. They are usually used to detect relative distances and local geometric relationships in the visually occluded region [96]. Various proximity sensor forms, such as optical [97], capacitive [98] and inductive [99], have been widely studied to serve different proximity-sensing targets. Multi-site proximity information can provide real-time relative geometry to the controller for a stable and symmetrical grip. For example, Koyama et al. [100] arranged optical proximity array on the robotic fingertips and achieved symmetrically grasping for different objects synchronously. Hansen et al. [101] explored the effect of prosthetic collision avoidance during the grasping process by arranging proximity sensors on prosthetic fingertips. In addition, it indicated that pre-shape quality had a coherent effect on grasping quality and slippage probability [102]. Acquiring relative geometry information before contact would contribute to evaluating the pre-shape quality for proper adjustment of the finger state.

To achieve more comprehensive perception and intelligent control, multi-modal sensor fusion is the trend of dexterous hand perception. For example, the combination of vision and tactile sensing can provide more precise geometry information about the object [103]. Proximity and pressure dual-mode sensor arrays have been developed for continuous grasping perception [104], [105]. Besides, we also notice some promising sensors works that may be available on the prostheses, such as visuo-tactile sensors [106], multi-modal tactile electrical skin [73], etc. These more capable sensors will further enhance the anthropomorphism of prostheses function, however, there is still some gap from applying these technologies to five-fingered prosthetic hands.

B. Perception for Prosthesis Control

For upper-limb prostheses control, it is challenging to directly modulate an appropriate grip force and pre-shape for various objects. Inadequate grip force or closure may cause an unstable grasp and slippage. Humans can sensitively perceive the instabilities by tactile sensing and react to grasp tightly [107], while amputee users must rely on visual feedback to grasp objects. Once the slippage happens, the grasp result is often irreversible. Therefore, the abilities of slip detection and grasp quality measures are expected to achieve reactive control for stable manipulations. In this part, we mainly focus on event-level perception methods for slippage and grasp quality measurement, as outlined in Table I.

1) Slip Detection: The current approaches for slip detection are mainly classified into four types: vibration-based, friction model-based, contact relationship-based, and data-driven method. When slipping happens, the diverse shape and textures of the grasped objects would introduce a vibration of contact force [75]. Hosoda el al. [108], [109] built an elastic finger with a dynamic force sensor (PVDF film) embedded to detect this change. Sharp jitters in the PVDF film signal were thought to imply that slippage had occurred. Besides, time-frequency domain analysis methods, such as short-time Fourier Transformation (STFT) [110], discrete wavelet transform (DWT) [111], [112], empirical mode decomposition (EMD) [23] can also be used to detect the high-frequency vibration of normal force. In addition to vibration characteristics, the ratio of tangential to normal forces (the friction coefficient) would abruptly change at the moment of slipping [113], [114]. For example, Song et al. [115] achieved the identification of friction properties through haptic surface exploration and built break-away friction ratio-based method to detect slip.

Recently, the development of optical (*e.g.,* TacTip [130]) and visuo-tactile sensors (*e.g.,* GelSight Series [106], [131]) has provided researchers with more contact information at the interaction surface. The contact displacement and the change of force distribution are directly related to the slippage. Yuan et al. [116] and Dong et al. [117] successfully measured slip based on the movement on the membrane surface of the Gelsight sensor and James et al. [118] achieved high-accuracy slip detection by the movement of local pins embedded in TacTip's compliant skin. Furthermore, with high-resolution dense tactile information, data-driven methods such as support vector machine (SVM) [119], deep neural network (DNN) [120], long short-term memory (LSTM) network [121], and conventional LSTM [122] are widely used to predict the occurrence of sliding. However, these data-driven approaches are very sensitive to training data, and it is still difficult to consistently collect large volumes of data.

2) Grasping Quality Measurement: Apart from slip detection, researchers have presented many approaches to measuring the grasp quality so as to prevent slippage. In the early stage, analytic methods (*e.g.*, form closure, force closure and hand configuration approaches) are used to estimate grasp quality [123], [124]. The analytic approaches are highly dependent on the geometric and physical models of an object as well as the kinematic model of the hand, which is not available in actual grasping. Learning-based grasping quality prediction methods are popular in recent years. For example, Cockbum et al. [125] used an unsupervised feature learning algorithm to improve the SVM classifier for grasp quality prediction. Hogan et al. [126] combined the GelSlim sensors with a deep convolutional neural network (CNN) and constructed a tactile-based grasp quality metric. Garcia-Garcia et al. [127] presented a graph convolutional network (GCN) to predict grasp stability by leveraging graph-like representations of tactile data.

Visual information as well as proprioception are also useful in grasping quality measurement, and researchers have developed sensory-fused methods to evaluate grasp stability. Kwiatkowski et al. [128] used a CNN to learn from tactile and proprioceptive data, and Calandra et al. [30] presented multi-modal convolutional networks to predict the grasp quality by tactile-visual information. Liang et al. [129] proposed a PointNetGPD to localize grasp configurations from the point clouds and evaluate grasp quality. These studies indicate that multi-modal information has a complementary effect on grasp assessment. Besides, Spatio-Channel-Temporal Attention mechanisms [132], [133], as well as ensemble learning [102], have been used to overcome the problems of redundant tactile information and grasping-lifting interconnected action phases, respectively.

C. Perception of the Objects

The human can simultaneously obtain the shape and pose of the object by vision, and perceive the detailed physical properties by tactile sensing. Two types of information work together

TABLE I
SUMMARY OF PERCEPTION FOR CONTROL EVENT WITH REGARD TO SLIP DETECTION AND GRASPING QUALITY MEASUREMENT

Perception event	Approach type	Sensors forms	Detection methods	Literature
Slip detection	Vibration-based	Dynamic force sensors (PVDF film)	Signal sharp change	[108], [109]
		Pressure sensor arrays	Time-frequency domain analysis	[23], [110]–[112]
	Friction model-based	Three dimensional tactile sensors	Friction ratio change	[113]–[115]
	Contact relationship-based	Optical or visuo-tactile sensors (TacTip/GelSight series)	Contact displacement	[116]–[118]
	Data-driven	Multi-modal or visuo-tactile sensors (BioTac/GelSight series)	SVM/DNN/LSTM/Conv-LSTM	[119]–[122]
Grasping quality measurement	Analytic	Tactile/visual sensors	Form closure or force closure	[123], [124]
	Data-driven	Multi-modal or high-spatial resolution tactile sensors	SVM/CNN/GCN	[125]–[127]
		Tactile and visual sensors	CNN/PointNetGPD	[30], [128], [129]

[1] PVDF: polyvinylidene fluoride; TacTip: tactile fingertip; SVM: support vector machine; DNN: deep neural network; LSTM: long short-term memory; Conv-LSTM: conventional LSTM; CNN: convolutional neural network; GCN: graph convolutional network.

to build the complete cognition of external objects. Though most prosthetic users still retain visual feedback, applying this perception to the dexterous manipulation is a daunting task. Moreover, since the loss of tactile sensing ability, amputees are unable to recognize the physical characteristics of objects, which brings a severe cognitive burden. Thus, estimating the state and properties of the target objects is a key part of reconstructing the manipulative and perceptual abilities for amputees. The representative works with respect to the perception of object's properties are summarized as Table II.

1) Pose and Shape Perception: To acquire a reliable grasp gesture in the preshape phase, upper-limb prostheses need to acquire the pose and shape of the objects. Additional vision or tactile exploration methods have been used to estimate probabilistic models of the pose and shape. With a camera on the prosthetic hand or on the head, shape information and 6D pose of objects can be calculated through analyzing the sequential image [84], [86], [89]. However, vision sensors would fail in visually occluded situations when close to the target [147]. For example, in first-person perspective, the hand partially overlaps with the object as the hand approaches the object, making it difficult to estimate the relative pose between the hand and the object. As for the eye-in-hand system, due to the limited field of view distance, image defocus and the loss of object target would occur during the approach process. Tactile sensing is especially useful in such situations and plays a complementary role [134]. By touching the surface, the perception of contact geometry including positions and normals of surface patches, can be used to estimate the local shape [135]. The global shape of the target object also can be obtained by multiple tactile exploration [103], [136], [137], [138]. Recently, proximity sensors or depth sensors are studied to detect objects' local geometry with the advantages of non-contact and data sparsity [88], [95]. They can provide additional multiple frames of relative distance data before touch, which can be used to estimate the local shape and pose in the absence of vision [139].

2) Perception of Material Properties: Interactive tactile sensing allows artificial hands to perceive the material properties of objects. Researchers have defined 15 different properties of objects using tactile information [148], of which we suggest that stiffness, temperature, and surface texture are the key perceptual information for prosthetic operation and sensory feedback. Stiffness is useful for grasping force modulation and can be acquired by measuring the displacement with the finger pressing on the object at a specified contact force [140], [141] or analyzing the contact angle of the fingertip sensors [142], [143]. The temperature information can be measured by thermal-sensitive elements (*e.g.*, thermistor [144]), and is often used in our daily life, such as determining the temperature of water in the cup or avoiding getting burned. For prosthetic users, thermal tactile sensing can be combined with feedback devices to help them classify objects [49]. Surface texture is an important cue for differentiating among materials. The perception of texture relies on the analysis of time series signals generated by tactile sensors (*e.g.*, Biotac) when sliding across objects' surfaces [145]. Various frequency-domain analysis methods and diverse classifiers, such as K-nearest-neighbor (KNN) algorithm and recurrent neural networks (RNNs), can be used to capture abstract temporal features and classify the different textures [142], [146].

TABLE II
PERCEPTION OF OBJECT'S PROPERTIES INCLUDING POSE, GLOBAL/LOCAL SHAPE, STIFFNESS, TEMPERATURE AND TEXTURE

Perception content	Information	Sensors	Methods	Work
Pose and shape	6D pose	Visual (head or hand)	Point cloud registration	[84], [86], [89]
		Tactile	Tactile exploration	[134], [135]
	Global shape	Visual (head or hand)	3D reconstruction	[103], [136]–[138]
	Local shape	Proximity/tactile	Pre-shape or tactile exploration	[88], [95], [139]
Material properties	Stiffness	Tactile and proprioceptive	Press	[140]–[143]
	Temperature	Thermal tactile	-	[49], [144]
	Texture	Tactile	Frequency domain analysis and classifier	[142], [145], [146]

IV. PRE-GRASP PLANNING AND SHARED CONTROL OF UPPER-LIMB PROSTHESES

The bidirectional neural interface helps to integrate the amputee into human-in-loop hand prostheses via designing a myoelectric control and feedback stimulation strategy. However, the efficiency and quality of task completion are still miles away from intact human hands [149]. Beyond trying to reconstruct the motor control and sensory feedback neural pathways for amputees, researchers have begun exploring additional sensory information and control algorithms to integrate a higher level of autonomy into the prosthesis system. The autonomous motion planning of prosthetic elbow/wrist/hand joints inspired by the progress in robotics will be discussed in this section, combined with literature analysis on the pre-shape planning and grasp control of prostheses.

A. Integrated Planning of Robotic Arm and Hand

As the existing grasping methods in prostheses control are still far from state-of-the-art practices in robotics, the robotic researches in industrial scenarios have great potential to migrate to rehabilitation field to help develop next generation of smart prosthesis. In robotics, grasp planning can be roughly divided into optimization-based and learning-based methods. Previous works have achieved significant progress in grasping known objects using an analytical approach that explicitly models the interaction between the object and the hand.

1) Optimization-Based Grasp Planning: The optimization methods are proposed to find optimal hand configurations that can immobilize the object by balancing any external force, such as the metric in [150]. While optimization algorithms using grasp quality metrics can generate theoretical optimal grasps, recent works focus on improving the efficiency of the optimization process. Liu et al. [151] assumed zero contact friction to simplify the force-closure criteria, and [152] penalized the distance between the fingertip and the object surface to relax the contact constraint for faster grasp synthesis. Schulman et al. [153] used a simple support function to fit the largest-minimum resistible wrench. Moreover, a dual-stage iterative optimization strategy was proposed to search separately for the palm and the finger configuration in [154], [155]. Researchers also explored object geometry and demonstrations to narrow the scope of grasp synthesis. Jain and Argall [156] approximated objects into primitive shapes before using heuristic rules to generate grasp candidates. In [157], Kiatos et al. presented a power grasp planning method based on heuristic rules using local geometry features. Subsequently, the shape complementary metric that penalized the distance between the gripper points and the object points was used to refine grasps further. The optimization-based method can usually produce precise wrist and finger joint angles for complex-shaped objects.

2) Learning-Based Grasp Planning: Learning-based grasp planning methods have gained more popularity in recent years. These methods train a network using annotated grasp datasets collected in actual or simulated environments. Then the network is used to predict grasp directly from raw sensor input [158], [159]. However, most works use parallel grippers instead of the multi-fingered hand, despite the latter having higher dexterity. It is probably due to the simplicity of generating training data and small DoFs with parallel gripper [86], few works focus on the multi-fingered hand. Varley et al. [160] trained a network to take RGB-D images as input to predict contact points and used a grasp planner to refine the finger configurations of multi-fingered hand. Shao et al. [161] proposed a similar method composing a multi-stage model that predicted one contact point at each stage and an inverse kinematics solver. Liu et al. [162] trained a network that directly regressed an anthropomorphic hand's grasp from a voxel grid. Additionally, Lundell et al. [163] presented a viewpoint-independent generative model that took RGB-D images and a fixed grasp orientation as input to predict hand configurations. In [164], Wei et al. trained a variational grasp generator and an iteratively refined module on 1.5M annotated grasps. Learning-based methods can predict multi-fingered grasps more quickly than optimization-based methods, making them applaudable in real time. However, the learning-based method usually requires a massive dataset with millions of grasps, and the generalizability to novel objects and grippers is weaker than optimization-based methods.

3) Integrated Grasp and Motion Planning: The integrated grasp and motion planning provides automatic control for

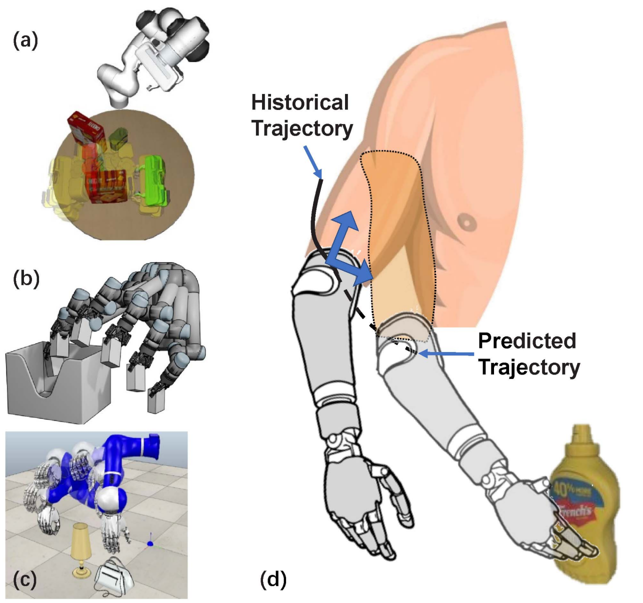

Fig. 5. Inspiration from the integrated grasp and motion planning in the field of robotics research for the shared control of the upper-arm prosthesis: (a) manipulation trajectory optimization with online grasp synthesis and selection [165]; (b) accelerated grasp-optimized motion planning based on deep learning [166]; (c) multimodal trajectory optimization for motion planning and reaching the goal configuration (bag grasping task) without collision [167]; (d) automatic trajectory prediction and replanning during the manipulation of upper-arm prosthetic hand.

Fig. 6. Connection and focus of different research areas including rehabilitation engineering and computer vision in the pre-shape planning problem of prosthetic hands.

the trajectories of robotic arms and the grasp of artificial hands, which brings enlightenment for the shared control of the upper-arm prosthesis, as shown in Fig. 5. In 2007, Berenson et al. established an offline grasp dataset for the target object [168]. They then used a path planning method to filter collision-free grasps. Fontanals et al. optimized the grasp gestures and the path online to explore larger hand configuration space for better performance [169]. They modified the rapidly-random exploring tree (RRT) algorithm to sample the coarse gestures and refined the grasp online according to a grasp quality metric. With the rapid development of machine vision, integrated planning has gradually moved toward real-world experiments. Haustein et al. further improved the efficiency of the algorithms by using RRT-Connect to speed up motion planning [170]. Wang et al. first generated a set of grasps for the object (Fig. 5 (a)), then selected the appropriate grasp gesture online according to the reachability [165]. In 2020, Ichnowski et al. used a neural network to predict the contact points of the gripper, then optimized the trajectory (Fig. 5 (b)) and final grasp gestures for a fast and collision-free path [166]. To achieve trajectory optimization for motion planning, Osa proposed a framework that determined multiple trajectories (Fig. 5 (c)), which enabled selecting a preferable solution from multiple candidate trajectories of robotic arm and hand [167]. All the existing integrated planning research assumes a static environment in which the objects and the obstacles are stationary. Therefore, most integrated planning methods do not have online replanning ability. For the upper-arm prosthetic hand with a floating base, the online trajectory prediction and replanning of the elbow/wrist/hand joints is required (Fig. 5 (d)). The migration of existing robotic planning algorithms to prostheses still faces many challenges, such as faster motion/grasp planning based on multi-model perception.

B. Vision-Guided Pre-Shape Planning of Prosthetic Hands

The goal of pre-grasp planning is to adjust the prosthetic hand and wrist joint angles according to the object's geometry to achieve a robust grasp. Traditionally, the identification of possible grasp gestures is mainly accomplished by prosthesis users via sEMG interface. However, the process can be significantly affected by individual differences. To achieve pre-grasp planning, the overriding objective is to make the automation component understand human's intent. From a top-level decision-making perspective, the automation component needs to complete tasks including action recognition, prediction and scene understanding. Recent studies show that the goal of predicting the object and the body's intention can be achieved by installing visual sensors on the prosthetic hand, thus increasing the possibility of flexible operation with the help of semi-automatic control [171]. There are two classification criteria for relevant work in this field: 1) Research areas: rehabilitation engineering and computer vision; 2) Approaches: end-to-end grasp mapping and multi-target probabilistic modeling. Fig. 6 illustrates the connection and focus of different research areas in the pre-shape planning problem.

1) Rehabilitation Engineering: The aim of the related research in the field of rehabilitation engineering is mainly to implement grasp prediction in grasping tasks and thus output pre-grasped poses. According to recent researches, relevant approaches in this field can be divided into sensor fusion-based and machine learning-based approaches. The sensor

TABLE III
DETAILS OF DIFFERENT STUDIES IN END-TO-END GRASP MAPPING AND MULTI-TARGET PROBABILISTIC MODELING

End-to-end mapping					
Year	Author	Experiment paradigm	Camera position	Mode (Method)	Index
2017	Ghazaei *et al.* [175]	1). Pick & Place 2). 500 objects (train set)	Hand	RGB (CNN)	Classification accuracy; Time
2019	Taverne *et al.* [176]	1). Reach & Pick up 2). 200 different objects 3). 6 grasp types and a no-grasp type	Hand	RGB (ResNet + LSTM)	Accuracy; Precision & Recall
2020	Shi *et al.* [93]	1). Reach & Pick up 2). 20 objects of 4 grasp patterns 3). 320 trials	Aside	RGB, RGB-D (CNN)	Time
2020	Gardner *et al.* [181]	1). Reach & Pick up 2). 3 objects of 7 grasp patterns;18 initial position 3). 11 subjects (10 healthy & 1 amputee)	Egocentric	MMG RGB IMU	Misclassification rate
2020	Krausz *et al.* [182]	1). Pick & Place 2). 1 bottle; 7 able-bodied subjects, each 600 trials	Egocentric	Gaze Motion tracking (SVR; Kalman Filter)	Target position error
Multi-target probabilistic modeling					
Year	Author	Experiment paradigm	Camera position	Mode (Method)	Index
2020	Liu *et al.* [178]	1). Reach; EGTEA dataset 2). Network Architecture design, training and inferring	Egocentric	RGB (3D CNN)	Action accuracy; Map estimation
2021	Jiang *et al.* [184]	1). Reach; Epic dataset 2). Network Architecture design, training and inferring	Egocentric	RGB (CNN)	Next-active-object; prediction accuracy
2022	Zhong *et al.* [177]	1). Reach & Pick up; 4 objects 2). In virtual scenes and with real arm-trajectory data	Hand	RGB (BNN; Monte Carlo)	Predictive entropy; Target accuracy

fusion solution combines machine vision information and bioelectrical signals (*e.g.,* sEMG), and can be traced back to 2010, when Dosen et al. [172] identified the size of the target object by installing a RGB camera on the prosthetic hand with the help of object segmentation technique. Subsequently, Markovic et al. [173] developed a novel closed-loop control system using AR feedback. The virtual box size was proportional to the hand opening/closing size, and thus could be adjusted/corrected by the user in real time. Results showed that this semi-autonomous control system reduced the user's effort while increasing the success rate of grasp task. Similarly, [84] fused the user's motion signals via IMU on the basis of first-view stereo vision, reducing task time and burden in a multi-DoF prosthetic hand control. Recently, with the development of artificial intelligence, the machine learning-based control framework for prosthesis is gradually called the mainstream of research. In these studies [93], [174], [175], [176], researchers build datasets by categorizing everyday objects with each category corresponding to one or more grasp types, and train them using convolutional neural networks to create mapping relationships. The research focuses on the accuracy of gesture prediction and the reliability of target prediction. However, the current limitation is that most of the articles only implement single-target gesture output, without incorporating multi-target daily scenarios, and the generalization ability is insufficient.

2) Computer Vision: Similar studies have been emphasized in the field of computer vision research. The task belongs to action recognition and prediction in video understanding, and there are many backbone algorithms, including 3D CNN, LSTM and attention mechanism. Specifically, Zhong et al. [177] accomplished target prediction based on Bayesian deep learning for hand perspective, quantifying the uncertainty in the prediction process. The reliability of model prediction was improved by introducing Bayesian neural network (BNN) and probability correction. Moreover, [178] predicted human-object-interaction and grasping contact hotspots in multi-target scenarios using first-view captured hand motions as cues, and [179] defined next-active-object as the predicted target. Some other researchers [180] equipped camera recorders on human hands to record daily activities such as picking up cell phones and operating door handles, and trained recurrent neural networks and policy networks to perform prediction of these behaviors. Such related research in the field of computer vision mainly lies in the generalization of scenes, but the response time is slow and most reports basically do not mention the inference time and speed of the models.

3) Approaches: From a methodological point of view, relevant studies can be divided into end-to-end grasp mapping and multi-target probabilistic modeling, and Table III lists typical studies and their research details. The end-to-end mapping is characterized by building object-grab type datasets, and the experimental scenario generally has only a single target object in the field of view. For example, Shi et al. [93] built RGB and depth image datasets of everyday objects and trained gesture mapping based on CNN. However, the camera was placed aside from the user, capturing a third-person perspective. Besides, some other works [174], [175], [176] mounted the camera on the end of the upper limb or prosthetic hand. Reference [181] assumed that an object corresponded to multiple grasping methods, and introduced sensors such as IMU for accurate grasping classification based on trajectory detection. Another study [182] had fused EMG, vision, and gaze information for intention recognition of prosthetic hand control for patients with total arm amputation. These researches focused on the accuracy of gesture prediction and the reliability of target prediction. In multi-objective

TABLE IV
REPRESENTATIVE STUDIES ON THE SHARED CONTROL OF UPPER-LIMB PROSTHESIS

	Year	Prosthesis	EMG Interface	Perception	Autonomic Control	Tasks
Markovic *et al.* [84]	2015	Hand & Wrist	Trigger	Vision & IMU	Simultaneous & Proportional	Grasp
Furui *et al.* [18]	2019	Hand	Joint angles & Impedance	Encoder	Simultaneous & Proportional	Grasp
Zhuang *et al.* [25]	2019	Hand & Arm	Joint angles	Pressure sensors	Simultaneous & Proportional	Grasp
Volkmar *et al.* [13]	2019	Hand & Wrist	Trigger	IMU	Simultaneous & Proportional	Bimanual
Mouchoux *et al.* [14]	2021	Hand & Wrist	Trigger	Vision & IMU	Simultaneous & Proportional	Grasp
Starke *et al.* [88]	2022	Hand & Wrist	Trigger	Vision & IMU & Proximity	Simultaneous & Proportional	Grasp
Zhong *et al.* [177]	2022	Hand & Wrist	Trigger	Vision	Simultaneous & Proportional	Grasp

probabilistic modeling, related studies are relatively new and sparse, including [177], [178], [179], [183], [184]. The common denominator of such studies is that multiple possible target objects appear in the field of view, and the system needs to complete the selection of targets based on human motion information or features brought by the motion, and thus predicts the user's operational intention.

C. Shared Control of Prostheses With Multi-Sensor Fusion

Previous works show that automatic or semi-automatic control can significantly expand the ability of prosthetic hands in dexterous manipulation tasks, mimicking human-like behaviors and increasing stability without additional human effort [18], [22], [25]. There are several studies that assist users with shared control of prosthetic hand according to the efficient environment perception from multi-sensory information, as summarized in Table IV.

In 2015, Markovic et al. developed a prosthesis controller that simultaneously controlled both the hand and the wrist [84]. The authors fused the visual perception that extracted the size and orientation of the target object, and the IMU that detected the wrist orientation to control the grasp type and the wrist angle automatically. A myoelectric interface was used to trigger the automatic operation. The results demonstrated that the semi-autonomous system outperformed the myoelectric interface with minimal user adaptation and training. Volkmar et al. developed a prosthetic hand system capable of bi-manual interaction [13]. The prosthesis system mimicked the intact arm to control wrist rotation and grip type in a bimanual task. As a result, the perceived workload decreased by 25%. Subsequently, Mouchoux et al. proposed an artificial sensing and semi-autonomous sEMG prosthetic control framework, which incorporated depth camera, IMU, AR glass and sEMG pattern recognition to significantly improve the operational efficiency of prosthetic hand and wrist [14]. Starke et al. used a similar sEMG-based interface to select target objects and grasp types, and the grasp trajectories were learned from human demonstrations and triggered by a distance sensor at the thumb [88]. In addition, Hu et al. [185] and Zhong et al. [177] combined vision, fingertip force perception, spatial audio rendering to build an autonomous control loop for the forearm prosthesis, which could output grasping path hints and achieve pre-grasping of target objects.

The existing share control approaches focus on replacing the sEMG interface for low cognitive burden and faster task completion. However, most methods adopt the idealistic assumption that only one grasp corresponds to the target object, and then use heuristic rules or learning-based image classification methods to predict grasp gesture. Although it is more tractable to implement, there are many limitations. The possible grasping gesture of an object is not only determined by the object, but also depends on the approaching direction. It is hard to grasp an object with a more complex shape by limiting the configuration space of prosthetic hand to only one gesture. The precise angles of the prosthetic fingers are undetermined if only the grasp type is specified, which may cause failure by not closing simultaneously. Moreover, the movement of the prosthetic hand system's base (*i.e.*, the amputee's stump) is not controllable during the prosthesis approaching and grasping. Therefore, the control system may need to replan grasp gestures and elbow/wrist movements online to achieve accurate and stable execution of the grasp tasks. Most studies only consider the output of grasping gestures, but do not consider planning wrist movements. They usually rely on the user to accurately locate the wrist orientation to achieve successful grasping, which undoubtedly increases the cognitive load and probability of failure.

D. Autonomous Grasp Control of Prosthetic Hands

After successfully obtaining the pre-shape gestures, traditional prosthetic hands usually neglect the grasp control in the closing phases, which cannot ensure simultaneous contact of all fingers on the object, proper grasp forces on fragile objects, and adjust grasping force according to human intention. Considering the scenario in which a prosthetic hand is asked to carry a target object to another location. The prosthetic hand system needs to dynamically adjust the finger force to actively neutralize the inertial force caused by the movement of the amputee's stump. Integrating tactile sensors into a close-loop grasp control will significantly increase the success rate. In 2019, Furui et al. decoded the synergies of the fingers and the impedance into a biomimetic impedance controller. They could produce precise and intuitive finger movements of the prosthetic hand [18]. Zhuang et al. utilized a multilayer perception (MLP) to decode the angles of each finger and a compliance controller to grasp the object firmly using an array of pressure sensors [25].

Recently, researchers have begun to use methods based on deep learning and reinforcement learning to extract information related to grasping selection from tactile information, which is applied to re-plan new grasping gestures in the case of grasping failure [30], [186]. Romano et al. proposed a fusion of IMU and tactile sensors to generate tactile signals and used tactile cues to switch between six different grasping controllers [187]. Veiga et al. predicted sliding events based on a multi-modal tactile sensor and fed it back to the grasping controller to achieve stable grasping of unknown objects [188]. Furthermore, Pfanne et al. utilized the joint angles and moments of the human hand to predict the pose of the object in hand [27]. The tactile information can also be used to evaluate and predict the results of grasping actions. Bekiroglu et al. used an array of tactile sensors and a learning-based method to predict grasp gestures' success rate to decide whether to perform the following lifting action [189].

V. Concluding Remarks

This paper presents a systematic analysis of current literature on the human-in-the-loop shared control for upper-limb prostheses. It is found that the acceptability of upper-limb prostheses is limited by excessive cognitive burden and unnatural operating behavior. Due to the inherent defects of time-varying and non-stationary bioelectrical signals, it seems difficult to make a fundamental breakthrough only through neural interface. Therefore, it is necessary to realize the anthropomorphic prosthetic operation through novel technical approaches. We believe that a prosthetic hand with environmental perception capabilities and automatic grasp planning algorithms can achieve human-like smooth even when the performance of the HMI is limited.

In summary, the challenges for autonomous operation planning of upper-limb prosthetic hands are multiple controlled DoFs and floating base (*i.e.*, the amputee's stump). Specifically, prosthetic systems generally include multifingered hand with more than 5 DoFs and bionic wrist with 1 to 3 DoFs. Elbow and shoulder DoFs may also be involved depending on the degree of amputation. In the process of the prosthetic hand approaching and grasping, the base movement of prosthetic system is not controlled by the machine. Therefore, coupling the movements of residual limb, the control system needs online planning of grasping gestures and elbow/wrist movements to achieve accurate and stable manipulation. An unavoidable problem in the future research is how to develop adaptive human-machine shared control interface to achieve natural and efficient integrated arm-hand cooperation. Moreover, the future researches should cover the complex interaction between intuitive motion control, proprioception/touch, and autonomous motion planning of multiple joints. Highlighting the latest emerging avenues of research, we hope that this review would be beneficial in investigating technological implementations of upper-limb prostheses.

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