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Brain Computer Interfaces for Supervisory Controls of Unmanned Aerial Vehicles *

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***Abstract* — To deal with changes and uncertainties in controlling a Unmanned Aerial Vehicle (UAV) reliably, a new platform is proposed to synergize human and machine intelligence, and it is based on a new Brain Computer Interface (BCI) to (1) quantify human's affections in arbitrating human and machine intelligence and alleviating adverse effects by human's mistakes, (2) fuse human and machine's control commands in different frequencies seamlessly and generate control commands at motor levels for real-time performance. In this paper, existing works on BCIs are discussed to identify the limitations of traditional Human-Machine Interactions (HMIs), a new framework of HMIs is proposed for a supervisory control of UAV; in particular, it is equipped with an arbitrating mechanism to optimize the shared control of UAVs based on quantified states of human' affection. It is expected to improve adaptability, agility, and reliability, responsiveness, and resilience of UAVs. This is an ongoing project, and the development platform for the feasibility study of the proposed method is introduced as our plan for future work.**

Keywords: Human machine interactions (HMI); brain control interface (BCI); unmanned aerial vehicles (UAVs); supervisory control; machine learning (ML); artificial intelligence (AI); affection qualification

I. Introduction

A machine or system for NASA mission is most likely tele-operated where humans and computers share the authorities in controlling. Existing techniques for shared human and machine controls are mostly implemented by human-machine interfaces (HMIs) where humans are engaged in machine controls by some intermediate hardware or software such as a driving wheel, pedal, and gear shift in an advanced driver assistance systems (ADAS). It will be desirable to advance brain computer interface (BCI) so that the brain activities can be captured and interpreted to control a machine directly. This paper investigate the applications of BCI in operating space vehicles such as unmanned aerial vehicles (UAVs) in the real-world environment with high-level uncertainties and dynamics.

Since the first target drone Lightning Bug was launched by Air Force in 1960s, more and more UAVs have been developed, and UAVs have gained their popularity due to their successful applications and potentials in providing base security, force protection, and reconnaissance. However, UAVs suffer from shortcomings in reliability and adaptability to deal with uncertainties and unanticipated events in dynamic environments. For example, UAVs are susceptible to extreme weather conditions and vulnerable to the threats from a kinetic or non-kinetic weapon. The reliability and adaptability may be reduced more significantly for large, low-altitude, and slow-moving UAVs in a hostile environment, and the statistical investigation by Williams [1] showed that 75% of recent accidents occurring to UAVs were due to human machine interface (HMI). Next-generation UAVs must enhance airworthiness and survivability that will be consistent with mission priorities significantly [2]. We hypothesize that the aforementioned problems can be alleviated by (1) developing a brain-computer interface (BCI) for a human to control a UAV directly by brain activities and (2) developing an arbitrating mechanism to weight and fuse the commends from a human and computer for shared controls.

II. Unmanned Aerial Systems and Controls

The U.S. military begun to develop various UAVs in 1960s and nearly 3,500 Lightning Bugs were used for tactical reconnaissance in the Vietnam War. The earlier control systems for UAVs such as the D-21 Tagboard/Senior Bowl program and Compass Arrow program were proven some unsatisfactory performance such as overrun cost, testing failures and invalidated requirements [3]. UAVs were not rapidly developed until some Israel unmanned systems were used to destroy the opponents' air defenses successfully in early 1980s [4]. The RQ-1 Predator model was developed by the joint U.S. and Israeli force, and it was used as an intelligence, surveillance, and reconnaissance (ISR) platform in 1996. The RQ-1 Predator model was later followed by the models of MQ-1 Predators and RQ-4 Global Hawks in 1998 and 2004, respectively [5].

Some UAVs exemplified in Fig.1 have become most demanded military systems to fight against terrorism or fulfill complex space missions such as tracking, identifying, fixing, or targeting objects or locations. By a comparison of the investment in the last decade, the Department of Defense (DoD) has almost tripled its investment in advancing UAVs; it has been estimated that the global UAS market in 2017 was expanded significantly with a total expenditure of 7.3 billion for new UASs. The US military is among the greatest contributors to the rapid growth of UASs; in particular, the civil UAS market was expected to grow rapidly in the next decade [6]. For example, the US Air Force was partnered with the German Air Force to develop an RQ-4 "Euro Hawk" as an

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unmanned combat air vehicle (UCAV), and the US Navy and Special Operations Command (USSOCOM) were expanded their funds in advancing unmanned aerial systems [7].

Despite of the significance improvements of modern UAVs in comparison with early manned aircrafts, how to improve the reliability in operation still poses a big challenge to the controlling system of an UAV, it is susceptible to unpredicted weather conditions and vulnerable to an attack by kinetic or non-kinetic weapon, and it affects the survivability of UAVs, specifically large-size, low-altitude, and low-speed UAVs. The statistical data showed that while the overall accident rate was decreasing gradually, the average accident rate of RQ-1/MQ-1 Predators was still high with around 24 mishaps per 100,000 flying hours in conservative years, and the accident rates of predators and Global Hawks were at an order of magnitude greater than those of manned aircrafts. The capabilities of UAVs must be improved at multiple aspects such as (1) developing low observable systems, dynamically planning missions, and equipping air-to-air self-defensing to mitigate the vulnerability to enemy attacks, (2) advancing the intelligence of UAVs via effective human machine collaboration, high-performance sensors and processors, smart mission management tools to deal with complexity, uncertainties and dynamics [8, 9].

III. Proposed Brain Computer Interface (BCI) for Supervisory Controls

Over 75% of the accidents occurring to UAVs were due to human machine interface (HMI). To improve the reliability and survivability of an UAV, it is logic naturally to re-examine human's roles in a shared control of UAVs. Fig. 3 shows the schematic of traditional human-machine interface of an UAV. A *multiple-layer control architecture* is usually deployed to control the UAV: *the lower level* controls the operations of actuators and motors, *the upper level* takes the pilot's intentions such as 'wide search', 'deep search', 'return to home', 'return and search', and 'directed search' [10] and converts these intentions into the movements and actions of the UAV, and *the intermediate level* translates the behaviors of the whole UAV into those of the components at the motor-level; the examples of control commands at this level are 'taking off', 'landing', 'cruising', 'descending', 'ascending', 'turning left', 'turning right', and 'accelerating', 'decelerating' [11,12]. The control architecture supports the shared control in sense that the high-level decisions are made by the pilot for the intentions of UAV operations, and the embedded UAV controller interprets the pilot's commands into the actions. All of the communications must be supported by either of a sophisticated wireless network or *a global positioning system* (GPS). It is clear that the control loop (i.e. loop II in Fig. 1) at the high-level is not fully closed since the discrepancy of expected and actual performance of UAV can only be justified by the pilot own. In the traditional human-machine architecture, there is no effective way to fix either the error in human's decision or the error when the pilot provides the inputs to the control system via a control console.

It can be seen from Fig. 1 that a low reliability or survivability of UAV is attributed greatly by the lack of appropriate mechanism to justify (1) if the pilot's intentions are input to the controlling system correctly via human-machine interfaces and/or (2) if the pilot makes decisions at the full capability of operating an UAV. In other words, even if the pilot's command is a mistake or a correct decision is wrongly input, the UAV controller just follows the command to fail the mission.

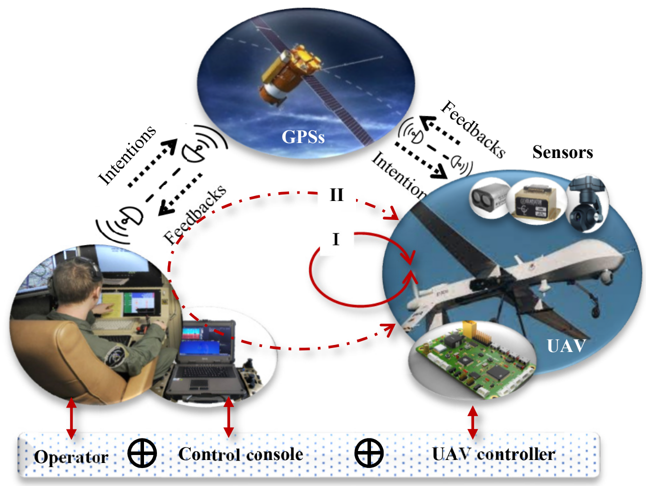

Fig. 1. Traditional Human-Machine Interface (HMI)

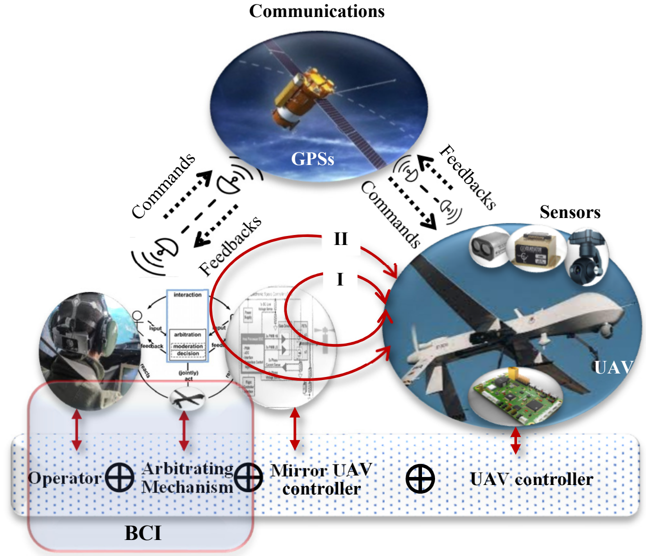

Fig. 2. Schematic of Proposed Supervisory Control

Fig. 2 shows the schematic of the proposed supervisory controls for an UAV. In comparison with the human-machine interfaces in traditional UAVs in Fig. 1, three new components are incorporated into a supervisory control to minimize the adverse effect of human factors. *Firstly*, new instrumentation is introduced to monitor and acquire brain signals, and brain signals will be processed to serve for two purposes, i.e., (1) identify the pilot's intentions directly and use them in controls to eliminate the probability of making mistakes in inputting a command and (2) classify the pilot's physical or physiological conditions and determine the corresponding weight in the arbitrating mechanism for shared controls. *Secondly*, an arbitrating mechanism is introduced for the computer to take over the responsibilities of high-level decision-making supports when brain signals indicate the pilot becomes incapable of making right decisions for UAV operations. *Thirdly*, the capabilities of an UAV controller must be expanded to incorporate the implementations when no right command will be issued by the pilot; in such cases, a mirror UAV controller is introduced in the arbitrating mechanism, so that high-level decisions will also be made by computers instead of incapable pilot at given moments. Integrating above three components allows to close the high-level control loop (i.e., II in Fig. 2) to tackle with the adverse effects of human factors in supervisory controls of UAVs.

IV. Development of BCI

Two critical tasks to make the proposed supervisory controls successfully are to (1) automate high-level decision-making processes in uncertain environment when the pilot is absent and (2) develop an arbitrating mechanism for a trade-off the human and computer's authority in shared controls based on a human's physical and physiological conditions.

A. Brain Signals

A brain consists of a forebrain, a midbrain, and a hindbrain. The hindbrain controls the vital functions such as heart rate and respiration of body. It includes brain stem, upper spinal cord, and a cerebellum that is a wrinkled ball of tissue. The forebrain is the largest and most developed part of brain; it consists of cerebrum and its structures beneath. A half of the cerebrum divided by a deep fissure. It can be further divided into six sections or lobes as *frontal brain*, *motor cortex*, *parietal lobes*, *somatosensory cortex*, *occipital lobes*, and *temporal lobes* whose specialized functions [13,14].

B. Data Acquisition

The methods used to acquire brain signals can be (i) *noninvasive* where sensors are placed on the scalp to measure electrical potentials by brain (i.e., *electroencephalogram* (EEG)) or magnetic field (i.e., *electromyogram* (MEG), (ii) semi-invasive where the electrodes of sensors are placed on the exposed surface of brain (i.e., *electrocorticography* (ECoG)), and (iii) invasive where the micro-electrodes of sensors are placed directly into the cortex to measure the activities of a single neuron. As shown in Fig. 3, different types of signals are acquired from different ranges; therefore, these signals reflect different brain activities.

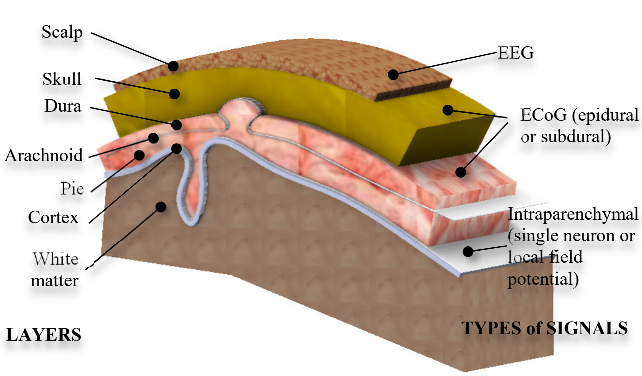

Fig. 3. Brain Layers and Corresponding Types of Signals [13]

Brain signals from different sources are also distinguished with each other in terms of temporal and spatial resolutions [15]. The performances of bio-signals such as EEG, MEG, EOG, and ECG are also affected by many other factors. For example, Fang et al. [16] investigated the impact of subject gender on the performance of electrooculography (EOG), and male-group showed better performance than female-groups in classifying tasks. The selection of brain signals must also consider many other factors such as reliability and costs. For example, fMRI is capable of achieving a better spatial resolution but lower temporal resolution in comparison with MEG or EEGs offer a high temporal resolution. The need of data processing is another concern. For example, the quality of a brain signal acquired non-invasively is significantly affected by some random factors in environments and the data must be preprocessed to suppress noises before it can be used to extract and classify features. The portability is also critical to mobile applications, from this perspective, the instruments for fMRI and MEG signals are usually too bulky and expensive, and EEG becomes most attractive due to its affordability and portability [15]. Common electrophysiological signals used to understand brain activities include bio-signals by *micro-array*, *positron emission tomography* (PET), *surface electromyography* (sEMG), *electroencephalography* (EEG), e*lectrocardiography* (ECG), *magnetoencephalography* (MEG), *functional Near-InfraRed spectroscopy* (fNIRs), *Electrooculography* (EOG), *functional Magnetic Resonance Imaging* (fMRI), and *Galvanic Skin Response* (GSR) [17-19].

EMG was known to the researchers in human-machine interface from 1990s. Early EMG signals were collected from three arm muscles, and processed by sampling, high-pass filtering, low-pass filtering, and amplifications to identify hand gestures such as opening, closing, and relaxation of hand; EMG was considered a reliable approach to detect muscle movement [20]. EEG has its advantages of high-time resolution, portability, and the cost-effectiveness of brain signal acquisitions in comparison with *functional magnetic resonance imaging* (fMRI) and *magnetoencephalography* (MEG). EEG-based controls are classified into two types, i.e., evoked (exogenous) and spontaneous (endogenous). *An evoked system* used external stimulation such as visual, sensing, or auditory stimulation, and the responses by brains are identified by BCI to determine user's intention. *A spontaneous system* takes control actions based on mental activities without external simulations. Two main categories of evoked signals are visually evoked potentials (VEPs) and event related potentials (EPRs); moreover, steady-state VEP (SSVEP) are the most widely used to identify users' intention quickly with minimum training [21-23].

The body movements are also controlled by brain signals; therefore, brain signals can also be monitored by using the sensors placed on other parts of a human body/ EOG measure the corneo-retinal standing potential spanned between the front and the back of the human eye, and the primary applications of EOG are for ophthalmological diagnosis and analyzing eye movements. ECG is a physiological signal representing electrical activity of a heart in real time; the most commonly used setup to capture ECG is to use nine sensors distributed on left area, left leg, and right leg called a 12-lead ECG device. *Photoplethysmography* (PPG) can be alternatively used to detect a change of microvascular blood volume in tissues as electrical signals related to brain activities. Similarly, a *galvanic skin response* (GSR) is known as skin conductance (SC) or electrodermal activity (EDA) to record to a body response to environmental changes; skin conduction is not subject to conscious control but depends on the variation of sweat reaction that reflects the changes in a sympathetic nervous system, i.e., the outputs of a sympathetic nervous bursts lead to the changes of skin conductance [24]. The *adaptive control of through, rational* (ACTR) theory was used to analyze a pilot's cognitive processes for situational awareness (SA) based on the feedbacks from external sensors such as eye movements by a vision system. Eye-movements such as fixation/saccade ratio are closely related to the ability of information perception and extraction; therefore, measuring and assessing eye-movements helped to characterize the pilot's SA quantitatively [25]. An artificial robotic skin was engineered by Cheng et al. as a multi-modal sensing instrument; it was networked with large-area skin patches to acquire and process a large amount of tactile data in sensor-driven robotic controls. Anomalous signals often occur to noninvasive bio-signals and this will degrade the performance of BCI; moreover, bio-signals may not be monitored continuously. Sagha et al. [26] suggested detecting anomalous data samples caused by misplaced electrodes, degraded impedance, and loosen connectivity online to minimize anomalous signals; they measured the deviation of data in each channel to evaluate its reliability and add the corresponding weight in data processing.

When brain signals are collected from multiple sources, and these signals have to be fused to extract features; it will bring the challenges to assure security, reliability, and privacy of brain signals [27]. Kuan et al. [28] discussed the challenges when a large amount of brain signals from neurons would be recorded and transferred over the Internet; they proposed a wireless data telemetry system to ensure a high data rate at an affordable power consumption of an implantable device. Cui et al. [29] proposed a framework to fuse multimodal signals (i.e., EEG, EMG, and MMG) and extract features associate with the multi-joint motions of lower limbs.

C. *Classification, Detections and Applications*

In developing a BCI, a preliminary task is to select and acquire right signals that are associated with (*i*) a human's intentions to control an object or (*ii*) a human's physical or psychological conditions that affect decision-making activities in an environment. On the other hand, one has to understand brain signals thoroughly before they can be processed, classified, analyzed and mine to extract expected features adequately. One of the most critical features of a brain signal is its frequency range in a temporal domain since most of the BCI applications require real-time controls [13, 30-32].

Numerous researches have worked on the development of AI or ML models to decode brain singles for various BCIs. For examples, Owusu et al. [33] surveyed the techniques used to recognize humans' facial expressions; humans' emotions were recognized from physiological signals (EEG, ECG, EMG, fMRI, MRI, PET, MEG, and NIRS). Hwaidi and Chen [32] proposed a *convolutional neural network* (CNN) to analyze and classify *Motor Imagery* (MI) signals; CNN was incorporated in an auto-encoder to classify EEG signals, and CNN was trained to replicate its inputs to outputs by encoding and decoding. Fu et al. [34] combined EEG and near infrared spectroscopy (NIRS) to decode brain signals in the sensorimotor areas; NIRS was acquired when the subject imagined to adjust force and speed in hand clenching, and the features of NIRS and EEG were combined in *a state vector machine* (SVM) to classify imagined force and speed at three levels. When ML is used to classify brain signals, raw data must be abundant to achieve expected accuracy and it might become a practical issue not to have sufficient data. Li et al. [35] address this by data augmentation to improve the utilization of existing datasets, and *contrastive learning* was adopted to extract features from limitedly labeled data.

Physiological signals are widely used to recognize humans' emotions in HMIs, autonomous driving, healthcare and entertainments. For examples, Hu et al. [36] classified psychophysiological signals to determine the trust level in the human and machine collaborations. Ikenishi et al. [37] processed physiological and vision signals to identify a driver's intentions on pedals, steering wheels. Jose and Lopes [38] used the feedbacks from the lower lip of a user in a human computer interface; it was design for patients with tetraplegia, and its application to control an input device was evaluated against an ISO standard on the Fitts' law. To reduce power consumption in data processing over embedded platform, Kartsch et al. [39] developed a parallel ultra-low power system-on-chip with nine RISC-V cores to perform *canonical correlation analysis* (CCA) over SSVEP. Corresponding EEG signals from different channels helped to increase the accuracy of classification; Wang et al. [40] developed used *partial directed coherence* (PDC) to establish a causal network based on their functional connectivity, and features were then extracted from the network using *common spatial patterns* (CSP).

Motor imagery (MI) reflects brain activities relevant to motions of limbs; therefore, MI signals were used widely to control neuro-rehabilitative, prosthetic, and haptic devices; MI signals acquired from brain are decoded in to motion commands to control a machine or device. Jeong et al. [41] developed CNN to classify rotational movements of a subject's forearm using EEG signals. The existing techniques to select and extract features from MI-based EEG were surveyed by Padfield et al. [21]. Minati et al. [42] developed a consumer-grade wearable device to acquire EOG, jaw EMG, EEG, and head movement simultaneously; this showed its potentials of using BCIs to control assistive robots. In prototyping, a robotic arm with 6 DOF was controlled in form of four control modes based on human's intentions recognized from multi-source biosignals. Wang et al. [43] applied tactile stimuli on a subject's forearm to record and decode the subject's response by EEG signals; they found a high-level accuracy in detecting a location of touch based on EEG signals.

Despite of the relevance of MI signals to the motions of the subject's limbs, the kinematic structure of a machine is usually different from that of limbs, and it is unrealistic to control the machine directly based on the identified human's intentions. In fact, it still poses a significant challenge to decode kinematic information from brain signals to control a machine with multi-degrees of freedom. In the BCI by Mao et al. [44], human's intentions were identified from P300 and SSVEP signals, machine intelligence was mined by a fuzzy logic algorithm to process multi-source images, human's intentions and machine intelligence were fused to (1) alleviate human's mental workload and (ii) enhance the performance robotic controls. Moritz et al. [45] discussed the barriers in developing BCIs to restore patients' motor or sensory functions. They found three main challenges were to (1) capture right neural activities adequately, (2) decode motion intentions in the presence of plasticity, and (3) address social and ethical concerns in market entrances.

V. Development Platform

The setup of the proposed platform consists of two instrumentations to acquire brain signals, i.e., (1) Epoc X 14 Channel Mobile Brainwear by Emotive and (2) Muscke SpikerShield by Backyard Brains; three devices to be tested by a BCI-based supervisory controller are (1) a collaborative robot by Elephant Robotics, (2) an educational robot arm by TinkerKit Barccio, and (3) a small-size drone with HD camera by Thames and Kosmos Robotics. Everything will be networked as IoT for data transmission and communications [46, 47].

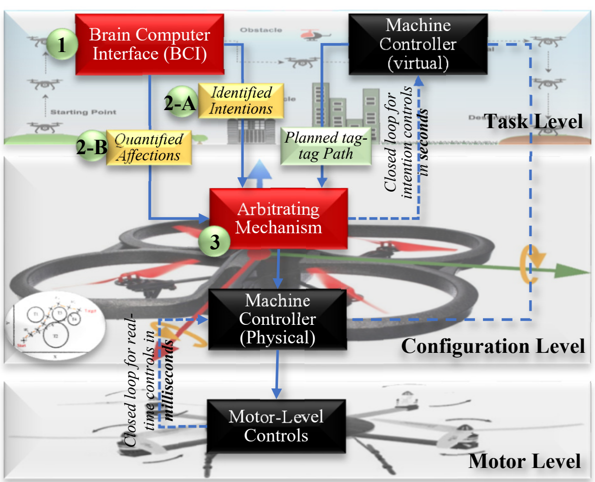

Fig. 4. BCI for Supervisory Machine Control

The proposed supervisory control in Fig. 4 includes three main functional components in comparison with a conventional control system for an autonomous machine:

1) a comprehensive BCI is developed to collect brain signals from multi-sources not only to (*i*) represent a human's intentions in controlling a machine based on specified mission and the subject's *Situation Awareness* (SA) but also to (*ii*) reflect the human's affections for the trustiness and quality of the subject's control decisions.
2) A set of ML algorithms will be developed to (2) classify and extract the human's intentions and (3) quantify the human's affections that are associated with the trustiness and quality of human's decisions.
3) A new arbitrating mechanism will be developed to (*i*) fuse human and machine intelligence to transfer control commands from task-level to configuration-level and then to motor-level; (ii) determining whether or not the human should take main control authority rather than machine intelligence.

VI. Summary and Future Works

Recent development of UAVs has been surveyed and the focus has been put on the technologies of human-machine interfaces (HMIs) to assure safe UAV operations. It has been found that despite of the rapidly development of *sensing*, *information technologies* (ITs), *Artificial Intelligence* (AI), and *machine learning* (ML), there is an emerging need to advance HMIs in reducing an average accident ratio in operating UAVs since most of existing HMIs lack the mechanisms to (*i*) fuse human and machine's intelligence and (*ii*) deal with humans' errors appropriately. A new development platform is proposed to acquire abundant brain singles from multi-sources, and a set of ML algorithms will be developed to identify human's intentions and quantify human's affections in making decisions on machine controls; more importantly, an arbitrating mechanism will be developed to fuse human's and machine intelligence appropriately based on the quantified human's affections, and the arbitrating mechanism will also be able to transfer high-level control commands at low frequency to these commands at low-leave at high frequency for real-time performance. The proposed platform will be capable of tackling with human's mistakes or poor-quality decisions by human when the subject is not at good conditions for SAs or decision-making.

The proposed platform is at its preliminary development stage that demands further research effort at multiple aspects: *firstly*, more advanced instruments will be introduced and evaluated to ensure sufficiency and appropriateness of brain signals for classification and extraction of control intentions and evaluation of human's emotions; *secondly*, ML algorithms will be advanced to identify human's intentions accurately, reliably, and promptly and quantify human's affections comprehensively. *Thirdly*, the arbitrating mechanism will be advanced to alleviate adverse effects of human's mistake or low decision-making performance. *Fourthly*, the case studies for a number of UAV missions will be designed and tested to verify and validate the proposed development platform in real-world applications.

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