Editorial
IEEE Transactions on Human–Machine Systems: Year in Review for 2013

THE IEEE TRANSACTIONS ON HUMAN–MACHINE SYSTEMS (THMS), with its focus on the dissemination of results in the area of human–machine systems (HMS) that inform theory and improve engineering practice, has completed the first year of publication since "splitting off" from the IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS PART A: SYSTEMS AND HUMANS and the sunsetting of the IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS PART C: APPLICATIONS AND REVIEWS [1]. While the journal did inherit manuscripts from the former *Part A* and *Part C*, almost 400 new manuscripts from corresponding authors in 43 countries (Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Cyprus, Denmark, Finland, France, Germany, Greece, Hong Kong, India, Islamic Republic of Iran, Israel, Italy, Japan, Jordan, Republic of Korea, Lebanon, Malaysia, Mexico, New Zealand, Norway, Pakistan, Poland, Portugal, Saudi Arabia, Singapore, Slovakia, Slovenia, Spain, Sweden, Switzerland, Taiwan,Tunisia, Turkey, United Arab Emirates, United Kingdom, United States) were submitted to the THMS in 2013.

Some authors appeared not to know about the changes to the scopes of the journals of the IEEE Systems, Man, and Cybernetics Society (SMCS) as 117 manuscripts submitted to THMS were rejected due to lack of fit. When considering the remaining manuscripts, 26 have been accepted and 101 have been rejected, yielding an acceptance rate for 2013 of 20.4% (including the 117 would bias the acceptance rate to an artificially low 6.8%). The rest are either under review or awaiting the authors' submissions of revisions. On behalf of the editorial board, I would like to express profound gratitude to all of the authors and reviewers and the hope that they will continue to support this high-quality journal.

In 2013, THMS published 47 regular papers, 9 technical correspondences, and 1 editorial. Next, the articles published in 2013 are summarized. Note that several can fit into more than one category but are only discussed within one.

I. Manual Control, Movement, and Motor Skill Development

With respect to manual control, movement, and motor skill development modeling approaches such as McRuer's crossover model [2]–[4], as well as interventions such as input shaping [5] (where reference commands reduce controlled element oscillations and associated displays [6]), continue to be of interest. While many forms of controlled-element dynamics have been studied, Potter and Singhose's [7] modeling, analysis, and evaluation of manual control of systems with oscillatory dynamics show promise for continuous tracking ability of such systems. A study investigated tracking behavior using controlled elements with both low-frequency (1.25 rad/s) and high-frequency (5 rad/s) oscillatory modes. While the high-frequency oscillatory mode did not greatly decrease the tracking performance from the nonoscillatory case, input shaping did cause a decrease in the average subjective task difficulty and made the system closely resemble McRuer's "crossover model." For the low-frequency case, the addition of input shaping significantly improved the tracking performance and reduced the tracking difficulty.

Human operators are often challenged by control of high-order systems or unstable systems near the limits of controllability. Lupu *et al.* [8] propose a control-theoretic framework to estimate the rate of information transmission in manual control as a way to characterize such interaction. They demonstrate the method using an example of stabilizing an inverted pendulum. They derive the information-transmission rate of manual control with one degree of freedom (DOF) ranges between 3 and 4 bits/s. This quantitative indication reveals the potential and limitations of human manual control.

The human body has many biomechanical DOFs, and thus, multiple movement strategies can be employed to execute a given task. Joint loading patterns and risk of injury are highly sensitive to the movement strategy employed. Choudry and colleagues [9] develop a computational framework to automatically identify and recognize different movement strategies from human motion data. A divisive clustering approach is developed to identify movement strategies. Hidden Markov models (HMMs) are trained with the clustered observation sequences to generate strategy-specific models that are improved iteratively by using the maximum likelihood to relocate sequences to the most suitable cluster. Differences in individual joint trajectories are compared across strategies using a stochastic distance measure. The algorithm is compared against three existing algorithms: joint contribution vector, decision tree, and HMM-based agglomerative clustering. Results indicate that the approach performs better than existing algorithms in detecting motion strategies and finding differences between the strategies.

Ueda *et al.* [10] introduce a method for measuring golf swing angular motion in a global coordinate system using three- dimensional (3-D) acceleration and the angular velocity detected by a local motion sensor embedded in a golf club. Optical

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direct linear transformation (DLT) is the conventional method for measuring sports motion; however, accurate localization of global coordinates and precise setting of infrared high-speed cameras in the test field are essential. Furthermore, infrared reflectors must be attached to the moving object. An accurately set system can provide precise positions for the moving reflectors. It is effective for measuring translational motion but not angular motion that is based on the principles of measurement. The method in [10] is easier in terms of setting and fine-tuning, more reasonable in cost, and more accurate in measuring rotational motion compared with the DLT method. Furthermore, the system's wireless transmitter enables noninvasive measurement. When addressing the golf club, its initial angles and posture matrix are calculated using the 3-D acceleration; when the swing begins, the motion sensor measures the changing angular velocity and the acceleration. The application of step-by-step Euler transformation for each sampling interval yields the angular velocity and angle in the global coordinate system.

Ground reaction forces (GRFs) vary with posture and motion for bipedal mechanisms or systems. In digital human modeling, specifically posture prediction, the GRFs are predicted, as they are unknown in a virtual environment. Traditionally, models in which the GRFs are predicted have been presented; however, they are always assumed to be on flat ground. Little work has been done to predict the GRFs on uneven or arbitrary terrain. Yang *et al.* [11] presents a generic method to calculate the vertical GRFs for given standing postures with uneven terrain. The vertical GRFs are predicted based on the generalized forces (torque in revolute joints; force in prismatic joints) calculated using the recursive Lagrangian formulation and a 3-D zero moment point. Motion capture experiments were used to obtain postures for common standing reaching tasks. Force plates were employed to record GRF information for each task. Experimental postures were reconstructed, and the GRF prediction algorithm was used to predict the associated vertical GRFs for each task. Experimental and predicted vertical GRFs are compared to validate the prediction model. The prediction method proved to be valid, with an overall error of 6%.

Filippeschi and Ruffaldi [12] discuss the Skills Professional Rowing Indoor Training (SPRINT) system that includes a configurable instrumented rowing apparatus for sculling and sweep rowing. The system is coupled with a virtual reality display and haptic feedback. The system includes models that aim at improving force rendering and at simulating the rowing dynamics. These models support the rendering of vertical and horizontal forces on the hands and they estimate the effects that actions performed on SPRINT would produce on an actual rowing shell. A proof of concept evaluation with one expert and one intermediate rower included a comparison of data gathered on an actual boat and with SPRINT. Outputs of the boat dynamics model were consistent both with the literature and on-boat data. These data suggest boat dynamics output to be useful in discriminating expertise. In addition, subjective ratings of kinematic features and force rendering by expert and intermediate rowers indicated that they find SPRINT suitable for training.

II. Person Tracking

Brscic *et al.* [13] presented a tracking method that supports the real-time estimation of position, height, and body angle inside a space containing 3-D range sensors mounted above maximum human height level. A computationally simple tracking method works on single sensor data and combines multiple sensors so that large areas can be covered with a minimum number of sensors. The method was implemented in a shopping center. False positives (about 45% of cases) were objects such as baby carts and suitcases as the tracking method does not explicitly distinguish between human and nonhuman objects. In the case of misses and ID changes, more than 60% were children. Due to their smaller size, children are more likely to be occluded by other pedestrians. As children tend to walk close to their caregivers, the system sometimes failed to cluster them correctly.

III. Supervisory/Aided Control

Saffarian *et al.* [14] consider distributing control information (in this case to drivers of nonequipped cars). Vehicles that are equipped with cooperative adaptive cruise control (CACC) provide state data and advice on the rear window. In a simulator study, drivers directly control the vehicle and have access to the rear window notification display (RWND) showing visual feedback on lead-car acceleration and time headway. The RWND supported reducing time headway without increasing the occurrence of potentially unsafe headways of less than 1 s.

The ballistic missile defense system problem is reflective of the function allocation conundrum faced in many supervisory control systems: how to determine which functions should be mutually exclusive and which should be collaborative between humans and automation. Rathje *et al.* [15] present two experiments that quantitatively investigate human/automation tradeoffs in the specific domain of tracking. Participants in both experiments were tested in their ability to smooth trajectories in different scenarios. In the first experiment, they demonstrated an ability to assist an algorithm in more difficult, shorter timeline scenarios. The second experiment combined the strengths of both human and automation in order to produce a collaborative effort. Comparison of the collaborative effort to the algorithm showed that adjusting the criterion for having human participation could significantly improve solutions.

IV. Alerting System Design

Bolton *et al.* propose a framework to support the development of evaluation scenarios that are capable of assessing system level performance while considering the system, the humans that interact with it, and the environment. The following five step framework is presented: 1) identify entities critical to system design, development, and operation and define their goals and properties as they relate to the system being studied; 2) define a subset of functionality for evaluation (define an execution sequence); 3) map entity properties to the execution sequence to identify independent variables; 4) translate entity goals into a set of system goals that can be used to identify dependent measures; and 5) iterate through each step to ensure the models produced are internally consistent. The framework was applied to the design of an alerting system for a pilot self-separation task.

In a simulator study, Haberkorn *et al.* [17] evaluated the benefits and limitations of a collision warning system for flight according to visual flight rules (VFR). Pilots were confronted with traffic, visible both on a moving map display and on the visual system of the simulator. The results demonstrate the benefits of the collision warning system in identifying the traffic. However, the avoidance maneuvers initiated by the pilots did not always conform to the regulations. Under multiple traffic conditions, pilots exhibited slower reaction times when confronted with the traffic warning. They also reported higher levels of workload and reduced situational awareness as compared with a single aircraft. The authors identified technical requirements for the future development of collision avoidance systems for VFR.

V. Human–Robot Interaction (HRI)

A. Measures of Performance

In bilateral teleoperation, a human operator manipulates a remote environment through a pair of master and slave robots. The transparency quantifies the fidelity of the teleoperation system, and is typically defined as the ability to accurately display remote environment properties to the operator. Nisky *et al.* [18] propose a multidimensional measure of transparency which takes into account the human operator and consists of three components: 1) perceptual transparency, which quantifies human perception of the remote environment, 2) local motor transparency, which quantifies how far is the movement of the human operator from ideal, and 3) remote motor transparency, which describes how far is the movement of the remote device from ideal. They suggest that for many practical applications, the goal of transparency optimization is to maintain perceptual and remote motor transparency while sacrificing local motor transparency, and that it is plausible to take advantage of the gap between perception and action in the operators' sensorimotor system. In a palpation and perception of the stiffness task, they prove analytically that for a teleoperation channel with a position and force scaling and a constant transmission delay, it is possible to find gains that ensure perfect perceptual and remote motor transparency while maintaining stability. They also show that stability depends on the operator maintaining sufficient arm impedance relative to environment impedance and delay.

B. Physical Interaction

As physical interactions between robots and humans become more common, there is a growing need to design robots that are kinesthetically perceived as human-like. One approach to implement human-like mechanical impedance is to physically simulate models of the human neuromuscular system. However, the level of model complexity needed to achieve perception of human-like properties is unknown. Lin *et al.* [19] investigated the ability to discriminate kinesthetically between a model-defined impedance and that produced by human muscle. They tested the hypothesis that a nonlinear muscle model is necessary to obtain perception of human-like muscle mechanical impedance. Fifteen participants were presented with a mechanical impedance of either a simulated muscle model or an electrically stimulated wrist muscle and were asked if they were interacting with a "machine" or a "human." The impedances were randomized for a total of 30 presentations. A robot that stimulates with either linear viscoelastic properties or a nonlinear Hill muscle model could be distinguished from a human wrist muscle by almost all participants. However, participants were less able to discriminate between the Hill model and human muscle, perhaps due to the larger overall impedance of the viscoelastic model.

C. Remotely Piloted Vehicles (RPV)

1) Guidance: In [20], Kong and Mettler present the foundations for the analysis and modeling of human guidance behavior based on emergent patterns in a closed-loop agent-environment dynamics. The central hypothesis is that these patterns, which can be explained in terms of invariants inherent to the closed-loop dynamics, provide the building blocks for the organization of human guidance behavior. The concept of interaction patterns is first introduced using a toy example and then detailed formally using dynamical system and control principles. They demonstrate interaction patterns in human guidance behavior based on experiments with a miniature helicopter. The results confirm that human guidance behavior exhibits invariances as defined by interaction patterns. The trajectories that are associated with each interaction pattern are then further decomposed by applying piecewise linear identification. The resulting elements are then combined under a hierarchical model that provides a natural and formal description of human guidance behavior.

In [21], a mapping method to support the investigation of human guidance behavior and its associated optimal control model has been described. The method employs an ensemble of trajectories distributed spatially over an extended task space. The method is evaluated using precision interception tasks with a miniature helicopter. As behavior can be meaningfully embedded in a spatial value function map, it supports understanding guidance performance from a spatial standpoint. Map-based performance and optimality metrics support the determining level of coordination and bandwidth and how these requirements change over the task space. The results indicate that guidance performance can be modeled as a guidance policy based on a simple closed-loop point mass model.

Prior research and development to improve the HRI of RPVs have largely focused on flight and navigation, while support for the acquisition of data and mission-related information is less studied, particularly for small-scale systems. Peschel and Murphy [22] focus on the mission specialist role in human-RPV teams for smaller systems. Their study surveys the mission specialist role in more than 40 papers covering 17 fielded systems. The most significant finding is that the mission specialist and pilot roles for micro and small RPVs share the pilot interface. Sharing violates the principle of dedicated interfaces for distinct roles and suggests an interface interaction conflict that could develop leading to suboptimal performance and loss of robustness.

Microaerial vehicles (MAVs) are small lightweight RPVs used by dismounted soldiers for aerial reconnaissance and acquiring information for local situation awareness. They require a portable handheld ground control station (GCS) that allows the operator to control and monitor the flight of the MAV. Hou *et al.* [23] investigated two methods of presenting the map and sensor information, either simultaneously on one display or separately on two displays, requiring operator navigation. In addition, two input devices are evaluated: a touch screen display with a stylus as well as a joystick with an OK button. The findings suggest that MAV GCSs that use touch screen inputs and simultaneous presentation of map and sensor information will result in better operator performance and reduced operator workload.

2) Shared Control in Remote Maintenance: Stefanov *et al.* [24] introduce a computer-assisted teleoperation system, where the control over the teleoperator is shared between a human operator and computer assistance. Two units, an action recognition and an assistance unit, provide context-specific assistance. The action recognition unit can evaluate haptic data, handle high sampling rates, and deal with human behavior changes caused by the active haptic assistance. Repairing of a broken hard drive as the scenario and three different task-specific assistance functions are used in the two-step evaluation. First, the performance of the action recognition unit is evaluated, Second, the performance of the integrated computer-assisted teleoperation system is compared with an unassisted system by means of a user study with 15 participants. Overall action recognition rates of about 65% are achieved. Multivariate paired comparisons show that the computer-assisted teleoperation system significantly reduces the human effort and damage possibility compared with a teleoperation system without assistance.

VI. Interface Technologies

A. Speech Technologies

With respect to support for the sight-impaired, Keefer *et al.* [25] describe the development of a stochastic Petri net (SPN) [26] for use in the development of a voice user interface (VUI) of a mobile reading device for the blind. A decision ladder [27]–[29] was used to describe the interaction. Task analytic methods were used to develop a model and grammar for the VUI. Three field studies with blind participants were conducted to develop and refine the models and the SPN.

B. Haptic Technologies

Gurari and colleagues [30] showed that one need not overload the visual channel to provide proprioceptive information. They describe a novel experimental apparatus that mimics the usage of a myoelectrically controlled upper limb prosthesis in a one-DOF rotational spring discrimination task. Fifteen intact individuals controlled a virtual prosthetic finger. Using the psychophysical method of constant stimuli [31], the authors quantified their performance. Spring discrimination performance, with a reference stiffness of 290 N/m, was tested for three experimental sensory conditions: visual motion, proprioceptive motion, and visual and proprioceptive motion. The participants perceived proprioceptive motion to be more useful than visual motion for the experimental task. These results imply that relaying proprioceptive information through a nonvisual channel could reduce visual attention during prosthesis control while maintaining task performance.

Tsagarakis and Caldwell [32] investigates the use of a 2-D haptic device as an assistive robotic aid to minimize the effects of the pathological absence of motor control in the upper limb in impaired users when using a mouse. The assistive functionality is evaluated in 2-D tracking tasks using a participant with failure of the gross coordination of the upper limb muscle movements: (muscle ataxia). The results demonstrate that with this system, the capability of the participant to track predefined trajectories with computer generated 2-D is significantly improved. The average of the means of the error distance for the trajectories performed under the assistive mode was significantly lower (more than 40%) than that of the trajectories without assistance. In addition, when using the assistive device, the participant was able to complete the tracking tasks in less time.

Kurita *et al.* [33] present a proof of concept evaluation involving a wearable sensorimotor enhancer intended to improve tactile sensitivity in the fingertips. As briefly exposing tactile receptors to subsensory vibration is known to enhance tactile sensitivity due to stochastic resonance in the somatosensory system, applying white-noise vibration to a fingertip may improve the sense of touch and associated motor skills. A prototype of a wearable device called a sensorimotor enhancer is attached to the radial side of the fingertip and stimulates tactile receptors by applying vibration from a lead zirconate titanate piezoelectric stack actuator. This design keeps the palmar region free, thereby helping to maintain the wearer's manipulative ability. Sensory and motor tests were conducted to determine the efficacy of the device. White-noise vibration from the radial side of the fingertip has a significant positive effect on tactile sensitivity. The results of the motor skill test also indicate that the sensorimotor enhancer improves grasping force optimization.

Lee and colleagues [34] investigate the effect of haptic feedback on the learning of a 2-D sequential selection task, used as an abstraction of complex industrial manual assembly tasks. This mnemonic-motor task requires the memorization of the selection order of points scattered on a 2-D plane and reproduction of this order using entire arm movements. Four information presentation methods (visual information only, visual information plus enactment, visual information plus haptic guidance, and visual information plus haptic disturbance) are considered. The latter three methods provide different levels of haptic kinesthetic feedback to the trainee. A user study assesses the quantitative performance differences of the four training methods using a custom-built visuo-haptic training system. Results showed the relative advantages and disadvantages of each information presentation method for both short-term and long-term memorization. In particular, training with only visual information was the best option for short-term memory, while training also with haptic disturbance was the most effective for long-term memory.

C. Gesture Technologies

Cornelius *et al.* [35] present a framework for characterizing approaches for communicating gestures in a virtual environment. The study compares the use of natural gestures (natural hand videos projected on the drawing surface) with virtual-sketching (sitting at separate tables where pairs could hear but not see each other while they sketched together in a shared virtual drawing space created by the virtual sketching tool) and face-to-face gestures (jointly sketching while sitting next to each other at the same table, using an electronic drawing tool). The users' cognitive workload (mental demand, physical demand, temporal demand, performance, frustration level and effort) was significantly reduced when natural hand videos were added to a virtual-sketching environment. These results suggest that natural gestures provide benefits over sketched gestures in terms of reduced cognitive workload and may warrant incorporation in collaborative design tools.

Skripcak *et al.* [36] introduce a methodology for designing alternative human–machine interfaces for industrial process control visualization and plant monitoring. The system is based on a multiagent approach in order to allow visualizations using nonconventional display devices (e.g., power-wall or table) combined with the natural user interaction paradigm. A simulation of an absorption refrigeration process was used as a process model on top of which a prototype was designed. Interoperability was gained via the automation standard of the openness, productivity, and connectivity unified architecture (UA). A user testing application was developed for the evaluation of exploratory interaction tasks in a power-wall display scenario. An evaluation was performed in order to identify the quality and robustness of algorithms used for the activation gesture detection in the power-wall/skeleton setup.

D. Wearable Computing

Fortino and colleagues [37] present their approach to the development of body sensor network (BSN) applications. They lay out the requirements and then describe SPINE, an open-source programming framework, designed to support rapid and flexible prototyping and management of BSN applications. They evaluate SPINE's computational performance (execution time, memory usage, energy consumption, communication bandwidth). They define and implement an application profile using SPINE, CodeBlue [38], and Titan [39]. They indicate the benefits from using SPINE. They also present applications implemented using SPINE (physical activity recognition and rehabilitation support, handshake detection, emotional stress indication, physical energy expenditure estimation, and gait analysis).

Current methods used to monitor performance for swimming do not offer real-time feedback to coaches. Chakravorti *et al.* [40] discuss a performance analysis tool to measure swimmer performance using wireless technology. The Computer Integrated Manufacturing Open System Architecture (CIMOSA) has been coupled with a software architecture based on object-oriented techniques to formalize and structure the development of a computer integrated real-time monitoring system. Filtering and signal processing algorithms are applied to extract performance indicators in real time, hence allowing faster access of feedback that can be used to enhance the swimming performance during each training session.

E. Avatars and Virtual Humans

In [41], Rincon-Nigro and Deng investigate the use of conversational avatars as a means to improve the user experience with instant messaging (IM) for mobile devices. They describe the design and implementation of an interface for IM featuring a 3-D facial avatar that is driven by text messages being exchanged between chatting participants. They evaluate user acceptance and reaction via user studies, by comparing the interface with a more conventional IM interface. They provide recommendations for the effective design of conversational avatar interfaces for mobile applications.

F. Eye Gaze Technologies

Ubeda *et al.* [42] presents interfaces that combine two means of communication. The ocular interface uses electrooculography (EOG) to detect eye movements. The manual input device tested included the Phantom Omni from SensAble, which has six DOF and force feedback in three DOF. Three control strategies were tested in proof of concept evaluations. The first control strategy (EOG-based control) was designed for people with a severe motor disability, such that desktop device inputs cannot be made. For the latter two control strategies, the desktop device was added as a six-DOF input in combination with the ocular interface. The supervised control with EOG strategy consists of having the desktop input device as the main controller and using EOG as a supervisor of the movement. The EOG interface controls the axis of the movement, while the desktop device controls the direction of the movement. The shared control of a trajectory strategy has speed control and is aimed at users without motor disabilities. The desktop input device controls the speed of the robot end effector, while the EOG interface controls the direction of the robot end effector.The bimodal approach produces less error as compared with the desktop device alone.

The accuracy limitations of gaze estimation algorithms and the fatigue imposed on users when overloading the visual perceptual channel with a motor control task have prevented the widespread adoption of gaze as a pointing modality. Rozado [43] investigated the use of gaze to complement traditional keyboard/mouse cursor positioning methods during standard human–computer interaction. Bringing the mouse/keyboard cursor to a target still requires a manual action, but the time and effort involved are substantially reduced in terms of mouse movement amplitude incurred or number of keystrokes pressed. This is accomplished by the cursor warping from its original position on the screen to the estimated point of regard of the user on the screen as estimated by video-oculography gaze tracking when a keystroke or mouse movement event is detected. The user adjusts the final fine-grained positioning of the cursor manually. The results of the user study carried out on the effects of cursor warping in common computer input operations that involve cursor repositioning when using one or several monitors as well as on its learning dynamics over time show that cursor warping can speed up and/or reduce the physical effort required to complete tasks such as mouse/trackpad target acquisition, keyboard text cursor positioning, mouse/keyboard based text selection, and drag and drop operations.

G. Night Vision Technologies

Superimposed luminance noise is typical of imagery from devices used for low-light vision such as image intensifiers (i.e., night vision devices). In four experiments, Allison *et al.* [44] measured the ability to detect and discriminate motion-defined forms as a function of stimulus signal-to-noise ratio at a variety of stimulus speeds. For each trial, observers were shown a pair of image sequences: 1) dots in a central motion-defined target region that move coherently against the surrounding dots, which moved in the opposite or in random directions and 2) the same random/uniform motion in both the center and surrounding parts. They indicated which interval contained the target stimulus in a two-interval forced-choice procedure. In the first experiment, simulated night vision images were presented with Poisson-distributed spatiotemporal image noise added to both the target and surrounding regions. As the power of spatiotemporal noise was increased, it became harder for observers to detect the target, particularly at the lowest and highest dot speeds. The second experiment confirmed that these effects also occurred with low illumination in real night vision device imagery. The third experiment demonstrated that these effects generalized to Gaussian noise distributions and noise created by spatiotemporal decorrelation. In the fourth experiment, the researchers found similar speed-dependent effects of luminance noise for the discrimination (as opposed to detection) of the shape of a motion-defined form. The results are discussed in terms of physiological motion processing and for the usability of enhanced vision displays under noisy conditions.

H. Brain–Computer Interface (BCI) Technologies

A typical BCI is composed of signal acquisition and signal processing (including preprocessing, feature extraction, and classification). An electroencephalogram (EEG)-based brain-controlled robot receives the human input via EEG-based BCIs. In [45] Bi *et al.* review EEG-based BCIs and propose a classification of various brain-controlled mobile robots from the perspective of their operational modes: "direct control by the BCI" meaning that the BCI translates EEG signals into motion commands to directly control robots and "shared control," where a user (using a BCI) and an intelligent controller (such as autonomous navigation system) share the control over the robots. They describe and analyze the key techniques and the evaluation issues for the overall performance of brain-controlled mobile robotic systems. For example the metrics used to evaluate brain-controlled mobile robot systems can be classified into two major categories: 1) task metrics that focus on how well specified tasks can be performed with the brain-controlled robots and 2) ergonomic metrics based on the user such as workload, learnability, and level of confidence experienced by the participants. They also discuss current challenges and future research directions of brain-controlled mobile robots.

VII. Human–Computer Interface Design and Visualization

To support the resolution of air traffic conflicts, automated systems detect conflicts and provide resolution advisories to the pilots. Using principles from ecological interface design [46]–[50], the work presented in [51] focuses on the design of a constraint-based 3-D separation assistance interface that can present relevant properties of the spatiotemporal separation problem. The design philosophy combines the existing spatial representation of airspace elements, with a velocity action space that relates own aircraft maneuver variables (velocity, track angle, and vertical speed) to the identified internal and external constraints. The reachable area that defines the velocity action space is bounded by constraints that are internal to the own aircraft. In an unmanaged airspace, the reachable area that is enclosed by the internal aircraft constraints is further restricted by several external factors, such as weather, terrain, and traffic. A display concept presents speed, heading, and altitude action possibilities in two planar projections of the maneuver action space. The interface also visualizes how these projections interact with each other.

In [52], two experiments, an active conflict resolution task and a passive situation awareness assessment, were conducted that compare two versions of the constraint-based coplanar airborne separation assistance display. A baseline display showed a maneuver space based on 2-D projections of traffic and performance constraints. A second augmented display also incorporated cutting planes that take the dimension orthogonal to the projection into account, thereby providing a more precise visualization of traffic constraints. Seventeen experienced glass-cockpit pilots participated in the experiment. Results showed that although pilots performed well with either display, the augmented display scored consistently better in terms of performance, efficiency of conflict resolutions, the amount of errors in the initial resolutions, and the level of situation awareness compared with the baseline display. On the other hand, more losses of separation were found with the augmented display, as pilots tried to maximize the maneuvering efficiency according to the precision with which constraints were visualized.

VIII. Classification

A. Person Identification and Biometrics

McLaughlin *et al.* [53] presents a method of audio–visual feature-level fusion for person identification where both speech and facial modalities may be corrupted, and there is a lack of prior knowledge about the corruption. The method assumes that there are limited amounts of training data for each modality (e.g., a short training speech segment and a single training facial image for each person). A new multimodal feature representation and a modified cosine similarity are introduced to combine and compare bimodal features with limited training data, as well as differing data rates and feature sizes. Optimal feature selection and multi-condition training are used to reduce the mismatch between training and testing, thereby making the system robust to unknown bimodal corruption. Experiments were conducted with a bimodal dataset created from the SPIDRE speaker recognition database [54] and AR face recognition database [55] with variable noise corruption of speech and occlusion in the face images. The system's speaker identification performance on the SPIDRE database and facial identification performance on the AR database are comparable with the literature. Combining both modalities using the method of multimodal fusion leads to significantly improved accuracy over the unimodal systems, even when both modalities have been corrupted. The new method also shows improved identification accuracy compared with the bimodal systems based on multi-condition model training or missing-feature decoding alone.

Fingerprint authentication is impacted by low-quality input fingerprint images due to cracks and scars, dry skin, or poor ridges and valley contrast ridges. Usually, fingerprint images are enhanced in either the spatial or the frequency domain. However, the enhanced performance is not always satisfactory because of the complicated ridge structures that are affected by unusual input contexts. In [56], Yang *et al.* propose a two-stage enhancement scheme in both the spatial and the frequency domains by learning from the underlying images. To remedy the ridge areas and address the contrast of the local ridges, the scheme enhances the fingerprint image in the spatial domain with a spatial ridge-compensation filter by learning from the images. With the help of the first step, the second-stage filter (a frequency bandpass filter that is separable in the radial- and angular-frequency domains) is employed. The parameters of the bandpass filters are learned from the original image and the first-stage enhanced image. It enhances the fingerprint image significantly because of the fast and sharp attenuation of the filter in both the radial and the angular-frequency domains. Experimental results show that the algorithm is able to handle various input image contexts and achieves better results compared with some state-of-the-art algorithms using public databases.

Lu and Tan [57] proposes an ordinary preserving manifold analysis approach for human age and head pose estimation. While a large number of manifold learning algorithms have been proposed and some have been successfully applied to age/pose estimation, the ordinary characteristics of the age/pose information of samples have not been fully exploited to learn the low-dimensional discriminative features for these estimation tasks. The approach seeks a low-dimensional subspace such that the samples with similar label values (i.e., small age/pose difference) are projected to be as close as possible and those with dissimilar label values (i.e., large age/pose difference) as far as possible. Subsequently, multiple linear regression models are used to uncover the relation of these low-dimensional features and the ground-truth values of samples for age/pose estimation. Experimental results on facial age estimation, gait-based human age estimation, and head pose estimation demonstrate the efficacy of the proposed approach.

A new approach for static signature verification is presented in [58]. It uses optical flow to estimate local stability among signatures. In the enrollment stage, optical flow is used to define a stability model of the genuine signatures for each signer. In the verification stage, the stability between the unknown signature and each one of the reference signatures is estimated and consistency with the stability model of the signer is evaluated. The results, using signatures in the GPDS database, demonstrate the effectiveness of the approach.

The spatiotemporal movement of an individual, to and from different geographical locations, is regularly linked to particular patterns. How often and to what extent, one deviates from his or her regular pattern could be key attributes of a particular behavioral action. The measurement of this location predictability, or unpredictability, is the basis for the work presented in [59]. Computing predictability of an individual's behavior comprised of modeling the probability distributions of geographical areas of interests followed by configuring a hidden Markov model (HMM) to represent an individual's typical behavior. The HMM is then utilized to compute temporal entropy vectors, taking into account an individual's transitions to and from different geographical areas of interest over the course of a day. Principal component analysis is then utilized to transform the temporal entropy vectors to a set of linearly independent components, where each component could potentially represent different characteristics about the individual. The authors performed a set of quantitative experiments to identify features which best describe particular demographic and social characteristics. Results, using data recorded from 29 participants, showed that the proposed method, on average, could infer demographic and social characteristics from location data with true-positive and false positive rates of 0.801 and 0.188, respectively.

B. Classification of Context

An analyst who monitors task execution or inspects a trace of the events that took place could discover/identify the contexts that are faced by the actor. However, analysts' identification of the contexts evident in these data may not match those of others. In [60], Trinh and Gonzalez introduce a process called the contextualization of the performance trace: determining contexts from traces of time-stamped values of variables from the performance of tactical tasks in a simulated environment. They devised a context discovery algorithm called context partitioning and clustering (COPAC). The relevant variables that were observed in the trace were selected a priori by an analyst. The output of the COPAC algorithm was qualitatively compared with manual (human) contextualization of the same traces. The authors quantitatively compared the results of using the COPAC-derived contexts with those obtained with human-derived contextualization in building autonomous tactical agents.

C. Activity Recognition

Automated monitoring and the recognition of activities of daily living (ADLs) are key challenges in ambient-assisted living (AAL) for the assistance of the elderly. A formal approach may provide a means to fill the gap between the low-level observations acquired by sensing devices and the high-level concepts that are required for the recognition of human activities. Magherini *et al.* [61] describe a system named automated recognizer of ADLs (ARA) that exploits propositional temporal logic and model checking to support automated real-time recognition of ADLs within a smart environment. The logic is shown to be expressive enough for the specification of realistic patterns of ADLs in terms of basic actions detected by a sensorized environment. The online model checking engine is capable of processing a stream of detected actions in real time. The approach is evaluated within the context of a smart kitchen, where different types of ADLs are repeatedly performed.

Activity recognition (AR) based on static activity models can lead to imprecise or incorrect results in a dynamic environment. In [62], Lu *et al.* develop a method for the AR model to adapt and conduct a proof of concept evaluation in a smart home environment. The AR method stages include data collection, feature handling, model learning, and activity inference. In the feature handling stage, all sensor readings (or raw data) are extracted into interactions. In the model learning stage, an activity model consists of an activity structure in the form of a probabilistic graphical model, where the system learns the relationship between the selected informative features and the activities of interest. In the activity inference stage, the activity recognizer makes use of the learned activity model to infer on-going activities and outputs activity estimates to meet the needs for activity-aware applications. For model adaptation, batch data collection supports an online learning approach: hybrid user-assisted incremental model adaptation. Model adaptation is reformulated into a problem involving the hybrid reduction of data annotation and the detection of changes: automatic initial data annotation annotates unlabeled data, preference-assisted data annotation incorporates a preference model to detect changes in a user's behavior, and active learning-assisted data annotation selects the most uncertain data instances (from the viewpoint of the current AR model) to limit data annotation. Experiments conducted in an equipped smart-home lab demonstrate the efficacy of the approach.

Reducing the standby power used by home appliances is critical in a household energy management system. Although significant effort has been made to minimize the standby power use of appliances, manual operation is still required. Additionally, the current regulation strategy of standby power typically focuses on real-power consumption, and it does not consider the apparent power and power factors. Lee and colleagues [63] propose an automatic standby power reduction system that is based on user-context profiling. The system profiles and analyzes the occupancy pattern, as well as the appliance usage. The system then actively manages standby power utilization by predicting the probabilities of future appliance usage. Lee and colleagues built a prototype smart meter to monitor and control the power lines and developed software that implemented the proposed scheme. Experiments, conducted for three to five weeks in four households, show that power consumption in standby mode can be reduced.

Windridge *et al.* [64] address modeling driving behavior with the goal to classify driver intentional behavior using a perception–action (P-A) hierarchy. Percepts are discrete internal representations of observable objects for an embodied cognitive agent, actions cause changes in percepts, and intentions are planned actions performed by the embodied agent. Thus, such models consider that one's perceptual domain is learned in response to the action outcome so that it is appropriately maintained in relation to one's motor capabilities. Intentional behavior is characterized by a high-level perceptual goal that requires subtasks to be carried out, each with lower-level perceptual goals. The authors classify driver intentions with respect to *a priori* extended control model (ECOM) [65] and highway-code derived driving protocols by linking the *a priori* ECOM intentions to stochastic low-level features such as computer vision, eye gaze, and control inputs. The authors perform a proof of concept evaluation of the model with respect to logic-based methods. The results indicate that a deductive model provides better intentional classification performance due to the structure the driving environment.

Recognizing human aggressive behaviors underlines how a taxonomer models such actions to perform recognition. Theodoridis and Hu [66] investigate both the recognition and modeling of aggressive behaviors using kinematic (3-D) and electromyographic performance data. For this purpose, the Gaussian ground-plan projection area model has been assessed as an evolutionary paradigm for the multiclass action and behavior recognition problem. It has superior classification accuracy with and without the use of ensemble models compared with the standard Gaussian (distance and area) models and other metrics of divergence, when dedicated groups of actions (behaviors) are being modeled. Genetic Programming is used to construct behavior-based taxonomers with a biomechanical primitive language. The modeling process revealed a representative subset of parameters (limbs, body segments, and marker coordinates) that are selected through the evolutionary process.

D. Emotional State, Sentiment, and Perceived Measures

Subjective rating techniques [67] may be useful but researchers have been looking for ways to enhance their utility by integrating them with other measures. Swangnetr and Kaber [68] developed an algorithm using physiological responses and subjective ratings of valence (happy/unhappy) and arousal (excited/bored) for patient emotional state classification. A simulated medicine delivery experiment was conducted at two nursing homes using a robot with different human-like features. Physiological signals, including heart rate (HR) and galvanic skin response (GSR), as well as subjective ratings of valence and arousal were collected from 24 elderly residents. A three-stage emotional state classification algorithm was applied to these data, including 1) physiological feature extraction, 2) statistical-based feature selection, and 3) a machine-learning model of emotional states. A preprocessed HR signal was used. GSR signals were nonstationary and noisy and were further processed using wavelet analysis. A set of wavelet coefficients, representing GSR features, was used as a basis for current emotional state classification. Arousal and valence were significantly explained by statistical features of the HR signal and GSR wavelet features. Wavelet-based denoising of GSR signals led to an increase in the percentage of correct classifications of emotional states and clearer relationships among the physiological response and arousal and valence.

Wang and colleagues [69] present SentiView, an interactive visualization system that aims to analyze public sentiments from

Internet posts. SentiView combines uncertainty modeling and model-driven adjustment. By searching and correlating frequent words in text data, it mines and models the changes of the sentiment on public topics. In addition, using a time-varying helix together with an attribute astrolabe to represent sentiments, it can visualize the changes of multiple attributes and relationships among demographics of interest and the sentiments of participants on popular topics. The relationships of interest among different participants are presented in a relationship map. Using a new evolution model that is based on cellular automata, it is able to compare the time-varying features for sentiment-driven forums on both simulated and real data.

A quantitative evaluation method for ride comfort would support the automotive industry. In [70], actual-vehicle and driving simulator (DS) experiments were carried out to evaluate the sternocleidomastoid (SCM) muscle activity of a passenger in response to a car's lateral acceleration while slalom driving. The SCM muscle of the passenger on the side opposite the direction of the car's lateral acceleration contracts to keep the head stable against body shaking. The electromyography (EMG) signal of the SCM muscle in a modified car was significantly lower than in a normal car, because the 1–10 Hz low-frequency vibrations of the body frame of the modified car during the slalom driving were decreased through improvements of the rigidity of car's body frame. A passenger feels more discomfort when the EMG signal of the SCM muscle increases, and less as the signal decreases. The EMG of the SCM muscle shows promise as an objective and effective method with which to quantify the effect of vehicle properties on human discomfort in both actual-vehicle and DS experiments for slalom driving.

IX. Simulation/Virtual Environments

Li *et al.* [71] developed a new computer-based system for psychomotor skill assessment. The focus was on the simulation of the Rey–Osterrieth complex figure (ROCF) reproduction test incorporating a haptic interface. Various system functions were created to support customized testing protocols that are based on specific user requirements, facilitate semiautomated scoring of tests, and produce quantitative test output. Advanced technologies of pattern recognition were reviewed and adapted for the system development. This approach yielded an application for recording freehand drawings and recognizing and normalizing drawing strokes for semiautomated scoring according to a standard. The new simulator system was validated by comparison with traditional paper-based tests in which participants were asked to use their nondominant hand to simulate a minor motor impairment. Results demonstrated the simulator to be sensitive to functional differences between dominant and nondominant hand use. The computerized scoring software also appeared to be valid for generating ROCF scores, which were consistent with manual scores determined by a trained rater for the same drawing stimuli.

Advanced driving simulators aim at rendering the motion of a vehicle with maximum fidelity, requiring increased mechanical travel, size, and cost. Motion cueing algorithms reduce the motion envelope by taking advantage of limitations in human motion perception; the most commonly employed method is to scale down the physical motion. Little is known about the effects of motion scaling on motion perception and on actual driving performance. In [72], Berthoz and colleagues explore different motion scale factors in a slalom driving task. Three state-of-the-art simulator systems capable of generating displacements of several meters were used in four driving experiments: 1) to investigate the effect of lateral motion gain under normal driving conditions; 2) to analyze whether motion feedback improves driver performance and driving behavior during more advanced driving maneuvers; 3) to investigate the perceptual sensitivity of drivers to variations of the scale factors applied to lateral and yaw motion, compared with a reference condition; and 4) to investigate cueing conditions (amount of lateral movement with respect to the visual displacement). The presence of lateral motion increases the simulation fidelity and contributes to the driver's perception and control of motion. The participants indicated a preference for motion scale factors below 1, within a range of acceptable values (0.4–0.75). With motion feedback, participants drove more carefully and had better control of the car; therefore, they could better anticipate the car's dynamic behavior and were not as surprised when the car did crash. Very reduced or absent motion cues significantly degrade driving performance.

Gajananan and colleagues [73] present a framework for conducting controlled driving behavior studies using multiuser networked 3-D virtual environments. The framework supports: 1) the simulation of multiuser immersive driving; 2) the visualization of surrounding traffic; 3) the specification and creation of reproducible traffic scenarios; and 4) the collection of meaningful driving behavior data. The authors investigate the "rubbernecking" phenomenon (slowing down of a driver due to an accident on the opposite side of the road) and its effect on the following drivers. In [73], the Scenario Markup Language (SML) framework, which is composed of: 1) SML to specify dynamic traffic situations and 2) the scenario control system to ensure the reproducibility of particular traffic situations has been intrduced. To demonstrate the framework, they specified the traffic accident scenario in SML and conducted a study about the rubbernecking phenomenon. They report the results from two viewpoints: 1) the reproducibility of the traffic accident situation (i.e., state variables of interest are recreated successfully in 78% of the cases); and 2) the interactive car-following behavior of drivers embedded in the traffic situation of the virtual environment.

In [74], Popescu and colleagues demonstrate a simulation method to reliably generate collision avoidance advisories by the traffic alert and collision avoidance system (TCAS). The TCAS advisory issued to a pilot is highly sensitive to the trajectory of an intruder aircraft relative to the ownship flown by the pilot. In realistic piloted simulations, a prescripted intruder trajectory will not reliably result in the relative dynamics that lead to a desired TCAS advisory. Furthermore, the complexity of the TCAS logic requires a novel method for mapping trajectories to the range of possible advisories. Popescu and colleagues propose to use a rapidly exploring random tree algorithm in large-scale fast-time simulations to establish the mapping between the space of relative trajectories and TCAS advisories. These trajectories are then created in piloted simulations through guidance algorithms.

X. Teamwork and Culture

The healthcare system is moving from one primary physician who assumes responsibility for each patient to a more team-based approach. Thus, assessing team communication is critical. Meth *et al.* [75] characterized and assessed the quality of hospitalist handover communications at shift change using the literature recommended content and language form elements. Quality handovers should contain the following content: patient identifiers, active issues, and care plans. Quality handovers also should include utterances in the following language forms: explanations, rationales, and directives. Interviews, observation, recording, and conversation analysis of hospitalist handover communications were used. Hospitalist handover utterances were assigned both content and language form codes. The proportion of quality element verbalization across all patient handovers was calculated. In addition, the impact of patient factors (new admission, new problem, acuity level) and handover receiver knowledge on the inclusion of quality elements was examined. The 106 individual patient handovers across 16 handover sessions were recorded. 39% contained all six quality elements. While the majority of handovers contained five out of six quality elements, only 48% included directives. There was also no difference in the inclusion of quality elements based on patient factors or handover receiver knowledge. Hospitalist handovers are lacking in directives. Efforts to improve handovers through enhanced electronic medical record systems and training may need to expand to hospitalists and other attending level physicians.

Hodgson *et al.* [76] examine mismatches between the procedures and automation technologies of sociotechnical systems and their operators from the viewpoint of human culture and capabilities, with a particular focus on flight deck automation. Following an introduction to culture, its sources, its measurement, and its effects, the authors describe recent theories of thinking and decision making, and the influence of culture on decisions. Problems that are associated with automation are presented and it is concluded that current automation systems perform as very inadequate team members, leaving the human operators or crew unprepared when failure occurs or unusual events arise.

XI. Internet Supported Collaboration and Decision Making

Techniques to discover, collect, organize, search, and disseminate real-time disaster information are necessary for crisis management and disaster recovery tasks. Zheng and colleagues [77] have developed techniques to facilitate information sharing and collaboration for major disaster recovery planning and management. They designed and implemented two parallel systems: a web-based prototype of a business continuity information network system and an all-hazard disaster situation browser system that run on mobile devices. Information extraction integrates the input data from different sources; report summarization techniques generate brief reviews from a large collection of reports at different granularities; probabilistic models support dynamically generating query forms and information dashboard based on user feedback; and community generation and user recommendation techniques are adapted to help users identify potential contacts for report sharing and community organization. User studies with more than 200 participants from emergency operations center personnel and companies demonstrate that the systems are very useful to gain insights about the disaster situation and for making decisions.

XII. Internet-Supported Education

One of the key challenges of internet-supported education (ISE) is augmented face-to-face interaction with geographically distributed participants. Tao and Zhang [78] have developed the online classroom model (OCM) to guide the design, development, and assessment of online education systems. This model is composed of seven-linked elements, including four learning theory-oriented components and three that deal with human–computer interaction. The OCM helps system designers to understand what underpins a successful synchronous ISE system from the perspectives of the learning theory and user experience. An online classroom system (OCS) has been developed under the guidance of this model. The OCS promotes augmented face-to-face interaction by providing functionalities for real-time educational activities, auxiliary asynchronous features, and user interface coordination based on a front channel-back channel partition. An OCM-based quantitative analysis template is proposed and used to evaluate the OCS.

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