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Intention Based Comparative Analysis of Human-Robot Interaction

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ABSTRACT Human-robot interaction is inevitable due to the increase of the autonomous intelligent machines in the human vicinity. The autonomous machines should synchronize with the interacting human. The key factor for synchronized Human-Robot Interaction (HRI) is a human intention. The interacting machine must have the clue about the intention of the interacting human for a useful interaction. In this review paper, recently proposed intention-based approaches for human-robot interaction are discussed. The approaches are categorized concerning different aspects, e.g., application area, specialized and generalized estimation techniques, etc. The review categorized the recently proposed approaches into five categories. The categorization is mainly based on the application areas of the intention recognition approaches. The type of approaches includes general and application-specific approaches. The application areas include synchronized physical human-assistance, human-synchronized vehicles, etc. The vehicles are synchronized with the driver and the pedestrian. The study highlighted the currently active as well as the dormant areas of the intention-based human-robot interaction and indicated new directions.

INDEX TERMS Intention recognition, intention based safe vehicles, intention based bionics, intention based teleoperation.

I. INTRODUCTION

The capability of interaction with one another is the most important feature in social life. The capability exists in almost all forms of living organisms. From humans to the animals, it exists according to different norms of nature in different species. The capability is built in all of the living organisms. To master this capability is another question. There can be different ways to best synchronize, between each other in different scenarios, among different living organisms. In order to complete a task in a shared environment, this capability is a basic requirement. The task may correspond to collaborative operation, resource sharing, collision avoidance, assistance, etc. Since the capability is built in the living being therefore given not much consideration if utilized efficiently. In the case of machines, it is not a trivial task to synchronize with the interacting entity (living) by the machine. Along with other factors (gesture recognition, language interpretation, context understanding, etc.), the intention of the interacting entity (living) is the most basic and key factor for synchronized interaction. Almost all the factors are governed by the intention of the interacting entity. Mostly the machines are expected to interact with humans by recognizing human intention. There have been direct and indirect contributions in the field of intention recognition for a long time. The direct contributions correspond to the approaches related to the intention estimation and indirect approaches correspond to the approaches for operations estimation, required for intention estimation, e.g., gesture/action understanding, context understanding, etc. The review paper discusses the direct approaches proposed in recent years. The old direct approaches exist in the literature, e.g., [1]. The recently published related review papers involve [2], [3]. The review paper is focused on only the intention measurement techniques applied on different problem domains, not like [2] where intention recognition is not the only focus but also intention definition, robotic response, and case studies. The research work in [3] discusses mostly Bayesian Based approaches for intention recognition. The presented review also highlights new emerging areas including intention recognition based

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improved road safety. Recently the area of human intention recognition has been dormant as the research community is not very much active in the core area of intention recognition. The core area means that the intention recognition algorithm proposition that can be applied in a problem domain. Rather the community is active in specific areas that require intention recognition as the basic ingredient in the solution, e.g., intention-based pedestrian safety, physical assistance, etc. The review paper covers the approaches in different application areas of intention recognition, features based intention recognition approaches, as well as the generalized intention recognition approaches proposed so far. The paper is organized as follows: In the comparative survey section, the overall approaches are summarized concerning different perspectives, e.g., Figure. 1 represents the number of approaches belonging to different application categories, year-wise. Figures 2 represents the focus of the research community in the area of the intention recognition year-wise, on the whole. Similarly, Figure 4 categorizes the approaches concerning the techniques applied for modeling human intention, year-wise. Section 2 discusses the generalized approaches proposed for intention recognition. Section 3 covers the approaches that are application-field specific, e.g., brain signals modeling for intention recognition, intention-based Road / Pedestrian synchronized safe vehicle, synchronized physical assistance based on human intention, less active subfield of intention recognition for teleoperation. The last Section 4 summarizes and concludes the presented review.

II. COMPARATIVE SURVEY

The recently proposed approaches of intention recognition concerning time and techniques are discussed using graphs. Time-based graphs describe the proposition of approaches with respect to time. Techniques based graphs represent the relation between the approaches and the time of proposition with respect to the techniques used for intention recognition/modeling. Another important aspect corresponds to the timeline along which different approaches are proposed in different domains of Human-machine interaction that are based on human intention recognition.

Figure 1 provides a compact perspective of the state of the art in the area of human intention recognition in HRI. It represents multiple contributions proposed for estimating human intention through different newly proposed and existing algorithms. The algorithms come from machine learning, deep learning, probabilistic modeling, etc., as described in Table 2. Figure 2 shows the relation between the papers published in the domain of intention recognition and the years in which the papers were published. It can be seen that the highest number of papers published in the year of 2018. The highest numbers of the paper published in the year 2018 in the category of robotic assistance in the field of human intention estimation as evident from Figure 1. Figure 2 shows that in the year 2003 to 2005, very few contributions were made in the domain of intention recognition in human-robot interaction.

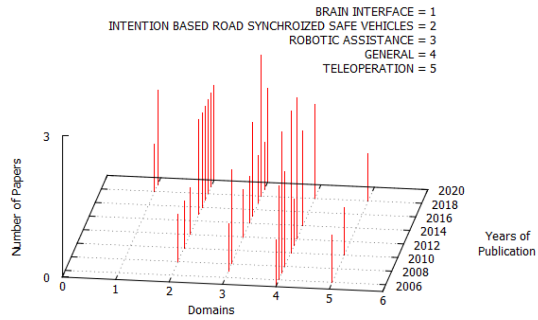

FIGURE 1. **The vertical lines represent the number of contributions. The location of the lines on the plane represents the year (axis-year of publication) in which that contribution was published and the other axis of the plane (Domain) represents the area in which the contribution falls.**

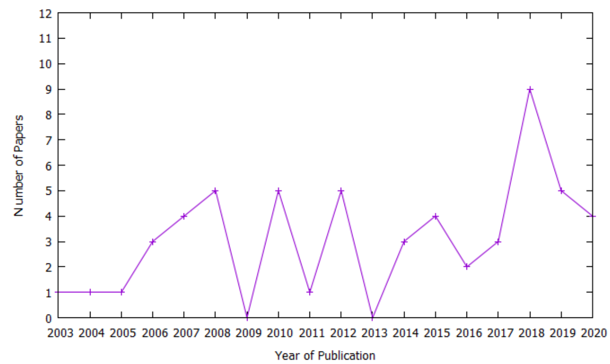

FIGURE 2. **The graph represents the total number of papers published each year in the domain of Intention recognition, in Figure 2.**

The contributions made from 2003 to 2005 were smooth in numbers, in a general category, shown in Figure 2.

Figure 3. represents the relationship between the techniques and the number of research papers published in the domain of intention recognition in the area of human-robot interaction. The abbreviations given in Figure 3 are described in Table 2.

The intention recognition approaches can be divided into two major categories, namely generalized approaches and application-focused approaches. The generalized approaches are the ones that involve the proposition of a general model for human-intention modeling, recognition, the reaction after intention recognition, both modeling and recognition, etc., without focusing an application at the time of proposition. The application-focused approaches involve the approaches that mostly use existing modeling techniques for intention recognition/reaction / etc., specifically considering an application-area.

III. GENERALIZED INTENTION ESTIMATION TECHNIQUES

Most of the existing general intention recognition approaches are general in all aspects, i.e., not only the modeling of intention is general but also the intended application is domain-independent, etc. It means that the general approaches are

TABLE 1. Summary of the Generalized intention recognition approaches.

General Intention Estimation Techniques	
Control based General, General using Gaze, General using object affordance for assembly task, General using torque, General using Gaze, General, General proactive, General using social model, Context-dependent General, General Fuzzy, Graph-based General	[35], [36], [37], [38], [39], [40], [41], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55]

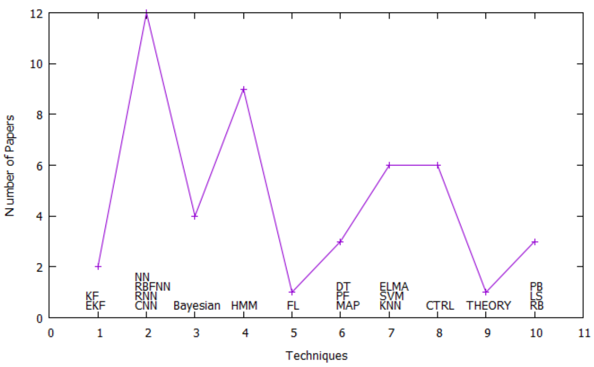

FIGURE 3. The graph represents the total number of papers using a specific technique in the domain of intention recognition, published each year.

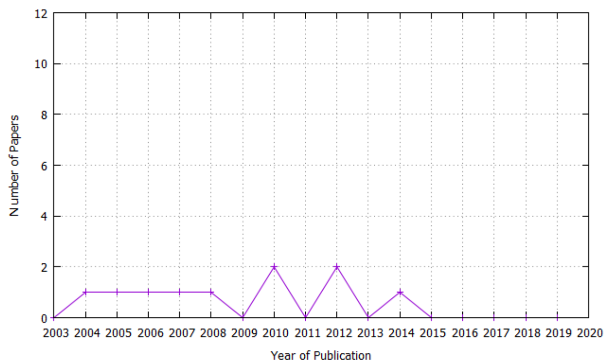

FIGURE 4. The graph represents the total number of papers published each year for proposing pure generalized intention recognition approaches.

feature independent, i.e., they can be applied for intention modeling as well as intention recognition in almost all domains requiring intention recognition. There exist a few generalized intention recognition approaches which focus specific input feature/s for modeling the human intention or for human intention recognition, as given in Table 1. The specialized input corresponds to the gaze-based input [36], object affordance for assembly task [37], torque [38], and context [39] in general intention recognition approaches. The approaches considered in Figure 1 also considered generalized approaches in a specific domain, using some specific features as described in Table 1. The approaches [40], [41], [45]–[48], [51]–[53], [55] correspond to the most generalized intention estimation techniques as shown in the graph in the Figure 3.

Figure 3 provides the graph of the general approaches published in the years from 2003 onwards. It can be seen from the graph that the rate of proposing the general approaches was quite low in the previous years and in recent years there is almost no contribution to such approaches. The graph in Figure 3 shows only the pure generalized approaches that are general in all perspective as compared to the approaches given in Table 1 that also contains control, gaze, etc., based general approaches.

The algorithm involved in proposing the generalized intention recognition approaches are described categorically in Table 2. In accordance to Table 1, Table 2 contains the pure and specific input feature-based generalized approaches. The years of publications of the approaches, mentioned in Table 2 describe that initially probabilistic algorithms are used for the proposition of intention recognition and Bayesian [36], [43], [51], [52], is the most frequently used technique for this purpose. HMM is also a well-known probabilistic modeling technique that is mostly used in application-specific intention recognition as given in Table 3 but also used for the proposition of generalized intention recognition as given in Table 2. A few examples of recursive probabilistic algorithms also exist for the proposition of generalized intention recognition [35], [45], given in Table 2. Classification algorithms from deep learning and other algorithms are rarely used for this purpose [38], [39], [50], [54].

The Section discusses different approaches for recognizing human intention. The proposed approaches do not focus on a specific application of the approach for intention recognition. A few less generalized approaches consider a specific feature for recognizing human intention. The gaze is one of the specific features that was used to recognize the intention. Most of the approaches used probabilistic algorithms to construct a general intention recognition solution. [35] used the Extended Kalman Filter (EKF) to estimate the human intention concerning its hand movement. To estimate the human intention multiple models of human hand motions are used based on EKF. Based on human intention the switching is performed among the models representing the human hand motion based on human intention. The models are updated in three steps that are Interaction / Mixing, Model Matched Filtering, and Model Probability Update. These steps correspond to the calculations of state belief and posterior probabilities of the models. [36] considered the combination of gaze and model-based human intention could improve the intention recognition. The gaze related data corresponding

TABLE 2. Summary of the application-focused intention recognition approaches.

Category		Models	Complete Name	Sub category	Numbers of Papers
Machine Learning	Supervised	NN	Neural Network	Deep Learning [59]	[38], [39],[50]
		RBFNN	Radial Basis Function Neural Network		
Probabilistic Algorithms		HMM	Hidden Markov Models	Layered Approach	[37] [47] [49]
		PB	Parameter Based		[52] [51] [43] [36]
		Bayesian		Bayesian	
		PF	Particle Filter	Recursive Algorithm	[35], [45]
		EKF	Extended Kalman Filter		
					[40], [41] [48]
Logic-based		FL	Fuzzy Learning		[54]
Theory-based		Graph			[55]
		Ontology			[46]
		Theory [66]	Mirror Neuron and Simulation Theory		[44]

to a specific human intention is probabilistically used to recognize the gaze-based human-intention. The features used in gaze-based human-intention-recognition involve fixation length and time. In the second part, the intention recognition model corresponds to the probabilistic representation of the action sequence. The generalization of existing approaches used for model-based human intention recognition. Both of the parts, i.e., gaze and model approaches are combined using the Bayesian. [39] classified intention as navigation and informational intention in gaze-based intention recognition. The informational intention corresponds to find objects with a goal, in a visual input to the human. The navigation intention corresponds to finding objects of interest without a goal. The features used to identify the navigational and informational intention involve fixation length, fixation count, and pupil size variation. For eye-tracking, Tobii 1750 system was used. Neural Network was used as a classification technique to recognize the human's implicit intention. [38] proposed adaptive impedance control function to synchronize the human intention with the developed humanoid Nancy. The force exerted by the human is sensed through the force/torque sensor and the arm of the humanoid moves accordingly. RBFNN is used to estimate human intention. [40] presented an approach named Intention-Driven Dynamics Model (IDDM) that is based on Gaussian Process Dynamics Model (GPDM). The GPDM model is inspired by the Gaussian Process Latent Variable Model (GPLVM). GPLVM models the joint probability of the observed data in low dimensional latent space without considering the time-based progression. IDDM is proposed as an Intention based extension of GPDM. IDDM considers the influence of intention for the transitions among the latent states. The hyperparameters are learned using the Expectation maximization in the IDDM. The IDDM best suits to model the human action at a lower level as GPDM is used to model different parts of the human body. The approach [45] used the Finite State Machines to model human intention. Different FSMs represented different human intentions to be modeled. A Particle Filter based algorithm was used to recognize human intention. As the human-robot interaction scenario proceeded the transitions in the different related FSMs occurred. The FSM that was near to reach the destination state was considered to be the most probable FSM that model the current human intention. The approach in [41] was based on the FSM proposed in [45]. The main idea was to recognize human intention as early as possible to make the intention recognition process proactive. The structure of a FSM was used to recognize the intention proactively. In case if the state sequence in the FSM becomes unique that represented the most probable intention then the intention was considered to be recognized before reaching the destination state. It made the intention recognition process proactive by early recognizing human intention. [43] used the existing (small structures) of Bayesian Networks (BN) to construct a bigger BN for modeling the human intention. The construction of BN is an incremental process based on existing BN and contextual information. The experiment was performed for Linux Plan Corpus as well as for Prisoner's Dilemma problem. The use of contextual information was claimed to be useful for better human intention modeling (constructing the incremental BN). Reference [51] claimed novelty by eliminating the cycle in Dynamic Bayesian Networks (DBN) for intention recognition. Reference [51] described that the cycles are produced by the feedback by the sensed (action/intention) states. A large number of prior and conditional probabilities are required in the proposed approach for intention recognition [53]. The modeling technique is so complex that there existed techniques [62] to reduce the complexities. The approach in [52] introduced an extension of DBN. The proposed approach was a pure general intention estimation technique. The performed extension corresponded to the proposition of Hybrid DBN. The concept of hybridity is related to the use of continuous as well as discrete-valued states in DBN. The approach [52] empathized the importance of continuous values as the probabilistic values and sensory outputs are mostly continuous. The approach in [48] proposed the proactive behavior of the interacting robot. The robot responded according to the already known human intentions. Each action for a proactive response was assigned a tendency value. If no intention was estimated, then all the response action received 0 tendency value. If estimated intentions were greater than a threshold value, then again action tendencies of response actions were zero. If the number of intention estimates is greater than 1 and less than the threshold value, then the response action was selected using conditional entropy, expected success rate, valence value, safety requirement, and most likely sequence. If only one intention is estimated, then the concerned response action was selected using Lorenz's psycho-hydraulic model [69]. Reference [46] proposed Ontology-based intention recognition. Rule-based approach RuleML was used for intention recognition. DBN was used to implement the ontology. The proactivity in human intention recognition is achieved by the application of information entropy. A simulated robot is used to evaluate the approach.

Reference [44] proposed mirror neuron and simulation theory-based cognitive architecture for human intention estimation. The architecture involves perception from environment, attention, memory, behavior mapping, behavior modeling, intention reading, and behavior selection modules. A behavior selection algorithm is also proposed that involves three cases for behavior selection. The cases occur if the object under attention does not has a mapping with behaviors in the memory. In the first case, one higher behavior is found. In the second case, more than one higher behavior is found and the uncertainty level is zero. In the third case, more than one higher behavior found with the uncertainty level is bigger than the threshold value. Simulation (Matlab) based experiments are performed for intention-based Human-Robot Interaction (HRI). Reference [42] proposes a pedestrian behavior model based on the social model proposed in [67]. The pedestrian model is composed of three virtual forces, i.e., are acceleration force towards a goal, repulsive force from other pedestrians, and obstacle. Different parameters are involved in this model including the position of sub-goals, distance to sub-goals, and velocities of the pedestrians. The pedestrian behavior involves the three concepts of reaching the goal, i.e., moving towards the goal (free walk), avoiding a pedestrian in the way to reach the goal (avoid), and following the other pedestrian towards the goal (follow). Reference [37] proposed the use of object affordance for intention understanding using the Hidden Markov Model (HMM). They used the scenario of the assembly line. The grasping of a specific object was used to estimate different actions intention through HMM that can be performed with that object. The forward algorithm in HMM is improved by predicting the most likely future state. The approach proposed in [47] used HMM to model the interaction intentions of a human. The different behaviors involved in a meeting, passing by, dropping, and picking up. The visible variables of HMM models were selected as the change in the position and the angle at which the robot is supposed to interact. The approach is comprised of modeling human activity as well as human intention. Reference [49] used HMM to model the human intentions for human-robot interaction. The goal of an intention was considered as a visible state parameter. The consideration was due to the reason that the goals represented the intentions. The approach novelty corresponded to the usage of changing parameters that encode the task goal. Dee proposed proactive agents based on internal states [50]. The internal state was generated using the sensory-motor information with the time. Different variations of Neural Networks were used to model the internal states. The proposed approach claimed that the understanding of the internal state could improve the proactive behavior of the agent. The approach [53] in proposed utility [48] based intention recognition. The plan of the agent was modeled as the agent's intention and the plan with maximum expected utility was considered as the estimated intention. The proposed approach emphasized the requirement of the outcome of an intended task and the outcome corresponded to the utility value of the task. The approach was more related to the plan of understanding. Reference [54] considered the use of a fuzzy inference engine to estimate the human intention without going into the details of the inference engine. It is argued that the physiological data is easy to measure and the qualitative mapping between the physiological measures and emotion recognition can be performed based on the recent research work. The qualitative mapping between physiological data and emotions/intention is performed through the fuzzy inference engine. The approach in [55] used graph representation for intention recognition. A three-layered graph approach was used. The layers consisted of action, proposition, and the goal/intention layer. All the layers used nodes and the connected nodes represented an intention graph. An action was modeled using preconditions and effects. The intention recognition process was comprised of goal recognition and intention recognition.

TABLE 3. Summary of the application-focused intention recognition approaches.

	Categories / contributions	Reference
	Brain Interface	
	Brain signal processing, Human Monitoring Brain-Computer interface	[4], [5]
Intention based road	**Autonomous Navigation**	
	Safe autonomous navigation, Navigation prediction, driver intention inference	[6], [7], [8], [9]
	Intelligent Vehicle w.r.t Pedestrian	
	Pedestrian	[10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]
	Synchronized assistance	
	Robot assistance, Robot assistance, Robot assistance, Robot assistance, Grasping through tactile sensors, Robot assistance, Robot assistance, Exoskeleton, Robot assistance, Robot assistance, Robot assistance, Control based, Rehabilitation, Exoskeleton	[21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34]
	Intention estimation for Teleoperation	
	Teleoperation	[56], [57], [58]

IV. APPLICATION DOMAIN FOCUSED INTENTION ESTIMATION TECHNIQUES

The section discusses the application-domain specific intention recognition approaches. The application- domains are enormous as all distinct scenarios in which a human interacts with an artifact can be a potential domain, depending on the intelligence imparted to the artifact. There are a few application-domains that are under consideration by the research community, e.g., autonomous cars, synchronizes assistance, etc. The completely autonomous vehicles are in the test phase around the world. Although vehicles (robots) are not completely autonomous for all kinds of driving but driving in connection to a pedestrian is being made secure by making it semi-autonomous. Therefore, pedestrian intention-recognition for safe driving has emerged as a new application area of human-robot interaction. It is a human-robot interaction scenario in which the human is a pedestrian and the robot is a semi-automatic vehicle.

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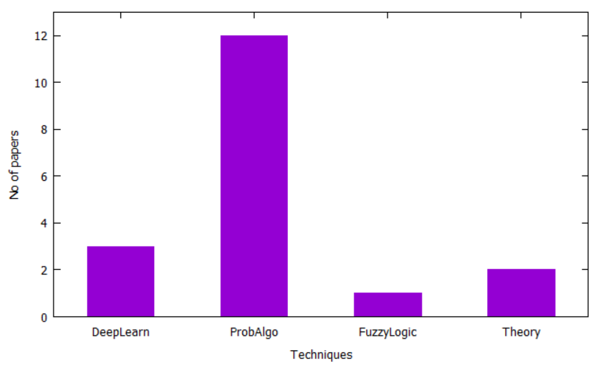

FIGURE 5. Histogram of the technique by the approaches proposed in the category of the Generalized intention recognition.

It is a human-robot interaction scenario in which the human is a pedestrian and the robot is a semi-automatic vehicle.

Similarly, a lot of research work is done in the synchronized robotic assistance. The category involved robotic assistance, exoskeletons, and tactile sensors. A few approaches also exist in the brain interface and autonomous navigation. The autonomous navigation category does not specifically consider the humans in the environment as a pedestrian but considers the humans as moving obstacles with intention. Whereas the pedestrian represents a specific human behavior. The approaches concerning intention estimation are discussed in the order described in Table 3. On the pattern of Table 2, Table 4 describes the techniques used to propose the application-domain specific solutions.

The approaches are categorized into five categories, namely 1) Brain Interface, 2) Intention based road synchronized safe vehicle, 3) Synchronized physical assistance,

TABLE 4. Categorization of the proposed approaches in the domain of intention recognition in the field of human-robot interaction concerning the techniques, used to propose the solution.

Category		Models	Complete Name	Sub category	Numbers of Papers
Machine Learning	Supervised	NN	Neural Network	Deep Learning [59]	[4], [21], [10], [22], [11], [24], [15], [14], [9], [60], [33]
		RBFNN	Radial Basis Function Neural Network		
		RNN	Recurrent Neural Network		
		CNN	Convolutional Neural Network		
		ELMA	Extreme Learning Machine Algorithm		
		SVM	Support Vector Machine	Non-Deep Learning	[17], [25], [16], [13], [7], [22], [20], [61]
		DT	Decision Tree		
		KNN	K-Nearest Neighbor		
		RB	Rule-Based Algorithm		
Probabilistic Algorithms		HMM	Hidden Markov Models	Layered Approach	[6] [57] [19] [58] [29] [30]
		PB	Parameter Based		[62] [43] [18] [56] [27] [42]
		MAP	Maximum A Posteriori	Bayesian	
		Bayesian			
		KF	Kalman Filter	Recursive Algorithm	[8]
Logic-based		FL	Fuzzy Learning		[63]
Control based		CTRL	Control [64]		[32], [23], [28], [12], [5], [65], [66]
Statistical modeling		LS	Least Square		[26]

4) General Intention Estimation Techniques, 5) Intention estimation for Teleoperation.

A. BRAIN INTERFACE

The approaches correspond to intention estimation techniques that model the human brain signal. The approaches try to map what the human intends to do with the signal generated by the brain in response to that intention. Mostly modeled signals correspond to Electroencephalography (EEG). The techniques used for mapping involve deep learning models and probabilistic methods. Reference [4] used the Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) to model the EEG signals, obtained from the brain to model different human intentions. Both cascade and parallel application of CNN and RNN were used to capture the spatial and temporal features of EEG signals. They converted 1D data obtained from signals into 2D data using the location of the sensors placed on the human. Reference [5] provided a comparison of different techniques to calibrate the intention (human) decoder vector. The compared methods involved Piecewise Linear Model, Instant-OFC, Position Error, Unit Vector, ReFIT, Raw Decoder Velocity. The calibration vector is developed using a feedback control vector, using linear feedback control, by subtracting the target position from the cursor position, unit vector pointing from cursor to target, decoded velocity, velocity vector respectively. There is no discussion in both of the approaches [4], [5] about the definition of the human intention as it is mostly defined as action sequences [45], [46], [48], [51], etc. The presented approaches in this section proposed direct mapping between the EEG signal and intention using Deep learning models and simple modeling techniques.

B. INTENTION BASED ROAD/ZZZZZ/WWWWW/PEDESTRIAN SYNCHRONIZED SAFE VEHICLE

Intention recognition can play a vital role in the prediction of the next human position. In this regard, recognizing human intention can improve the safety of autonomous navigation by avoiding a potential collision.

Probabilistic techniques are applied to estimate the next human location for safety improvements. Reference [6] used HMM along with VORONOI diagrams for safe human-robot interaction in a warehouse scenario. The human intention in focus corresponded to the path adopted by the human. The paths in the warehouse are modeled using the VORONOI diagrams and the optimal paths between two points were calculated using D. The two points correspond to the current and goal location of the human. The paths followed by the human worker were monitored

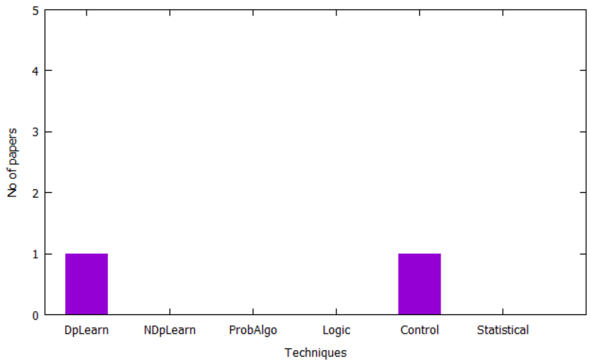

FIGURE 6. Histograms of the techniques used by the approaches proposed in the subcategory of Brain interface of application-specific intention recognition approaches.

and used as observation of the HMM for human intention estimation.

Reference [7] used the intention estimation for navigation of the autonomous robot among manually driven vehicles, other robots, and humans. Intention estimation corresponds to the behavior modeling of the other driven vehicles for the smooth navigation of the autonomous system in the above-mentioned scenario. The behavior was modeled using a set of trajectories related to the other driven vehicles. The intention estimation for behavior modeling was performed using the particle filter and the decision tree simultaneously. The reference trajectories were used as already known maps in the particle filtering algorithm. Similarly, the grid cell features were used as a reference to calculate the different categories. The experiments showed that for binary class problem decision tree and multi-class problem particle filter worked well.

Reference [8] proposed KF based human tracking to avoid the human-robot collision. The human behavior (intention) to avoid a collision or not is estimated using the social force model [67]. The social force model [67] provides four aspects to model pedestrian behavior. The proposed solution considers two of the four aspects of the social force model [67]. In the first aspect, acceleration is calculated using the relaxation time, actual velocity, and desired velocity of the pedestrian. In the second aspect, the repulsive effect of other pedestrians is calculated using the repulsive potential. A vision-based driver intention inference system is proposed in [9]. The modeled intention corresponded to the lane change during driving. The time-series driving data was modeled using a novel ensemble bi-directional RNN along with Long Short Term Networks (LSTM). The input data were obtained from different from cameras along with the VBOX vehicle data acquisition system.

The presented approaches [6]–[8] focused warehouse scenario, behavior modeling using trajectories, and collision avoidance considering the human intention to avoid a collision, to model the human behavior for navigation and successful navigation in warehouse scenario. Once again the prior definition of human intention was not defined. Either the human actions are or the change in the environment is used to model the human intention It is related to the autonomous navigation but purely focuses on the pedestrian's intention to avoid the collision in case of a vehicle on the road. Mostly deep learning algorithms are used to recognize/classify the pedestrian's intention. A few examples also existed in which probabilistic solutions are provided.

Reference [10] used polynomial-time series approximation along with the Multi-Layer Perceptron (MLP) architecture to model the movement-behavior of road passersby (pedestrians, cyclists, etc.) for intelligent vehicles to avoid accidents. The behavior was modeled using the recognition of the motion states and the prediction of future trajectories of the passerby. The time series based observation is used to update the states that are modeled using polynomials and trajectory prediction is performed using MLP.

Reference [11] considered intention recognition in the specific case if the pedestrian intends to cross the road. The head pose and the motion of the human are focused to estimate the human intention. The algorithms used for feature extraction involve Histogram of Gradients, Local Binary Patterns, and CNN. The recognition is performed using the machine learning classification algorithms involving SVM, Artificial Neural Network, K Nearest Neighbor, and CNN. The head and legs of a human are segmented and then the feature is extracted. Based on the features the pose and motion direction are estimated that are combined with the pedestrian context information to estimate the final road crossing intention. The testing is performed on the video clips from the data set of Joint Attention for Autonomous Driving.

Reference [12] proposed the mixture of the driver and automated system to control the vehicle. The driver and system's input is combined to operate the vehicle. The driver's control model is calculated based on two simple assumptions, i.e., the driver can understand the combination function (driver and system input) and the driver's intention to control the vehicle. The intention recognition corresponds to the share (human and system) in the control of the vehicle according to humans.

Reference [13] estimates the pedestrian intention of crossing or not crossing the road using the accelerometers carried by the pedestrians by using simple classifiers.

Reference [14] applied different machine learning approaches on the pedestrian data to estimate the intention to cross the road. The machine learning approaches involve Support Vector Machine (SVM), Convolutional Neural Networks (CNN), Dense Neural Network, LSTM along with the LiDAR data. The earlier proposed approach [16] only used SVM for intention selection based on the classification by pedestrian data. The approach [16] used handcrafted for features for classification purposes. In the current research, CNN is used for feature selection, and the application of different approaches are evaluated for pedestrian prediction. The used features involve pedestrian-related (velocity, distance traveled, and distance from the crosswalk and to the road orthogonally) and relative data of vehicle and pedestrian (position and movement (velocity to reach crosswalk) of a car). The prediction rate of Dense NN (with handcrafted features) was better than SVM and Dense NN with CNN + LiDAR, for crossing pedestrians. In the case of non-crossing pedestrians, Dense NN and SVM performed comparatively better than the Dense NN with CNN + LiDAR The modulation of EMG for different human users decrease the ability to decode the human's movement intention. A human-user adaptive movement decoding method is proposed [15]. Reference [15] used the Convolutional Neural Network to learn the features of human biosignals obtained from EMG. The learned features can be used to decode the human movement intention.

Reference [17] proposed a rule-based algorithm for the driver intention detection concerning the pedestrian intention to cross the road. The algorithm is based on the data collected by a simulated driving test performed on 32 diverse drivers. The collected data corresponds to the driver gaze and the speed pedal position if the pedestrian is to cross the road. There were six different pedestrian scenarios (on the road or walking towards the road) related to which the driver data was collected.

Reference [18] constructs different Bayesian Network (BN) models for driver intention recognition. A model suitable related to the current road situation is selected out of different BNs. The road is divided into different regions to facilitate driver intention recognition. The factors affecting the driver's intention are considered as the nodes of the BN. The factors include a traffic signal, road condition, direction, and location of the vehicle.

Reference [19] used HMM for driver intention recognition to avoid an accident due to driver negligence. The approach discussed the simplification of the HMM models representing an activity. The considered activity involved a driving environment, i.e., paddle position, the position of a vehicle in traffic, etc. The simplification of models corresponded to the braking of the HMM model into sub-models. Each sub-model represented a discrete driving maneuver. The implication also involved the breakup of the state transition matrix concerning the number of sub-models.

A data analysis based pedestrian crossing intention estimation was discussed in [20]. The crossing pedestrian data was collected by a laser sensor and an HD camera. An (AT-LSTM) LSTM with an attention mechanism model was proposed and trained based on the data. The results of AT-LSTM were compared against SVM and were found better.

C. SYNCHRONIZED PHYSICAL ASSISTANCE

The synchronized assistance corresponds to the approaches that recognize the human intention for operating the machine, directly connected to the human body for assistance in performing different physical activities. Most of the discussed approaches used machine learning approaches and a few approaches used and probabilistic based solutions. Almost all the approaches used Torques as features to estimate human intention. Reference [21] proposed Radial Basis Function Neural Network (RBFNN) for the estimation of the acceleration, velocity, and position of the human limb. The

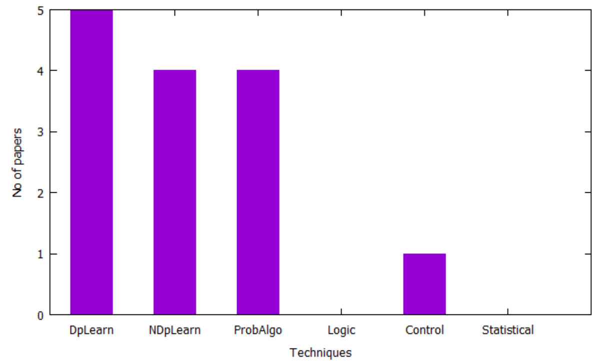

FIGURE 7. **Histograms of the techniques used by the approaches proposed in the subcategory of a pedestrian synchronized safe vehicle of application-specific intention recognition approaches.**

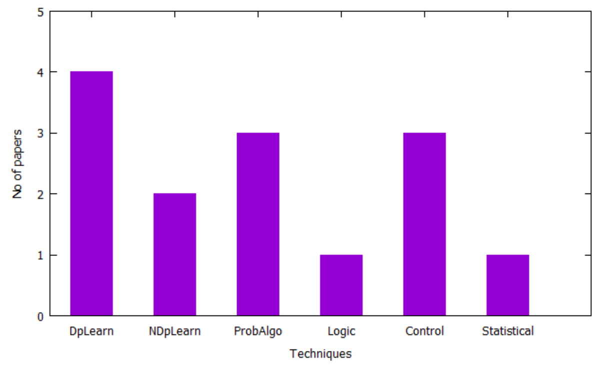

FIGURE 8. **Histograms of the techniques used by the approaches proposed in the subcategory of synchronized physical assistance of application-specific intention recognition approaches.**

intention corresponds to the human movement with which the robotic assistance is required to be synchronized. It is assumed that the human hand is in contact with the robotic hand. The data collection is performed using the adaptive impedance control method and the Network is trained offline. The graphs represented the experimental results that RBFNN based parameter estimation (corresponding to the human intention) is very close to the actual values of parameters as compared to the estimated parameter values of the adaptive impedance control method. Reference [22] used two Recurrent Neural Network (RNN) for intention estimation. First RNN is used to predict the future movement of the human and the second RNN is used to predict the trajectory of the human for a specific Goal location. The input of the first RNN is used as input to the second RNN. The history of trajectories is also the input of the second RNN. The output of the second RNN is used as the identification of human intention for which the robot is desired to assist proactively. Reference [23] proposed an inverse dynamic based approach for exoskeleton Joint Muscular Torque (JMT) calculation. The JMT calculation was performed for the lower limb. For both the legs, JMT values are separately calculated. They calculated inverse dynamics for each leg. The JMT was divided into mass-induced and foot-contact-force torque. Reference [24] used the Extreme Learning Machine (ELM) [68] algorithm for modeling human intention. The data obtained from the hand wearable sensors is input to ELM which is fast training deep learning technique. The output of ELM is used to classify human intention. The ELM algorithm is trained to classify the different human intentions using the related data obtained from a wearable hand sensor. The experiments focused the handing over tasks in the human-robot collaboration scenario. Reference [25] analyzed the human-grasping intention using the tactile sensors. The intention recognition was performed using the force distribution on the interaction surface, estimated through the tactile sensors. The analysis was performed using three machine learning approaches, i.e., KNN, SVM, and AdaBoost. The classifiers were trained using the data gathered for known intentions with the corresponding force distribution on the interaction surface. The machine learning models involving KNN, SVM, and AdaBoost were checked on the dynamic data sets and all the classifiers have a low error rate. The results of KNN and SVM were found optimal as compared to AdaBoost. Reference [26] estimated the human intention especially in case of joint manipulation of an object by humans and the robot. The considered scenario corresponds to the human and the robot holding an object and the robot estimate the twisting or wrenching intention of the human through wearable sensors. The inertial sensors are used to get the measurements. The measurements are obtained in terms of linear acceleration and angular velocity and are used to estimate the relative kinematics and orientation. Reference [27] focuses on the intention recognition problem of the human with the disabilities. As human intention can be recognized from its behavior, it is difficult to recognize the intention of a human that has disabilities. In the case of disabilities, human behavior is less visible as compared to a perfectly fit person. The proposed solution is based on the objects with a set of features in the surroundings and the actions that can be performed on the objects. The human intention is estimated using the Maximum A Posteriori (MAP) probability. The MAP is calculated using the argmax of objects and actions over the probability distribution of objects, actions, and features. Reference [28] discussed the human adaption to an exoskeleton giving a rough estimate of the human muscular torques through Electromyographical, without any customization. The paper discusses the adaption ability of the human with the exoskeleton that gave a rough estimation of human muscular torques. Reference [29] recognized the human intention by interpreting the finger worn inertial sensor data using HMM. The data obtained from the sensor was preprocessed. The preprocessing involved FFT based sensor usage detection and k-means based cluster selection. The experiments were performed based on five hand gesture types and five HMM models were trained and tested respectively. The goal of the approach is to facilitate the elderly in their daily life. Reference [30] used Hierarchical HMM (HHMM) to recognize the human intention exactly in the same scenario and with the same objective as discussed in exactly the [29] previous approach. The only difference is that in the current approach, the context information is also used to refine the human intention recognition process. The context-based intention recognition is modeled using HHMM. Cesta proposed the proactive behavior of the robot by activity monitoring [31]. The proposed approach focuses on elder care by the robot assistant. Two ways of interactions are described namely, On-Demand interaction and Proactive interaction. Proactive interaction corresponds to the activity monitoring and constraint-based proactive and warning giving the response. An abstract algorithm is described for adding and removing the constraints while monitoring the activities. The eldercare project is at its beginning as described by the authors. The described behavior appears warning or reminding of some operation forgotten by the humans. Reference [32] proposed a control-based approach for assistive robotics. The approach utilizes the intention of the human, wearing the assistive exoskeleton, for better assistance as per the human motion intention. A force-sensing resistor was designed for the estimation of the human motion intention. Intentional Reaching Direction (IRD) was used to detect the human intention for synchronization with the human motion. Different working modes were defined for the exoskeleton to work with the human arm. Two different algorithms were proposed for mode selection and IRD estimation. Reference [33] proposed Electromyogram (EMG) signal based solution for rehabilitation of post-stroke patients. The human muscles motion-intention sensed using EMG was mapped using the Back Propagation Neural Network model with a novel input feature vector. Joint torque estimation and prediction are proposed in [34] for the lower limb exoskeleton for walking. The proposed approach consisted of a dynamical movement primitives based model. The solution proposed in [63] claims to be adjustment-free as it is the common requirement for the usage of prosthetic legs. The approach used Fuzzy logic along with a gyroscope and accelerometer with other sensors. The focus of the presented research [61] is the complexity concerning the complexity involved in irregular daily motion trajectory during upper limb rehabilitation training. In this regard, a hierarchical multi-classification support vector machine is used to classify human motion intention and the motion model of the processed signal obtained from humans.

D. INTENTION ESTIMATION FOR TELEOPERATION

All the approaches concerning intention recognition in the subdomain of teleoperation used probabilistic methods to model human intention. The used probabilistic approaches involved recursive Bayesian and variants of HMM. Reference [56] proposed human intention estimation based on the Bayesian approach. A recursive Bayesian intent estimation algorithm was proposed that uses the Bayesian approach to estimate the intention for each human intended goal recursively. The distance to the intended goal location as well the human actions were used to estimate the human action. The focus of the presented solution was the teleoperated

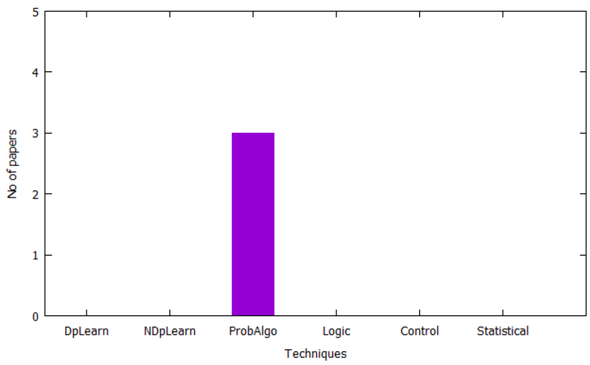

FIGURE 9. Histograms of the techniques used by the approaches proposed in the subcategory of teleoperation of application-specific intention recognition approaches.

assistance under shared autonomy. Reference [57] proposed HMM-based teleoperation. The intention of humans is recognized based on the haptic sensors. The focus was on the phase change of haptic data while manipulating an object. The phase change corresponded to either the transportation intention or the positioning intention of the human. A better online feature extraction approach was claimed to be used [70] as compared to the previously offline approach [71]. Reference [58] used Layered HMM (LHMM) to model human motion. Each of the body parts involved in the motion was modeled by a classifier that was used in the LHMM approach. The human motion was modeled for simple teleoperation tasks. The approach was evaluated by the trajectory data of the teleoperated robotic manipulator.

V. SUMMARY AND CONCLUSION

It can be observed that recently the research community has been quite active in the novel domain of pedestrian safety by recognizing the pedestrian intention, as evident by the presented approaches in Section 2. There is a potential motive of the auto industry behind the domain as it can improve the road safety enormously by making the vehicles more intelligent and semi-autonomous. The presented solutions are developed using deep learning and probabilistic algorithms. The recognized Intention of pedestrian and driver is used to improve road safety and collision avoidance. Different kind of aspects of the pedestrian is used to define pedestrian intention. In Section 2, almost all of the presented approaches consider pre-collision strategies. The consideration of soft collisions can open new directions in this application area of intention recognition. The soft collision can be defined as if the vehicle's automated system infers that the collision is inevitable then driving maneuver leading to the least damaging situation (soft collision) can be opted by the vehicle. The pedestrian safety (intention-based / other features) is the need of the time as many auto companies have tested or in the process of testing the self-driving vehicles [72], [73], etc. The topic is still new as the research community is working on it in multiple dimensions, e.g., [74]. Reference [74] discusses the general limitations and road scenarios with conventional and self-driving vehicles. Similarly approaches [9], [12], [17]–[19] also exist to make driving easy by recognizing the driver intention. For future directions, the vehicle may guide the driver in his driving maneuvers, e.g., by recognizing the driver intention that if the driver is going to overtake another vehicle on the road then is it to safe to perform the overtake maneuver or is it dangerous or lethal according to the traffic on the road? There can be automatic intention recognition based suggestions from the navigation system, telling the speed limits not only on motorways but also in city limits about hospitals, schools, etc. The research work [65], [75] is already in progress for inter-communication between the vehicles. Road safety can be further improved by inter-communicating the driver's intention with each other. Similarly, as pedestrian safety, physical assistance is another emerging field in which the research community is recently active as there exist different recent contribution in this application subdomain of intention recognition, i.e., [21]–[25], [61], etc. Most of the existing solutions in Section 3 use Control theory, Machine and Deep Learning approaches and a few probabilistic approaches also exist, e.g., recently [76] used voice modeled using Gaussian Mixture Model as means to interface between human and assistive hardware, [60] used deep learning for human intention-based object grasping. The presented approaches are more specialized for a specific problem rather than a generalized solution, applicable for multiple problems of this section. Almost all of the solutions focused on the psychical weakness of humans. A recent approach [33] presented a solution in connection to the post-stroke situation. More complex disability-diseases can be focused to address the disability problems. The research community has been active in the field of exoskeleton based human-physical assistance but the space of improvement exists in multiple aspects, namely, accuracy in intention recognition, still the need to wear the exoskeleton, usage of simplified and predefined human models for training, and the design of rigid-soft-soft coupling [77], [78]. Despite the improvements in the field of Physical assistance, bionic research is mostly restricted to wearable physical assistance. The joint venture of medical, mechatronics, and applied information science is necessary to develop bionic prototypes. There is a lot of room available in this area for the proposition of approaches that can provide bases for the development of bionic limbs. Recently, the research community in the field of information science is not very active in the field of general intention recognition. Most of the generalized approaches came from applied probabilistic research. Especially Deep Learning algorithms have not been used frequently to propose the generalized intention recognition solution. The generalized intention recognition approaches have gradually decreased as visible from Figure 3. As per the available literature, the latest general approach was proposed in 2012 in [40], [41] as shown in Table 1. There has been less generalized intention recognition approaches proposed in 2018 and 2014, [36]–[39], the approaches are generalized, based on gaze, object affordance, and torque based. It implies that in recent history there is a lack of interest in the research community in proposing a general intention recognition approach. Moreover, there has been no approach proposed specifically focusing on household tasks, etc. It is evident from the non-existence of the interacting robots in normal life. There is an example of Roomba robots [86] that are devoid of the capability of human-robot interaction. There also exist some other less active application domains of intention recognition, e.g., teleoperation, autonomous navigation, and brain signal understanding. As per the contributions in these application domains, brain signal is comparatively more active as compared to the others and has the potential to be carried on by the research community due to its wide application in human life. The purpose of Intention recognition in teleoperation means the interpretation of the human moves at another end. The interpretation corresponds to the autonomous execution of the auxiliary tasks related to human intention. In teleoperation, the auxiliary moves are of great importance as the moves relate to the current situation that the human at the other end may not be fully aware of. Moreover, as the human is not physically present at the teleoperated site, the intention estimation becomes more complex. Both of the above constraints make the intention recognition and complacence reaction a difficult task. Therefore, the intention recognition and the complacence reaction tasks are simple as discussed in Section 5 approaches. It implies that there is a space of potential intention recognition approaches for a complex task in the sub-area of teleoperation. The three areas discussed in this review paper have been ignored by the research community. The areas are generalized algorithms for intention recognition, intention extraction from the brain, and the intention recognition in teleoperation. Almost all of the proposed generalized intention recognition algorithms are probabilistic. As per the literature review, Deep learning is not utilized comprehensively in proposing a generalized intention recognition solution. Only one approach [38] considered torque to classify among human intentions using RBFNN. Intention estimation using brain signals must be again a joint venture of information and neuroscientists. The intention recognition through the brain signal will be the direct way to understand the human's intent. Currently, almost all of the intention recognition approaches use an indirect way. The indirect way corresponds to mostly the action sequences [41], [45], sequences of changes [35], [48], [49], [52], [54], [55], in the environment, object affordance [37], gaze [36] etc. All the features/aspects or sequences of changes in features/aspects used in the indirect way work as the mapping to a specific intention respectively. In the generalized approaches category, there has been no proposition of the novel algorithm or fusion of some existing approaches. Most of the recent solutions, proposed in the sub-area are focused or a specific problem [36] using a specific feature as input. The application domains of intention recognition exist everywhere humans exist. In a household scenario, there are a lot of intelligent machines that interact with the human, e.g., kitchen accessories, laundry, temperature control, etc. Similarly, in the mechanic's workshop there exists machines for vehicle repair, in the doctor's operation theater there exist delicate machines doing very delicate tasks, military with defense accessories, employees at assembly line with different assembling machines, workers in refineries, laborers in factories, etc. In almost every field of life, with the human presence, the machines must have the capability of intention recognition for synchronized interaction. Normally, machines with such characteristics do not exist in a common man's life. Therefore, intention recognition in all of its sub-areas is still very less explored territory. There can be some intention-based AI software that can be used to create good intentions for the software user. Such kind of software can be kind of good model makers, etc. Since the intention is the mapping between the sequences and a specific mode (intention) of the human. In the reverse direction, that is creating such a sequence that can change the mode from negative to positive can open a new field in this area. Moreover, as an application that software can be used for rehabilitation, teaching as well for entertainment purposes, e.g., for child engagement in specific activities, etc. Understanding the intentions of an infant and engaging the baby for different purposes can also be a new direction in intention recognition and interaction. The engaging may correspond to teaching some new activities interactively, etc.

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REFERENCES

[1] M. Awais. (2013). *Bayreuth University Library*. [Online]. Available: https://eref.uni-bayreuth.de/view/person/Awais=3AMuhammad=3A=3A.html

[2] D. P. Losey, C. G. McDonald, E. Battaglia, and M. K. O'Malley, "A review of intent detection, arbitration, and communication aspects of shared control for physical human–robot interaction," *Appl. Mech. Rev.*, vol. 70, no. 1, Jan. 2018, Art. no. 010804.

[3] T. A. Han and L. M. Pereira, "State-of-the-art of intention recognition and its use in decision making," *AI Commun.*, vol. 26, no. 2, pp. 237–246, 2013.

[4] D. Zhang, L. Yao, K. Chen, S. Wang, X. Chang, and Y. Liu, "Making sense of spatio-temporal preserving representations for EEG-based human intention recognition," *IEEE Trans. Cybern.*, vol. 50, no. 7, pp. 3033–3044, Jul. 2020.

[5] F. R. Willett, B. A. Murphy, D. Young, W. D. Memberg, C. H. Blabe, C. Pandarinath, B. Franco, J. Saab, B. L. Walter, J. A. Sweet, J. P. Miller, J. M. Henderson, K. V. Shenoy, J. D. Simeral, B. Jarosiewicz, L. R. Hochberg, R. F. Kirsch, and A. B. Ajiboye, "A comparison of intention estimation methods for decoder calibration in intracortical brain–computer interfaces," *IEEE Trans. Biomed. Eng.*, vol. 65, no. 9, pp. 2066–2078, Sep. 2018.

[6] T. Petković, D. Puljiz, I. Marković, and B. Hein, "Human intention estimation based on hidden Markov model motion validation for safe flexible robotized warehouses," *Robot. Comput.-Integr. Manuf.*, vol. 57, pp. 182–196, Jun. 2019.

[7] N. Muhammad and B. Åstrand, "Intention estimation using set of reference trajectories as behaviour model," *Sensors*, vol. 18, no. 12, pp. 1–19, 2018.

[8] Y. Tamura, T. Fukuzawa, and H. Asama, "Smooth collision avoidance in human-robot coexisting environment," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Taipei, Taiwan, Oct. 2010 pp. 3887–3892.

[9] Y. Xing, C. Lv, H. Wang, D. Cao, and E. Velenis, "An ensemble deep learning approach for driver lane change," *Transp. Res. C, Emerg. Technol.*, vol. 115, pp. 1–19, Jun. 2020.

[10] M. Goldhammer, S. Köhler, S. Zernetsch, K. Doll, B. Sick, and K. Dietmayer, "Intentions of vulnerable road users–detection and forecasting by means of machine learning," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 7, pp. 3035–3045, Jul. 2020.

[11] D. Varytimidis, F. Alonso-Fernandez, B. Duran, and C. Englund, "Action and intention recognition of pedestrians in urban traffic," in *Proc. 14th Int. Conf. Signal-Image Technol. Internet-Based Syst. (SITIS)*, Las Palmas de Gran Canaria, Spain, Nov. 2018, pp. 676–682.

[12] R. Li, Y. Li, S. E. Li, E. Burdet, and B. Cheng, "Driver-automation indirect shared control of highly automated vehicles with intention-aware authority transition," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Redondo Beach, CA, USA, Jun. 2017, pp. 26–32.

[13] S. G. Konrad and F. R. Masson, "Pedestrian intention estimation from egocentric data," in *Proc. 17th Workshop Inf. Process. Control (RPIC)*, Mar del Plata, Argentina, Sep. 2017, pp. 1–5.

[14] B. Volz, K. Behrendt, H. Mielenz, I. Gilitschenski, R. Siegwart, and J. Nieto, "A data-driven approach for pedestrian intention estimation," in *Proc. IEEE 19th Int. Conf. Intell. Transp. Syst. (ITSC)*, Rio de Janeiro, Brazil, Nov. 2016, pp. 2607–2612.

[15] K.-H. Park and S.-W. Lee, "Movement intention decoding based on deep learning for multiuser myoelectric interfaces," in *Proc. 4th Int. Winter Conf. Brain-Comput. Interface (BCI)*, Yongpyong, South Korea, Feb. 2016, pp. 1–2.

[16] B. Volz, H. Mielenz, G. Agamennoni, and R. Siegwart, "Feature relevance estimation for learning pedestrian behavior at crosswalks," in *Proc. IEEE 18th Int. Conf. Intell. Transp. Syst.*, Las Palmas, Spain, Sep. 2015, pp. 854–860.

[17] F. Diederichs, T. Schuttke, and D. Spath, "Driver intention algorithm for pedestrian protection and automated emergency braking systems," in *Proc. IEEE 18th Int. Conf. Intell. Transp. Syst.*, Las Palmas, Spain, Sep. 2015, pp. 1049–1054.

[18] B. Sun and M. Kameyama, "Driver's intention estimation based on Bayesian networks for a highly-safe intelligent vehicle," *J. Robot. Mechtron.*, vol. 24, no. 1, pp. 219–225, 2012.

[19] H. Berndt, J. Emmert, and K. Dietmayer, "Continuous driver intention recognition with hidden Markov models," in *Proc. 11th Int. IEEE Conf. Intell. Transp. Syst.*, Beijing, China, Oct. 2008, pp. 1189–1194.

[20] H. Zhang, Y. Liu, C. Wang, R. Fu, Q. Sun, and Z. Li, "Research on a pedestrian crossing intention recognition model based on natural observation data," *Sensors*, vol. 20, no. 6, pp. 1–21, 2020.

[21] Z. Liu and J. Hao, "Intention recognition in physical human-robot interaction based on radial basis function neural network," *J. Robot.*, vol. 2019, pp. 1–8, Apr. 2019.

[22] D. Nicolisl, A. M. Zanchettin, and P. Rocco, "Human intention estimation based on neural networks for enhanced collaboration with robots," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Madrid, Spain, Oct. 2018, pp. 1326–1333.

[23] M. Li, J. Deng, F. Zha, S. Qiu, X. Wang, and F. Chen, "Towards online estimation of human joint muscular torque with a lower limb exoskeleton robot," *Appl. Sci.*, vol. 8, no. 9, pp. 1–17, 2018.

[24] W. Wang, R. Li, Y. Chen, and Y. Jia, "Human intention prediction in human-robot collaborative tasks," in *Proc. Companion ACM/IEEE Int. Conf. Hum.-Robot Interact.*, Chicago, IL, USA, Mar. 2018, pp. 279–280.

[25] Y. Wang, Y. Sheng, J. Wang, and W. Zhang, "Human intention estimation with tactile sensors in human-robot collaboration," in *Proc. ASME Dyn. Syst. Control Conf.*, Tysons, VA, USA, 2017, pp. 1–8.

[26] D. Ćehajić, S. Erhart, and S. Hirche, "Grasp pose estimation in human-robot manipulation tasks using wearable motion sensors," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Hamburg, Germany, Sep. 2015, pp. 1031–1036.

[27] K. Duncan, S. Sarkar, R. Alqasemi, and R. Dubey, "Scene-dependent intention recognition for task communication with reduced human-robot interaction," in *Proc. Eur. Conf. Comput. Vis.*, in Lecture Notes in Computer Science, vol. 8927, 2014, pp. 730–745.

[28] T. Lenzi, S. M. M. De Rossi, N. Vitiello, and M. C. Carrozza, "Intention-based EMG control for powered exoskeletons," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 8, pp. 2180–2190, Aug. 2012.

[29] C. Zhu, W. Sun, and W. Sheng, "Wearable sensors based human intention recognition in smart assisted living systems," in *Proc. Int. Conf. Inf. Autom.*, Zhangjiajie, China, Jun. 2008, pp. 954–959.

[30] C. Zhu, Q. Cheng, and W. Sheng, "Human intention recognition in smart assisted living systems using a hierarchical hidden Markov model," in *Proc. IEEE Int. Conf. Automat. Sci. Eng.*, Washington, DC, USA, Aug. 2008, pp. 253–258.

[31] A. Cesta, G. Cortellessa, F. Pecora, and R. Rasconi, "Supporting interaction in the ROBOCARE intelligent assistive environment," in *Proc. Interact. Challenges Intell. Assistants*, 2007, pp. 18–25.

[32] J. Huang, W. Huo, W. Xu, S. Mohammed, and Y. Amirat, "Control of upper-limb power-assist exoskeleton using a human-robot interface based on motion intention recognition," *IEEE Trans. Autom. Sci. Eng.*, vol. 12, no. 4, pp. 1257–1270, Oct. 2015.

[33] Z. Yang, S. Guo, Y. Liu, H. Hirata, and T. Tamiya, "An intention-based online bilateral training system for upper limb motor rehabilitation," in *Microsystem Technologies*. Berlin, Germany: Springer-Verlag, Jun. 2020.

[34] S. Qiu, W. Guo, D. Caldwell, and F. Chen, "Exoskeleton online learning and estimation of human walking intention based on dynamical movement primitives," *IEEE Trans. Cognit. Develop. Syst.*, early access, Jan. 23, 220, doi: 10.1109/TCDS.2020.2968845.

[35] H. C. Ravichandar, D. Trombetta, and A. P. Dani, "Human intention-driven learning control for trajectory synchronization in human-robot collaborative tasks," *IFAC-PapersOnLine*, vol. 51, no. 34, pp. 1–7, 2019.

[36] R. Singh, T. Miller, J. Newn, L. Sonenberg, E. Velloso, and F. Vetere, "Combining planning with gaze for online human intention recognition," in *Proc. 17th Int. Conf. Auton. Agents Multiagent Syst.*, Stockholm, Sweden, 2018, pp. 488–496.

[37] M. Cramer, J. Cramer, K. Kellens, and E. Demeester, "Towards robust intention estimation based on object affordance enabling natural human-robot collaboration in assembly tasks," *Procedia CIRP*, vol. 78, pp. 255–260, Jan. 2018.

[38] Y. Li and S. S. Ge, "Human–robot collaboration based on motion intention estimation," *IEEE/ASME Trans. Mechatronics*, vol. 19, no. 3, pp. 1007–11014, Jun. 2014.

[39] Y.-M. Jang, R. Mallipeddi, S. Lee, H.-W. Kwak, and M. Lee, "Human intention recognition based on eyeball movement pattern and pupil size variation," *Neurocomputing*, vol. 128, pp. 421–432, Mar. 2014.

[40] Z. Wang, M. Deisenroth, H. B. Amor, D. Vogt, B. Scholkopf, and J. Peters, "Probabilistic modeling of human movements for intention inference," in *Proc. Int. Conf. Robot. Sci. Syst.* Sydney, NSW, Australia: MIT Press, 2012, pp. 433–440.

[41] M. Awais and D. Henrich, "Proactive premature intention estimation for intuitive human-robot collaboration," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Vilamoura, Portugal, Oct. 2012, pp. 4098–4103.

[42] Y. Tamura, P. D. Le, K. Hitomi, N. P. Chandrasiri, T. Bando, A. Yamashita, and H. Asama, "Development of pedestrian behavior model taking account of intention," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Vilamoura, Portugal, Oct. 2012, pp. 382–387.

[43] T. A. Han and L. M. Pereira, "Context-dependent incremental intention recognition," in *Proc. UAI Bayesian Modeling Appl. Workshop (UAI-AW)*, vol. 818, A. Nicholson, Ed. CEUR Workshop Proceedings, 2011, pp. 50–58.

[44] J.-H. Han and J.-H. Kim, "Human-robot interaction by reading human intention based on mirror-neuron system," in *Proc. IEEE Int. Conf. Robot. Biomimetics*, Dec. 2010, pp. 561–566.

[45] M. Awais and D. Henrich, "Human-robot collaboration by intention recognition using probabilistic state machines," in *Proc. 19th Int. Workshop Robot. Alpe-Adria-Danube Region (RAAD)*, Jun. 2010, pp. 75–80.

[46] H. Jeon, T. Kim, and J. Choi, "Ontology-based user intention recognition for proactive planning of intelligent robot behavior," in *Proc. Int. Conf. Multimedia Ubiquitous Eng. (MUE)*, Busan, South Korea, 2008, pp. 244–248.

[47] R. Kelley, A. Tavakkoli, C. King, M. Nicolescu, M. Nicolescu, and G. Bebis, "Understanding human intentions via hidden Markov models in autonomous mobile robots," in *Proc. 3rd Int. Conf. Hum. Robot Interact. (HRI)*, Amsterdam, The Netherlands, 2008, pp. 367–374.

[48] A. J. Schmid, O. Weede, and H. Worn, "Proactive robot task selection given a human intention estimate," in *Proc. Int. Symp. Robot Hum. Interact. Commun.*, Jeju, South Korea, 2007, pp. 726–731.

[49] A. Tavakkoli, R. Kelley, C. King, M. Nicolescu, M. Nicolescu, and G. Bebis, "A vision-based architecture for intent recognition," in *Proc. Int. Symp. Vis. Comput.*, in Lecture Notes in Computer Science, 2007, pp. 173–182.

[50] G. de Croon, S. Nolfi, and E. O. Postma, "Towards pro-active embodied agents: On the importance of neural mechanisms suitable to process time information," in *Complex Engineered Systems*. Berlin, Germany: Springer, 2006, pp. 338–363, doi: 10.1007/3-540-32834-3_15.

[51] K. A. Tahboub, ''Intelligent human-machine interaction based on dynamic Bayesian networks probabilistic intention recognition,'' *J. Intell. Robot. Syst.*, vol. 45, no. 1, pp. 31–52, Jan. 2006.
[52] O. C. Schrempf and U. D. Hanebeck, ''A generic model for estimating user intentions in human-robot cooperation,'' in *Proc. Int. Conf. Inform. Control, Automat. Robot.*, Barcelona, Spain, 2005, pp. 251–256.
[53] W. Mao and J. Gratch, ''A utility-based approach to intention recognition,'' in *Proc. Workshop Agent Tracking, Modelling Other Agents Observ.*, 2004, p. 59.
[54] D. Kulić and E. A. Croft, ''Estimating intent for human-robot interaction,'' in *Proc. IEEE Int. Conf. Adv. Robots*, 2003, pp. 810–815.
[55] S.-J. Youn and K.-W. Oh, ''Intention recognition using a graph representation,'' *Int. J. Comput., Electr., Autom., Control Inf. Eng.*, vol. 1, no. 1, pp. 1–6, 2007.
[56] S. Jain and B. Argall, ''Recursive Bayesian human intent recognition in shared-control robotics,'' in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Madrid, Spain, Oct. 2018, pp. 3905–3912.
[57] N. Stefanov, A. Peer, and M. Buss, ''Online intention recognition for computer-assisted teleoperation,'' in *Proc. IEEE Int. Conf. Robot. Automat.*, Anchorage, AK, USA, May 2010, pp. 5334–5339.
[58] D. Aarno and D. Kragic, ''Layered HMM for motion intention recognition,'' in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Beijing, China, Oct. 2006, pp. 5130–5135.
[59] Y. LeCun, Y. Bengio, and G. Hinton, ''Deep learning,'' *Nature*, vol. 521, pp. 436–444, May 2015.
[60] S. Rakhimkul, A. Kim, A. Pazylbekov, and A. Shintemirov, ''Autonomous object detection and grasping using deep learning for design of an intelligent assistive robot manipulation system,'' in *Proc. IEEE Int. Conf. Syst., Man Cybern. (SMC)*, Bari, Italy, Oct. 2019, pp. 3962–3968.
[61] W. Wang, L. Qin, X. Yuan, X. Ming, T. Sun, and Y. Liu, ''Bionic control of exoskeleton robot based on motion intention for rehabilitation training,'' *Adv. Robot.*, vol. 33, no. 12, pp. 590–601, 2019.
[62] P. Krauthausen and U. D. Hanebeck, ''A model-predictive switching approach to efficient intention recognition,'' in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Taipei, Taiwan, Oct. 2010, pp. 4908–4913.
[63] R. Kurniawan, A. S. Setiyoko, M. A. Jamiin, B. Herijono, F. I. P. Ramadhan, W. Astuti, F. Y. Rizaldi, M. B. Aji, M. Syai'in, Adianto, R. Indarti, and N. Rinanto, ''Electric bionic legs used gyroscope and accelerometer with fuzzy method,'' in *Proc. Int. Symp. Electron. Smart Devices (ISESD)*, Badung-Bali, Indonesia, Oct. 2019, pp. 1–5.
[64] K. J. Åström, *Introduction to Stochastic Control Theory*, Mineola, NY, USA: Dover, 2006.
[65] S. Wei, Y. Zou, X. Zhang, T. Zhang, and X. Li, ''An integrated longitudinal and lateral vehicle following control system with radar and vehicle-to-vehicle communication,'' *IEEE Trans. Veh. Technol.*, vol. 68, no. 2, pp. 1116–1127, Feb. 2019.
[66] M. Buckland, ''On the nature of records management theory,'' *Amer. Archivist*, vol. 57, no. 2, pp. 346–351, Apr. 1994.
[67] D. Helbing and P. Molnár, ''Social force model for pedestrian dynamics,'' *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 51, no. 5, pp. 4282–4286, May 1995.
[68] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew, ''Extreme learning machine: Theory and applications,'' *Neurocomputing*, vol. 70, nos. 1–3, pp. 489–501, Dec. 2006.
[69] K. Lorenz, *The Foundations of Ethology*. Vienna, Austria: Springer-Verlag, 1981.
[70] R. T. Olszewski, ''Generlaized feature extraction for structural pattern recognition in time series data,'' Ph.D. dissertation, School Comput. Sci., Carnegie Mellon Univ., Pittsburgh, PA, USA, 2001.
[71] H. Lin, I. Shafran, D. Yuh, and G. Hager, ''Towards automatic skill evaluation: Detection and segmentation of robot-assisted surgical motions,'' *Comput. Aided Surgery*, vol. 11, no. 5, pp. 220–230, Sep. 2006.
[72] D. R. R. B. J. Kuhlman. *NISSAN*. Accessed: Aug. 27, 2013. [Online]. Available: https://usa.nissannews.com/en-US/releases/nissan-announce sunprecedented-autonomous-drive-benchmarks
[73] J. Stewart. BBC World Service Radio. Los Angeles. Accessed: May 2014. [Online]. Available: https://www.bbc.com/news/technology-27587558
[74] M. Sivak and B. Schoettle, ''Road safety with self-driving vehicles: general limitations and road sharing with conventional vehicles,'' Transp. Res. Inst., Univ. Michigan, Ann Arbor, MI, USA, Tech. Rep. UMTRI-2015-2, 2015.
[75] M. Kato and M. Fujii, ''A study on time efficiency of CSMA/CA in inter-vehicle communication systems,'' in *Proc. IEEE 8th Global Conf. Consum. Electron. (GCCE)*, Oct. 2019, pp. 60–63.
[76] S. Poirier, F. Routhier, and A. Campeau-Lecours, ''Voice control interface prototype for assistive robots for people living with upper limb disabilities,'' in *Proc. IEEE 16th Int. Conf. Rehabil. Robot. (ICORR)*, Toronto, ON, Canada, Jun. 2019, pp. 46–52.
[77] D. Shi, W. Zhang, W. Zhang, and X. Ding, ''A review on lower limb rehabilitation exoskeleton robots,'' *Chin. J. Mech. Eng.*, vol. 32, no. 1, pp. 1–11, Dec. 2019.
[78] F. Wang, X. Wei, J. Guo, Y. Zheng, J. Li, and S. Du, ''Research progress of rehabilitation exoskeletal robot and evaluation methodologies based on bioelectrical signals,'' in *Proc. IEEE 9th Annu. Int. Conf. CYBER Technol. Autom., Control, Intell. Syst. (CYBER)*, Suzhou, China, Jul./Aug. 2019, pp. 826–831.
[79] J. L. Jones, ''Robots at the tipping point: The road to iRobot roomba,'' *IEEE Robot. Autom. Mag.*, vol. 13, no. 1, pp. 76–78, Mar. 2006.
[80] J. Forlizzi and D. DiSalvo, ''Service robots in the domestic environment: A study of the roomba vacuum in the home,'' in *Proc. Hum. Robot Interact.*, 2006, pp. 258–265.
[81] J. Miura and Y. Shirai, ''Parallel scheduling of planning and action of a mobile robot based on planning-action consistency,'' in *Proc. Workshop Scheduling Meet Real-Time Monit. Dyn. Uncertain World*, Stockholm, Sweden, 1999. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.6.7143
[82] K. M. Krishna, R. Alami, and T. Simeon, ''Safe proactive plans and their execution,'' *Robot. Auton. Syst.*, vol. 54, no. 3, pp. 244–255, Mar. 2006.
[83] G. Armano, G. Cherchi, and E. Vargiu, ''An agent architecture for planning in a dynamic environment,'' in *Proc. Congr. Italian Assoc. Artif. Intell.*, in Lecture Notes in Computer Science, vol. 2175, 2001, pp. 388–394.
[84] A. Finzi and A. Orlandini, ''Human-robot interaction through mixed-initiative planning for rescue and search rovers,'' in *Proc. Congr. Italian Assoc. Artif. Intell.*, in Lecture Notes in Computer Science, vol. 3673, 2005, pp. 483–494.
[85] M. Awais and D. Henrich, ''Proactive premature intention estimation for intuitive human-robot collaboration,'' in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Vilamoura, Portugal, Oct. 2012, pp. 4098–4103.
[86] Accessed: 2020. [Online]. Available: https://www.irobot.com/roomba

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