Smart Rollators Aid Devices: Current Trends and Challenges

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***Abstract*—Mobility loss has a major impact on autonomy. Smart rollators have been proposed to enhance human abilities when conventional devices are not enough. Many human-robot interaction systems have been proposed in the last decade in this area. Comparative analysis shows that mechanical issues aside, they mainly differ in i) equipped sensors and actuators; ii) input interface; iii) operation modes, and iv) adaptation capabilities. This paper presents a review and a tentative taxonomy of approaches during the last 6 years. In total, 92 papers have been reviewed. We have discarded works not focused on human-robot interaction or focused only on mechanical adaptation. A critical analysis is provided after the review and classification, highlighting systems tested with their target population.**

***Index Terms*—Shared control, Smart rollator, Mobility Aid Devices**

I. Introduction

The percentage of world population over 65 years is expected to grow 13.5% in the next decades [18]. Ageing is correlated with an increase of people with disabilities that, in extreme, leads to dependence. In the current overloaded healthcare system, this means a lower number of allocated resources per person. Hence, it is necessary to extend older people's autonomy as much as possible. This issue has been outlined by the World Health Organization (WHO) in its Global strategy and Action Plan on Aging and Health in strategic objective 2.1 [42]. WHO reported that assistive devices *When adapted to the individual and his or her environments [these mechanisms] can enable older people to retain the maximum level of control over their lives*. However, in order to maintain their autonomy, people will require personalized solutions, adapted to the user's needs to prevent issues like disuse syndrome, loss of residual skills, abandonment of assistive technology, etc.

Assistive devices to enhance mobility are a major tool to promote autonomy. Mobility loss negatively affects many Activities of Daily Living (ADL), such as leisure activities engagement, daily social contacts, residential location or public transport usage [17]. There are different types of mobility assistive devices depending on the users' needs, but they can be broadly divided into three [56]: canes, walkers, and wheelchairs.

Most mobility assistive devices allow some level of adaptation, mostly from a mechanical point of view (handle shape, height adjusting, seat tilt angle, etc). In extreme cases, devices can be designed and then manually adapted to the specifics of a given user. However, mechanical adaptation in conventional assistive devices is limited and must be manually tailored to users. Alternatively, the so called smart assistive devices also include sensors and/or actuators to manage the interaction between the human and the device [6], [54]. Specifically, this paper proposes a tentative taxonomy of smart rollators, including a comparative analysis of their weaknesses and strengths.

Smart assistive rollators including only sensors may be used to monitorize users' activity, biomechanical parameters, biometrics, etc, to gain knowledge about their condition and lifestyle. Devices including also actuators may use this information to provide some level of assistance, adapted to the environment (slope control, support to cross narrow areas, obstacle avoidance, etc) and/or user's condition (balance support, steering assistance, etc). Smart adaptation depends on reliable sensing and processing to determine how to help best depending on what the user plans to do at a given situation and their condition.

Users' intention can be estimated using different input interfaces (force couple, speakerphone, etc), depending on the device and the end-user profile. For example, in a smart rollator, the combination the hardware interfaces like camera and force-sensing resistor (FSR), estimate the user's intention based on face orientation and user's gait [48]. In any case, intention may need to be inferred from input hardware, situation, experience and even users' disability profile.

Even if user's intention is clear, providing assistance is not simple, as the system may determine that the best action at a given situation is not actually what the users intends to do. As a person and assistive rollator move as a single entity, it is important to determine how much each agent contributes to control at any given situation. There are different control modes depending on how much each agent contributes to control at a given instant and how control is traded between them. In many cases control is held either by the human or the machine, and users voluntarily hand it over when a situation is difficult to handle or a trade mechanism takes over in case of need. Other approaches rely on command blending and increased adaptation.

As a whole, mechanical differences aside, we can observe that the main differences among different assistive devices depend on: i) equipped sensors and actuators; ii) user interface; iii) operation modes; and iv) adaptation capability. Hence, we have conducted a review of smart rollators in scientific literature to tentatively provide a taxonomy according to these factors. A classification of devices based on these parameters

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is proposed in section II.

Our review focuses on papers published in the last 6 years including the following keywords in the title or abstract:*(smart OR intelligent OR robotic) AND (walker OR rollator)*; *(walker OR rollator) AND (control OR interface OR user intention)*; and *assistive devices*. We have searched in IEEE Xplore, Springer Link, ACM Digital Library, Taylor&Francis, and ScienceDirect, and 40 conferences and journals were found. We have selected only journals indexed in JCR and conferences indexed in CORE or GGS rankings. In total, 92 papers met these criteria. However, after reading these papers, 44 were discarded because they were not focused on human-robot interaction and focused on: rollator constructions (19 out of 44), hardware adaptations (18 out of 44), or reliable/secure communications (7 out of 44). Hence, this work analyzed 48 papers in the smart rollator area.

We have explicitly highlighted papers that engage the target population ,i.e. people with disabilities or elderly people, in their testing, as clinicians consistently report that healthy people do not walk and/or support weight on the device like these target users. Nevertheless. papers not meeting this condition yet are also included in this review as well, as they provide valuable insight on current trends.

II. Significant features in Smart Rollators

As commented, our goal is to review relevant works on smart rollators during the last 6 years, but also to find a set of parameters to establish a taxonomy (see Fig. 1). Through our analysis, we determined that the main differences among reviewed smart systems relied on the following factors: i) equipped sensors and actuators; ii) user interface; iii) operation modes; and iv) adaptation capability. Since these parameters are also employed in other fields with different meanings, this section clarifies how they are used in this paper.

A. Sensors, actuators and user interfaces

Smart rollators rely on different sensors to acquire parameters of interest about: i) the environment and ii) their user. Some systems are restricted to on-board sensors, whereas others may also require wearable sensors on users or even third party sensors (e.g. Motion Capture systems) to operate. Systems relying uniquely on on-board sensors are cheaper, require less configuration and adaptation to specific users and can be tested anywhere. Indeed, although we have not restricted our search to this respect, reviewed works mostly include rollators equipped only with on-board sensors. On-board rollator sensors typically include the conventional ones in robotics -e.g. sonars, laser, infrared sensors, encoders, accelerometers, motors, etc- but systems may also include additional sensors to gain knowledge on the user if necessary[1] -e.g. biometrics, biomechanics, pose, etc-. We do not rely on this hardware for classification, because i) similar devices may use different hardware for the same purposes -e.g. the same rollator could use a Time of Flight camera instead of a laser to avoid obstacles-; and ii) very different devices may use the same basic sensor set. However, this hardware partially defines what a given system may be able to do, plus it has a direct impact on its cost, weight, bulkiness, battery consumption, etc, so we will refer to it later when we classify systems according to their capabilities.

[1]These sensors are necessary if the device is meant to monitor the user and/or to adapt assistance to their needs.

We have chosen to separate operational sensors/actuators from user interfaces, i.e. the hardware that users need to (voluntarily) feed their intention to the system. User interfaces mostly provide information about where the user wants to go, while user sensors provide non-intention related parameters like balance or heart rate. As commented, input interfaces do not always return a clear command and intention may need to be inferred via data mining. We have categorized each type of input device in our review according to a common set of features. Specifically, we have selected the following ones:

- **Interface**: base input technology (speakerphone, cameras, force sensors, leap motion sensors, etc).
- **Measurement**: type of captured data (e.g. cameras can be used to measure the face orientation [47], [59]).
- **Input**: knowledge expected to be extracted from the measurement (e.g. a head movement may be used to steer a rollator).
- **Invasiveness**: comfort and simplicity of use, mainly how many sensors users have to wear, how long it takes to attach them, and how comfortable they are. A system that requires no wearable sensors nor calibration, such as an on-board sensor, presents *low* invasiveness compared to others with *high* invasiveness that require sensors attached to the body and long calibration procedures.
- **Cognitive Load**: attention and cognitive effort required from the user to guide the device. When users can easily interact with the assisted device and the environment, the cognitive load is *None*. Other interfaces require *Low* user concentration during navigation with the assistive platform. Another group requires significant concentration, and sometimes users may feel discomfort and fatigue in a short time, so their cognitive load is *High*.
- **Usability** according to literature and/or reported by users after tests via common questionnaires (e.g. The Psychosocial Impact of Assistive Devices Scale (PIADS)). It is classified into 3 groups. The *High* group includes interfaces that are transparent to the user, i.e. no adaptation is necessary. Interfaces in the *Medium* group are customizable but not intrusive, so users can remove hardware at any time and installation is easy. Finally, the *Low* group includes interfaces that are both intrusive and require adaptation, for example, EOG interfaces where electrodes need to be placed on the face at specific motor points.
- **Training**: how much it takes for a new user to learn to manipulate the device adequately and/or for the device to be adapted to the user if this is expected (including the calibration time). We have defined 3 categories. Interfaces in the *None* category require no training. Interfaces in the *Low* category require less than 5 minutes of training. Finally, *High* category, is selected when training and/or

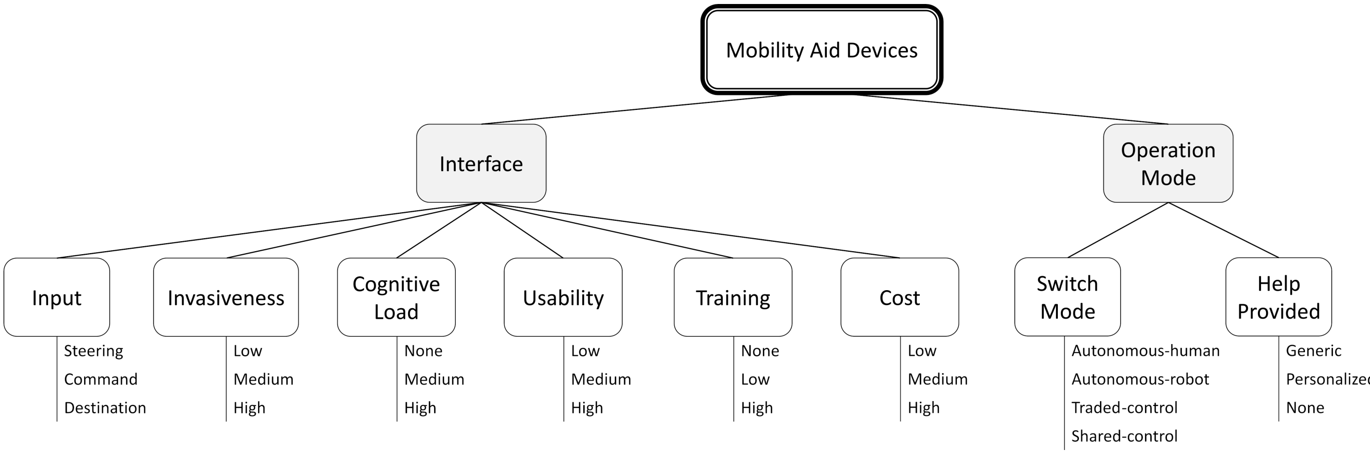

Fig. 1. Mobility aid devices taxonomy for smart rollators.

calibration time is greater than 5 minute. This value is extracted from the experimentation section of each paper. If it is not commented in a paper, it is assigned from another paper that used the same input interface.

- **Cost** of the input interface, including hardware and software -if any- required to operate it. We have established 3 ranges. In the *Low* range the cost of hardware is less than 100 USD. *Medium* range is from 100 to 400 USD. Lastly, in *High* range the cost is over 400 USD. This value is calculated as the addition of all components declared in the paper or the total cost, if it is specified.
- **Validated** It shows approaches validated with end-users and their reported target **patient** profile.
- **Verified** The last column shows the approaches tested only with healthy users.

Table I shows the input interface classification for selected rollators according to these parameters. The Measurement column specifies which type of data the system extracts from the associated sensors. It can be noted that some approaches have not been tested with the target population in the reviewed works. As expected, in the case of rollators, the most common choice is to attach force sensors to the rollator frame, but several alternatives are proposed to deal with low weight-bearing loads. We will discuss further on this on later sections.

B. Operation modes

The most relevant non-physical difference among different mobility assistive devices is their operation mode. There are solutions that give all the control to the users to just monitor them [14], [55], whereas others -typically in case of extreme disabilities- give all the control to the machine and focus on interfaces instead [39]. In general, all assistive devices control approaches fall within the spectrum of shared or traded control, that combines both user control and an automation component. Shared control is applied in other fields, like aerial vehicles, and sometimes definitions change from one field to another. In the field of assistive robotics, shared control can be roughly divided into different subcategories depending on how much autonomy the person retains. Originally, the first rollators [36], [39] operated mostly like an autonomous robot, meaning that users were only supposed to point out a destination and the device would take/guide them there. In cases like these, user contribution to control is minimal.

Another approach to control, the traded control, is to keep users in full control until they find a situation they can not cope with on their own, like crossing doors, navigating corridors, negotiating obstacles, etc. At this point, control is given to the machine until the situation is over. The decision to give control to one or the other may be automatic -if control switch situations can be reliably detected- or it can be initiated by the user via a proper interface. In extreme, some works rely on giving control to users as long as possible and only trigger robot control when a potentially dangerous situation is detected, e.g. imminent collision. It needs to be observed that in traded-control, user and machine do not contribute to control simultaneously. Instead, they take turns at absolute control.

A rollator using autonomous or traded-control modes where the robot may be fully in control at a given time can be loosely defined as an active device, meaning that the device may take action even if users are not moving [46]. As independent motion may affect user's balance, recent rollators tend to be passive, e.g. affect user's motion by selectively braking one or both wheels, so users need to walk to operate the system [1], [22], [29], [31], [38]. Passive systems may oppose to motion in a prefixed way, e.g. for rehabilitation purposes, modify motion direction to negotiate the environment [25], e.g. obstacle avoidance [30], or adapt to the user's needs to compensate disabilities [11], [59]. These so-called collaborative control approaches rely on assessing how much control should be given to user and machine at any given navigation situation to combine user's and robot intention into a single emergent command.

Operation modes in reviewed works are presented in Table II. We have explicitly included the following features:

- **Switch mode** describes how control switches from human to robot and vice versa. It can be *autonomous-human* if the user has full control or *autonomous-robot* if the robot has full control. In *Traded-control* mode, either user or robot may have control, but not at the same time. Finally, in *Shared-control* mode, user and robot contribute to the control simultaneously.

- The type of **Help provided** is represented in another column. Some system provide help adapted to the environment or to other non-person related parameters (*Generic*). Help may also be adapted to intrinsic user parameters (*Personalized*). Finally, if a device does not provide help, i.e it is only used for monitoring, Help provided is *None*.
- Information about the **Behavior** that systems yield is presented too.
- The last columns show approaches **verified** with healthy users and **validated** with end-users within their reported target patient profile.

It can be observed that, as commented, active rollators (autonomous robot/traded-control modes) have been abandoned recently in favor of collaborative (Shared-control) or monitoring rollators, that have a lower impact on balance, specially for users supporting significant weight on the device.

III. Current trends on smart rollators

After establishing our features for classification, this section presents our review on mobility aid devices. We provide two tables for reference, table I for input interfaces, and table II for operation modes. The following subsections present a comparative analysis of smart rollators input interfaces and operation modes.

A. User Interfaces

The first smart rollators, which basically operated like autonomous robot with an attached rollator frame, relied on conventional input devices like touchpads or joysticks to know the user intention. However, interfaces in rollators quickly evolved to become more transparent to the user by using on-board sensors to infer intention from physical interaction between human and device. Indeed, all reviewed approaches rely on on-board sensors, such as force sensors [8], [35], [47], [59], force and torque sensors [24] or load cells [50]. In addition, a platform contains a voice interaction system, the user uses speech to express their intention [40].

The cost of the on-board sensors vary, from simple force sensors to measure forces in one axis, ranging from $60 to $1800, to a tri-axial load cell to measure high accurate forces in three axes with a cost of $4500. This cost is very high when compared joysticks or microphone interfaces in assistive devices, usually cheaper than $250.

As commented, interfaces based on on-board sensors do not directly provide a explicit navigation command. In the reviewed approaches motion commands have been inferred from: i) differences in longitudinal forces [8]; ii) longitudinal forces and torques in a admittance controller [24], [50], [59]; or iii) adaptive neural fuzzy inference systems using grasping forces and the rollator velocity [35].

B. Operation Modes in Rollators

Assistance in rollators allows the device to modify the user's proposed trajectory using motors or brakes. Recent rollators tend to oppose to motion rather than to pull to avoid balance loss (passive assistance). Rollator users are expected to contribute to control at all times. Furthermore, traded-control modes may upset the balance, so at the very least, smart rollators operate under shared or autonomous-human modes. Indeed, the second most common operation mode in rollators (40% of reviewed works) is the Shared-control mode. Help provided in this mode is usually **generic**, i.e. not specifically adapted to each user. In the reviewed works, assistance: i) supports users to steer to correct orientation [1], [2], [3], [22], [35], [50]; and ii) keeps secure distances between rollator and user [46] and/or between rollator and obstacles, either at the current location [26], or in the near future [50].

All commented approaches are adapted to the environment, rather than to the specific users' condition. However, users facing the same situation may require different support depending on their disability profile. Hence, some works focus on **personalizing** assistance. For instance, [12] creates a model to forecast human motion. Then, the model is used to adapt the platform motion to the user's gait, while keeping all required constraints (i.e. separation distance and weight bearing on the platform). In [11], [24], admittance controllers are used to continuously adapt support to users, relying on a long-term user performance model (physical fatigue or velocity). In [59], a reinforcement learning method is used to select user contribution weight to control. This weight is optimized to maximize user's safety (distance to nearby obstacles) and trajectory smoothness (low changes in the platform velocities).

Rollators take users everywhere, so they are perfect to monitors users' conditions. This is observed in the reviewed approaches, where autonomous-human mode is the most commonly used operation mode (60%). In this mode, the device simply monitorizes users' gait and/or biomechanics to assess their condition and trends. The simplest approach focuses on measuring walking speed and distance traveled, via IMU [16], [51] or encoders [5], [6], [8]. This data provides rough information about users' conditions [23]. Other approaches analyze variability between left and right walking patterns (e.g. stride or step variability) to obtain a better users' condition understanding [9]. This can be achieved using LIDAR [14], [55], RGB-D cameras [5], or encoders and force sensors [6]. In some cases, medical scales like Tinneti Mobility Assessment [53] can be predicted using these parameters[6]. Other approaches focus on activity classification (straight movements, left-turn, forward-backward movements) with an IMU [51] or on push events detection [16].

Monitorization can be also used to provide non-physical help to users. Visual feedback [57] or combinations of visual and acoustic feedback [34] have been used to improve Parkinsonian gait. Visual feedback has also been used to correct some elderly gait abnormalities [25].

IV. Discussion

In this literature review, 48 works in the last years on smart rollators have been analyzed. After reviewing and discussing those papers, several findings have arisen in three main topics: the validation of proposals, the interfaces used, and the con-

TABLE I
CLASSIFICATION OF HARDWARE INTERFACES

Interface	Measurement	Input	Invasiveness	Cognitive load	Usability	Training	Cost	Validated	Verified
Force sensors	Force [5], [6], [8], [11], [13], [27], [29], [30], [31], [33], [35], [47], [59]	Steering	Low	None	Low	Low	Low-High	Users with a variety of physical and neurological disabilities (e.g. Parkinson's disease, Dementia, Ischemia, Intellectual disability) [5], [6], [8], [35], [59]. People with moderate to mild mobility impairment [11]. Elderly people [13], [27], [31], [47]	[27], [29], [30], [33]
Force/torque sensors	Force and torque [24]	Steering	Low	None	Low	High	Medium-High	elderly people [24]	
Load cells	Force [50]	Steering	Low	None	Low	Low	High		[50]
Leap Motion Sensor	Displacement of the handles [44]	Steering	Low	None	Low	Low	Medium		[44]
Force-sensing resistor (FSR) and Laser-range finder (LRF)	force and velocity [58]	Steering	Low	None	Low	Low	Medium		[58]
Camera and Force-sensing resistor (FSR)	face orientation and user's gait [48]	displacement	Low	None	Low	High	High		[48]
Torque sensor and Force sensor	Moments/forces [28]	Steering	Low	None	Low	High	High		[28]
Speakerphone	Voice [40]	Set of pre-defined intentions	Low	None	Low	Low	Low	User with mild to moderate cognitive and mobility impairment (stroke, multiple sclerosis, cerebral palsy, lower limb fractures and spinal diseases) [40]	

TABLE II
CLASSIFICATION OF OPERATION MODES

Switch mode	**Help provided**	**Behaviors**	**Validated**	**Verified**
Autonomous-human	Generic			
Autonomous-human	Personalized	Guide or improve users' gait using visual [25], [29], [57] or acoustic feedback [34]. Guidance the users to place they want to go using audio cues [40]. Guidance using resistive or assistive forces [47].	Elderly people [25], [34], [47]. Parkinson's disease [57]. User with mild to moderate cognitive and mobility impairment [40]	[29]
Autonomous-human	None	Monitoring walking speed and/or distance traveled [5], [6], [8], [16], [51]. Performing Tinnety Mobility Assessment [53]. Activities classification [51]. Detect push events [16]. Monitoring of gait parameters [13], [20], [21], [43], [49], [58]. Gait asymmetries [5], [6], [13], [14], [44], [55]. Walking styles [45].Human Gait Stability [10]. Gait events [15], Sit-to-stand transfer [27]	Users with a variety of physical and neurological disabilities (e.g. Parkinson's disease, Dementia, Ischemia, Intellectual disability) [5], [6], [8]. User with multiple sclerosis [16]. Elderly people [10], [13], [14], [15], [27], [41], [43], [51], [55]. Hemiplegic patient [41]	[20], [21], [27], [44], [45], [49], [58]
Autonomous-robot	Generic			
Autonomous-robot	Personalized			
Traded-control	Generic			
Traded-control	Personalized			
Shared-control	Generic	Steering control [1], [2], [3], [22], [29], [31], [35], [38], [50]. Keep distances between the human and the rollator [26], [46], [50]. Fall detection [52]. The walker synchronously follows the user [28]. Slope mobility assistance [32]	Elderly people [1], [2], [22], [31]. Disabled people [31], [35], [46]. People with diagnosis of ischaemic or hemorrhagic stroke [26]	[3], [28], [29], [32], [38], [50], [52]
Shared-control	Personalized	Creates a model to forecast human motion to keep the desired situation (separation distance and bearing in the platform) [12]. Admittance controllers and a long-term user performance [11], [24]. Reinforcement learning method to maximize the user safety and the smoothness [59]. Path following via simulated passivity [4], The rollator will follow in front of the person - the leader of the formation [48]. Support force modulated based on the user's gait [19]. Admittance control with spatial modulation to navigate in confined spaces [30]. Adjust the level of resistance depending on the gait phase [33]. Change the speed [58]	People with moderate to mild mobility impairment [11], [12]. Elderly people [24]. People with different physical and cognitive skills [59]	[4], [19], [30], [33], [48], [58]

trol modes implemented. The following sections cover those topics.

A. Testing and validation

A first conclusion is that, despite the significant number of recent works on smart rollators, six out of ten have not been tested by their target population. Instead, reported experiments were performed by volunteering healthy people, often by researchers or students themselves. Although understandable, given the difficulties of involving persons with disabilities in tests, this is a major drawback, because disabilities have an unexpected impact in many aspects of navigation. This is particularly important in the case of rollators, because healthy people do not support their weight on the device like target users do [7]. In conclusion, it is extremely important in this field to test systems with target population. We have split analyzed systems into $Validated$ (tested by at least a person among the target group) and $Verified$ (tested by healthy volunteers). Most validated systems were tested by elderly people, but some focused on specific disease like Parkinson, dementia or ischemia. Validated systems focused mostly on gait and support monitoring, usually by means of force sensors on the handlebars. Verified works presented more variation and paid significant attention to user intent prediction, involving different multimodal sensors.

B. Interfaces

Interfaces in rollators do not present as much variation as in other assistive devices (e.g. wheelchairs), as there are obvious constraints, both physical and cognitive, to what people can use while they walk. Invasiveness in rollator interfaces needs to be low, since restrictions to users' movements can affect their mobility and, thus, increase fall risk. For the same reason, rollator users need to focus on the task and keep both hands on the handlebars most of the time. Hence, although wearable sensors are sometimes used for testing, recent systems tend to keep interfaces on-board and as less intrusive as possible. While interfaces based on audio and visual data are feasible, most reviewed rollator interfaces rely on the upper limbs interaction with the handlebars to obtain the user intention by means of different sensors: force sensors [8], [35], [59]; force and torque sensors [24]; or load cells [50]. Feedback, if any, is often provided haptically (structure vibration or selective braking) or visually (LEDs) [25], [34], [57]. Other sensors can be used to monitor gait parameter, such as inertial measurement units (IMUs) [20], [45], [49], cameras [10], [15], [48], laser range finder (LRF) [41], [43] or ultrasonic sensors [25], but they are not used to obtain the user intention.

C. Control modes

Regarding control models, original assistive rollators operated on active mode, i.e. rollators could move autonomously, independently from the user. As active mode may upset balance, recent rollators operate in passive mode, meaning that users are expected to move the rollator, which, at most, may selectively brake one or both wheels to affect motion. To this respect, it needs to be noted that original rollators were basically autonomous robots with attached handlebars, and hence, quite heavy, whereas recent ones tend to be modified versions of easier to operate commercial rollators. This evolution has led to disuse of autonomous-robot and traded-control control modes in favor of autonomous-human and shared-control ones, where robots either do not contribute to motion (monitoring-only devices) or cooperate with humans in a non disruptive way.

In the first case, the device simply monitors user condition [5] or useful parameters, such as walking speed or distance traveled [16], [51]. In the second case, the device provides walking support: steering control [1], [2], [3], [12], [22], [35], [50], maintaining motor function (e.g using visual or auditory cues) [25], [34], [40], [57], collision avoidance [59], or saving energy cost of walking [46].

One of the major limitations of current control modes is lack of adaptation to the specific needs of users, as there is a wide variety of functional disabilities, present in the target population at very different degrees. As commented, continuous adaptation to (evolving) conditions is of key importance to reduce frustration and loss of residual skills. In this sense, it is expected that improvements and cost reduction in sensors, combined with learning algorithms will enhance human/robot integration in a near future.

V. Current challenges

As a whole, we can conclude that recent trends in rollator tend to develop systems structurally similar to commercial standard ones, which operate in passive mode (human propulsion) and mostly rely on on-board sensors. Typical hardware includes force sensors and, often, odometry on the wheels, although equipment like 360^o lasers or cameras is being progressively added as its cost keeps decreasing and embedded systems provide higher on-board computation power. Recent smart rollators are used either exclusively for monitoring or for providing haptic feedback by passively modifying trajectories in shared-control modes. In both cases, one of the main challenges working with users with disabilities is to determine their intent. Although weight balance on the handlebars is often transformed into a motion vector, depending on their disability profile, some users may not be able to steer the rollator in the desired direction. Besides, resulting data is very limited, as only upper limbs interaction between user and device is measured, and cheapest solutions like force-sensing resistors yield low precision and repeatability. Lasers and depth cameras may provide additional information on gait and pose to cope with this issue, plus multimodal sensors like microphones or eye trackers may also gather meaningful information. In any case, extracting intention from captured data from users with different disability profiles is still an open challenge.

Physical assistance also offers opportunities, as many smart rollators are only used for monitoring and remaining ones mostly focus on steering assistance for obstacle avoidance . Control approaches must avoid upsetting balance to minimize fall risk, so trade-control must be avoided and shared control must be as smooth as possible. Also, efficient algorithms to predict balance rather than to detect falls in order to act preemptively using only on-board sensors could be of major interest.

Assistance personalization remains one of the major challenges in smart mobility devices. Personalization allows the device to provide the amount of help that the user needs. This may increase acceptability [37] and may reduce frustration [28], plus it avoids loss of residual skills caused by excess of help. Recently, some approaches to assistance personalization have been explored by analysing how users operate the device (e.g model to forecast human motion to keep the desired situation [12]), but modelling people with disabilities still requires further work.

Finally, since disability is hard to measure and standard profiles are very difficult to set, a major effort is required to establish disability benchmarks and quantify help needed per task or situation. Current clinical scales are manually obtained, so any advance in automatizing these procedures would be helpful both for system designers and for clinicians.

We expect this review to be useful both for scientists and health professionals. To this end, frequent terms in the field of assistive rollators have been listed and disambiguated, so differences among existing systems can be adequately tackled. Information on hardware, software, control architectures and algorithms is provided so scientists can determine their contributions. Besides, information on applications, acquired knowledge, target population and degree of validation may be helpful to health professionals in designing tests or deciding whether they want an assistive robot to validate therapies and condition changes.

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