The Shared Control Paradigm for Assistive and Rehabilitation Robots

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1 Extended Abstract

One of the major risks of disability is a loss of autonomy that, in extreme, may lead to institutionalization. Lack of human resources for caregiving has led to designing robots to assist people in need. Assistive robotics are meant to help people cope with Activities of Daily Living (ADL). Most ADL are heavily affected by issues related to ambulation [1], so much effort in assistive robots has focused on robotic wheelchairs, rollators, walkers and even canes. These devices typically provide monitorization, physical support and help to cope with hazardous and/or complex situations. However, it is of key importance to provide just the right amount of help to people with disabilities. According to clinicians, an excess of assistance may lead to frustration and/or loss of residual skills. Lack of assistance, however, may lead to unacceptable risks and/or failure to accomplish the desired task. Hence, help must be adapted to each specific user.

The main problem with adapting assistance is that we need to establish how much help a given person needs at each specific situation. This need is a function of his/her disability profile. Unfortunately, it's hard to measure disability in a quantitative fashion. Disability is defined as difficulty or dependency in carrying out activities necessary for independent living, including roles, tasks needed for self-care and household chores and other activities important for quality of life [2]. There are several clinical indexes and scales related to different aspects of disability, like MMSE, Barthel, CIRS, IADL, etc. However, they cover only partial aspects of disability. Furthermore, skills are evaluated in a can do/can not do fashion, because it is hard to quantify to what degree a person can achieve a given task. Besides, from a practical point of view, these scales are typically estimated via questionnaires that take more than half an hour to be compiled and require intervention of professionals to be analyzed. For all these reasons, users fill them a few times at most, so they only reflect the condition of the user at the time they were completed.

Actually, to adapt help in mobility to a specific person, we would need to know : i) how the user copes with the problem at hand, which is related to the local environment; ii) how far he/she is from what we could consider an average performance; and iii) how to provide the minimum required amount of help in a safe, ergonomic way. A secondary, yet important concern is to minimize the cognitive load of the whole process, so the user is up to dual tasking.

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1.1 Metrics

In order to determine how well a person is coping with a navigation situation, it is necessary to establish a set of meaningful metrics. Task metrics are a popular choice [3]: they are task dependent, quantitative and objective. Typical metrics include Degree of Success, Task completion time, Number of collisions, Distance travelled, Deviation with respect to canon trajectory; etc. However, these are global metrics, so they might not be helpful to decide how a person is performing locally. Other metrics are focused on specific skills like Wheelchair propulsion, Negotiation of kerbs, Ascending slopes or Performing a wheelie[4]. However, they are typically obtained in a established obstacle course (e.g. VFM, TAMP, VST). Hence, they present similar problems that questionnaires. Alternatively, in order to evaluate local performance, we can focus only in local metrics. In this sense, safety, smoothness and directness are the best local estimators of performance according to Navigation Functions. They correspond to the overall skills of keeping away from obstacles, keeping a smooth, comfortable trajectory and moving towards a goal, respectively.

1.2 Standards

The main problem to establish how far from a standard user a person with disabilities performs at a given task is that no standard user exists. Typical approaches to check how far a person with disabilities is from standard performance include comparing his/her metrics to: i) a person with no physical nor cognitive disabilities [5] -usually researchers or students-; ii) to a previous try by the same user in the same test environment [6] -disregarding the learning effect-; and iii) to a robot navigation algorithm [7]. However, statistics can help with this problem at local level, where the number of possible navigation situations is reduced [8]. Given a large enough number of tests with a varied enough number of people, it is possible to estimate an average performance via clustering. In [9], we extracted such a profile using data from 3 years of tests performed by inpatients at a rehabilitation hospital. This study provided a set of clusters corresponding to each local situation found by volunteers during tests. In each clusters, we had information about what every person did to cope with the situation every time they faced them and how efficient their solution was. The prototype of each class was calculated as the average of these solutions weighted by their respective efficiencies. In brief, it represented the most frequent and efficient solution. The set of prototypes provides information about how an average user would respond to every potential indoor navigation situation.

1.3 Collaborative Control

In order to provide help, robots operate under the Shared Control paradigm [10]. Shared control ranges from *safeguarded navigation* [11] to autonomous navigation, where people simply choose the destination[12]. Traditionally, it is either the robot or the person in charge of control at any given time. However, a special branch of shared control known as collaborative control allows both robot

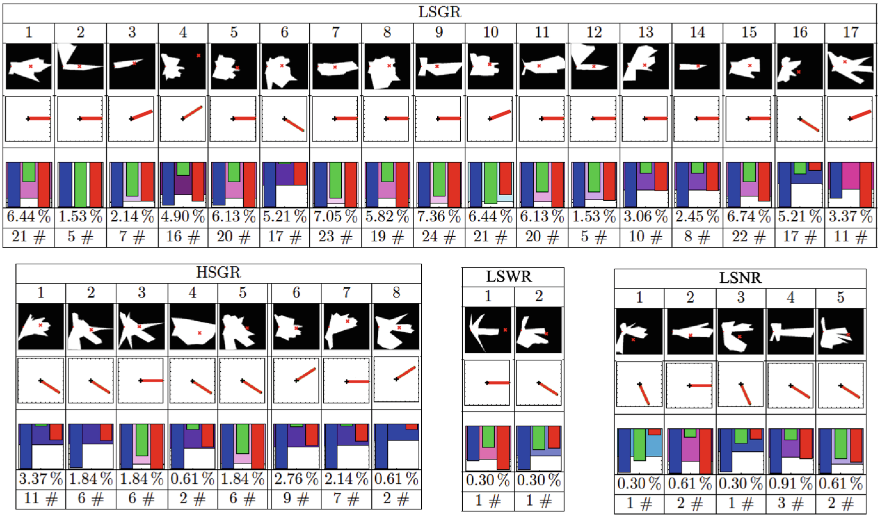

Fig. 1. Classes resulting for each of the 4 non-empty bins

and human to be in charge at the same time [13][14][15][16]. This approach prevents users from giving up on difficult situations and, hence, losing residual skills. A typical approach is to weight user's and robot's commands according to local performance metrics and then to combine them into an emergent vector. Adaptation is improved if we continuously modulate this combination using the difference between the user's performance and a standard. In these case, we can provide less assistance in average and, yet, achieve better results.

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