Predictive multiuser redirected walking using artificial potential fields

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Real walking is considered as the best locomotion metaphor to explore virtual environments in terms of user experience. In addition to being intuitive for the user, walking captures the true feelings of motion since the visual and proprioceptive sensations are harmonized well. The major disadvantage of choosing walking over other locomotion metaphors involves the physical constraints of the available space, which is usually considerably smaller than the virtual environment. To address this issue, redirected walking (RDW) introduces slight mismatches between a user’s visually perceived path and their actual walking pattern, compelling them to subconsciously compensate for the inconsistency by adjusting their walking trajectory. As a result, users are steered to a certain degree, and expansive virtual environments are effectively compressed into smaller physical spaces. Among others, particularly predictive RDW offers immense potential for growth since it unites various algorithmic systems, whereas many approaches from literature depend on drastic restrictions like single-user constraints or architectural limitations to ensure real-time performance. This work presents two novel predictive RDW systems that allow multiple physically colocated users to explore independent and unconstrained virtual environments. The systems rely on two new implementations of prediction systems based on clothoid trajectory generation combined with a cost-based planning concept built on non-harmonic artificial potential fields (APFs), which inherently allow non-convex and dynamic physical environments. Using the APFs, three additional RDW conditions popular in the literature are implemented for comparison purposes. The five RDW concepts are then validated in an extensive user study with 150 participants conducted in 75 pairs. The results indicate that the novel predictive RDW systems outperform the three systems from literature, except for particular sections of the virtual environment with specific architectural traits.

KEYWORDS
virtual reality, human locomotion, redirected walking, redirection techniques, user study

1 Introduction

Choosing an ideal locomotion metaphor to navigate in virtual reality (VR) while ensuring the highest user presence possible has been a challenge for years. Multiple metaphors have been investigated as substitutes for walking, such as simple teleportation or flying using a handheld controller (Usoh et al., 1999; Bolte et al., 2011) to more elaborate systems like motion platforms (Bouguila et al., 2002; Bouguila and Sato,
In this work, we present a novel approach to predictive RDW based on clothoidic trajectories (see Figure 1) that allows multiple users to be steered simultaneously in a common artificial potential field (APF). Specifically, we highlight the following contributions:

- two different technical implementation strategies of the prediction concept;
- a novel combination of prediction, steering, and non-harmonic APF-based costs that is fully functional in virtual open spaces with multiple colocated users;
- a user study with 150 participants highlighting the merits of the new algorithms.

The remainder of this manuscript is organized as follows. The related works are presented in section 2, which focus on RDW mainly in the predictive landscape. Then, subsection 3.1 introduces the APFs, subsection 3.2 discusses prediction and its implementation, and subsection 3.3 summarizes and combines the APFs with prediction and redirection implementation. Section 4 presents a user study, and section 5 provides an overview of the gathered data and its analysis. Finally, the findings are summarized in section 6, and the potential applications and consequences of RDW for future works are discussed in section 7.

2 Related works

In this section, we describe the work related to RDW, mainly focused on the predictive perspective.
2.1 Redirected walking

Over the years, it has been shown that the walking trajectories of users can be manipulated by applying RDW gains, such as linear, rotational, or curvature gains in the virtual environment (Razzaque et al., 2001; Razzaque, 2005; Nitzsche et al., 2004; Williams et al., 2006, 2007; Langbehn et al., 2017), which effectively compress the expansive virtual environment into a small physical space. Furthermore, when these RDW gains are only applied within certain thresholds, the users tend to not notice these redirections, while mostly avoiding simulator sickness (Steinicke et al., 2008); (Kennedy et al., 1993). However, a crucial example of applying redirection outside these detection thresholds are the so-called resets (Williams et al., 2007); resets are introduced as emergency strategies to prevent collisions shortly before impact and resemble external interventions, often breaking the sense of presence of a user. Such resets can be designed in multiple ways, and the most popular type is rotational reset, which demands that the user spin in place through an interface in the head-mounted display (HMD). Although this virtual reorientation often visually corresponds to a full 360° turn to ensure easier continuation of the experience, a rotational gain is applied to divert the real rotation to a different target orientation (i.e., toward an open space). Although this rotational reset has a rather simple implementation, it can be incorporated well in many redirection concepts. Furthermore, since resets tend to invoke at least partial breaks in presence, they are well-established as quality criteria for evaluating the performances of redirection strategies.

Arguably, the most important concern to date is the choice of when a technique must be optimally applied and at what intensity, as this strongly depends on the virtual architecture (Hodgson et al., 2014)). Generally, there are three core concepts in redirection techniques: reactive (Razzaque, 2005; Thomas and Rosenberg, 2019; Bachmann et al., 2019), predictive (Peck et al., 2012; Zmuda et al., 2013; Nescher et al., 2014.) and scripted (or semi-predictive) (Azmandian, 2018; Yu et al., 2018).

Since the focus of this work is mainly predictive approaches, we primarily discuss related examples. Peck et al. (2012) presented RFED as the first algorithm that resembled the predictive nature; they derived a skeleton graph consisting of nodes and segments that described the walkable paths within the available area in the virtual corridors to create a prediction to the next node based on the user’s head orientation. Similarly, Zmuda et al. (2013) created a skeleton graph with probabilities assigned to the crossings, which were used to prioritize the final score of a predicted and redirected path; this final score was calculated by evaluating the distance a user could walk straight ahead at the end of a redirected prediction multiplied by the path probability. Finally, Nescher et al. (2014) introduced MPCRed as a method that recursively evaluates a cost function consisting of actions, such as applying redirection, while also following predefined bidirectional skeleton graphs. Recently, approaches utilizing reinforcement learning have been reported (Lee et al., 2019, 2020) that have drastically reduced real-time calculations; however, these algorithms demand sophisticated setups with neural networks that must be trained based on previously recorded user data, which makes them less applicable to more general use cases.

2.2 Artificial potential fields

APFs were first introduced to RDW in 2019 via two slightly different implementations (Thomas and Rosenberg, 2019; Bachmann et al., 2019) and follow the simple principle of assigning high potentials to potentially dangerous physical environments and low potentials to safe equivalents. Following the derivatives of such potential fields always guarantees flow from higher to lower potentials, which can be described by a force vector “pushing” and “pulling” the user. Accordingly, aligning the redirection with such force vectors ensures that the users are always steered away from dangerous regions while being pulled toward safety. These two first implementations follow a classic reactive approach and straightforwardly align a redirection vector with the repulsive force vectors generated by obstacles. They only differ in the manner in which the force vectors are generated but essentially apply the same principles. Later, Dong et al. (2020) enhanced this concept of repulsion by adding attractive forces to influence the redirection vector toward a real open space. APFs inherently offer the advantage of superimposing multiple layers of potentials, both static and dynamic, which enables incorporation of multiple users roaming the same physical space. All of these APF RDW applications have only considered the current states of the users and are thus categorized as reactive RDW approaches, while any predictive attempts were only suggested conceptually (Hirt et al., 2019a).

3 Methodology

This section presents different algorithms and describes how the elements of these algorithms are implemented. First, an overview on the APF is shown, followed by introduction of the predictive algorithm and its details, and finally the description of the complete process with all concatenated elements.

3.1 Artificial potential field

The physical environment in which a user is tracked while walking and exploring the virtual environment has been hard-coded in early RDW approaches and is always assumed to be static and convex. Naturally, such static tracking spaces provide stable and uncomplicated boundary conditions but restrict dynamic adjustment of the tracking space size while mutually excluding multiple users exploring virtual environments in colocated spaces. There have been some attempts to study how such physical tracking space boundaries could be made more dynamic and accessible (Yang et al., 2019; Cheng et al., 2019; Hirt et al., 2018), but an entirely explorative RDW (e.g., RDW in the wild) is still subject to research (Lutfallah, 2023). However, given fixed boundary conditions around a tracking space, APFs are an elegant option to describe the space dynamically and were initially presented in robotics (Khatib, 1986; Krogh, 1984); they are indispensable in many modern robotic path-planning approaches. APFs can incorporate non-convex tracking boundaries (Messinger et al., 2019) and allow multiple users in colocated tracking spaces.
(Thomas and Rosenberg, 2019; Bachmann et al., 2019) by modeling the respective second users as dynamic obstacles influencing each user’s own potential field. Since there exist many options to model APFs, we briefly investigated three approaches, namely wavefront expansion (Barraquand et al., 1992), harmonic (Kim and Khosla, 1992), and non-harmonic (Thomas and Rosenberg, 2019; Bachmann et al., 2019) APFs, with some basic limiters added to avoid local minima. We compared the calculation time in a static environment encompassing 10⁴ grid cells, with three obstacles inside (see Table 1). Although the harmonic and non-harmonic algorithms perform sufficiently similarly with slight advantages for the non-harmonic APF, the wavefront approach lags considerably by a factor of almost 6×. Quadrupling the environment size shows linearly increased in the calculation times for the harmonic and non-harmonic approaches, with the wavefront approach again being more resource-intensive by a factor 10× compared to the others. Notably, none of the APFs were specifically optimized and were only implemented with their basic functionalities. From these qualitative comparisons, it was decided to pursue only non-harmonic APFs in the following implementations.

3.2 Prediction

Unlike the prediction algorithms employed in existing predictive RDW approaches, our system works in unrestricted virtual open spaces. Accordingly, we refrain from using the popular skeleton-graph-based predictions and implement two different algorithms derived from a recently suggested and evaluated concept (Hirt et al., 2019b, 2022). Accordingly, we employ clothoid trajectory shapes, which are bound by a lemniscate shape in the first case and by the inverse of their curvature in the second case. Both approaches were designed for a short-term prediction (Nescher and Kunz, 2012) to favor higher calculation frequency over long-term predictions.

3.2.1 Smoothing

To ensure more accurate and precise predictions, both algorithms relied on incorporating some historic data points recorded from the user’s previously walked trajectory. These historic data points are stored in the HMD data buffer with fixed sizes, and new recordings are captured while removing the oldest data points. If the HMD data buffer remains unprocessed, then the data acquired through the HMD contains unstable and oscillating gait artifacts from the user’s natural head veering (Hirasaki et al., 1999; Murray et al., 1964) and noise. Utilizing such perturbed data when extrapolating from the HMD data buffer can quickly and sustainably impair the results. Accordingly, a double-exponential smoothing approach intended for similar purposes (Nescher and Kunz, 2013) was extended by calibrating a damping factor (Hyndman and Athanasopoulos, 2018; Taylor, 2003) to capture the trend of a given path without compromising the smoothing result.

3.2.2 Lemniscate Path Prediction (LPP)

In LPP, the prediction origin is always defined by a number of steps T backwards in time, which can naturally be varied on the basis of how much the HMD data buffer is integrated in the prediction. The prediction itself creates a bundle of clothoids contained within a lemniscate shape, which are then evaluated based on a path similarity measure to identify the best trajectory.

The lemniscate is given by Eq. (1) and is created anew with each prediction iteration.

\[
\begin{align*}
x(t) &= ALem \cdot \frac{\sin(t)}{1 + \cos^2(t)} \\
y(t) &= ALem \cdot \frac{\sin(t) \cos(t)}{1 + \cos^2(t)}
\end{align*}
\]

where \(ALem\) denotes a constant defining the size of the lemniscate, and the running variable \(t \in (0, \pi)\) incorporated only the positive half of the lemniscate. In theory, \(ALem\) can be used to directly relate the size of the lemniscate with the current walking speed of the user; instead, we designated a rigid horizon of 3 m to reduce the number of variables and hence improve comparability among the approaches. To create the trajectories within the lemniscate, a set of endpoints is identified along the contour of the shape and generated by uniform discretization, notably with an odd number of endpoints to ensure that a straight prediction is always available in the symmetry. This discretized lemniscate is now transformed to the chosen user state at \(t = T\) and overlaid on the virtual environment, where a collision check is performed using Unity’s stacked overlap boxes. Collision events can thus be found, and the endpoints colliding with the virtual obstacles are labeled as infeasible trajectories for consequent removal. To create the clothoid trajectories, an external C# library called Curves was used and modified for seamless integration with Unity. Curves contains a convenient function that allows creation of 2D clothoids given a starting point (i.e., user position at \(t = T\)), direction (i.e., user heading at \(t = T\)), and final point (i.e., discretized endpoint). From this generated set of trajectories, a single best prediction is isolated using a simple mean-squared error enhanced by a discount factor. This ensures fast computation while providing stronger weights to more recent buffer states. The LPP with the functionalities of scene awareness and path isolation is shown in Figure 2.

3.2.3 Forward Path Prediction (FPP)

In FPP, a more analytical approach is chosen that inherently results in a single predicted trajectory. FPP revolves around solving the non-holonomic dynamic system of equations (Arechavaleta et al., 2006) presented in Eq. (2):

\[
\begin{align*}
x'(t) &= \frac{\cos(t)}{1 + \cos^2(t)} \\
y'(t) &= \frac{\sin(t) - \sin(t) \cos(t)}{1 + \cos^2(t)}
\end{align*}
\]

where \(x'(t)\) and \(y'(t)\) are the derivatives of \(x(t)\) and \(y(t)\) respectively, \(\cos(t)\) and \(\sin(t)\) are the cosine and sine of \(t\) respectively, and \(1 + \cos^2(t)\) is the denominator of the equation. FPP revolves around solving the non-holonomic dynamic system of equations (Arechavaleta et al., 2006) presented in Eq. (2):

1 https://github.com/SEilers/Curves, accessed: 01.08.2022
The general parametric definition of a curvature $\kappa$ given a curve $y(t) = (x(t), y(t))$ is

$$\kappa = \frac{\dot{x} \ddot{y} + \dot{y} \dddot{x}}{(\dot{x}^2 + \dot{y}^2)^{3/2}}$$  \hspace{1cm} (3)$$

and its derivative $\dot{\kappa} = \frac{d\kappa}{dt}$ is given by

$$\dot{\kappa} = \frac{2(\dot{x}^2 + \dot{y}^2)(\dot{x}^{(3)} \dot{y} + 2\dot{x} \ddot{y} + \dot{y}^{(3)} \dot{x}) - 5(\dddot{x} \dot{y} + \ddot{x} \dddot{y})(\dot{x} \dddot{x} + \ddot{y} \dddot{y})}{2(\dot{x}^2 + \dot{y}^2)^{5/2}}$$ \hspace{1cm} (4)

where the primes in both equations refer to derivatives with respect to time; the prime$^{(3)}$ corresponds to the third derivative.

Finally, in accordance with Wilde (2009), the clothoid constant $A_{C\ell}$ is related to $u_2$ as follows:

$$A_{C\ell} = \frac{1}{u_2} = \frac{1}{\kappa}$$ \hspace{1cm} (5)

To solve Eq. (2) using Eqs. (3)–(5), the derivatives of $x$ and $y$ need to be computed. These first- to third-order derivatives can naturally be found by various methods, such as the finite difference approximation of derivatives (Wilmott et al., 1995; Olver, 2014). Following the basic method of central finite differences (CFD) (Fornberg, 1988), the derivatives of the differential equations are numerically approximated with the coefficients $C_{CFD,a}$ (with $x = a$ for the first derivative, and analogs for second and third) given by

$$C_{CFD,a} = \left( \begin{array}{cccc} 0 & 4 & 0 & 0 \\ -1 & 169 & 1 & 0 \\ 10 & 3 & 10 & 0 \\ -1 & 120 & 5 & 0 \\ 1 & 240 & 5 & 1 \end{array} \right)$$ \hspace{1cm} (6)

The CFD method allows computing the derivatives within the given time steps from $t$ to $t - 8$, with the resulting derivatives corresponding to the time step $t - 4$ (c.f. "central"). Accordingly, the position vectors $\vec{x}$ and $\vec{y}$ are read from the HMD data buffer as

$$\vec{x} = \begin{pmatrix} x_{t-4} \\ x_{t-7} \\ \vdots \\ x_i \end{pmatrix} \text{ and } \vec{y} = \begin{pmatrix} y_{t-4} \\ y_{t-7} \\ \vdots \\ y_i \end{pmatrix}$$ \hspace{1cm} (7)

Once the coefficients $C_{CFD,a}$ are determined and positional vectors $\vec{x}$ and $\vec{y}$ are available, the derivatives are computed as

$$\dot{x}_{t-4} = C_{CFD,\dot{a}} \cdot \vec{x} \hspace{1cm} \dot{y}_{t-4} = C_{CFD,\dot{a}} \cdot \vec{y}$$

$$\ddot{x}_{t-4} = C_{CFD,\ddot{a}} \cdot \vec{x} \hspace{1cm} \ddot{y}_{t-4} = C_{CFD,\ddot{a}} \cdot \vec{y}$$

These derivatives in Eq. (8) often manifest evident oscillations or other tracking noise originating from amplifications through the CFD method. Hence, the tracking inputs are smoothed more rigorously at risk of losing relevant data or the derivatives are alternatively treated again with the extended double-exponential smoothing filter. To avoid the risk of data loss, the latter option is preferred and applied, which eliminates the occurrence of high-frequency content even while introducing a slight but tolerable latency.
By substituting the smoothed derivatives from Eq. (8) into Eqs. (3, 4), the clothoid curvature $\kappa$ and control input $u_2$ are fully determined. Furthermore, using Eq. (5), the clothoid constant $A_{c2}$ is computed. Utilizing $Curves$, the predicted clothoid is constructed through a different method that requires the starting position $(x, y)$, heading $\phi$, curvature $\kappa$, clothoid constant $A_{c2}$, and clothoid length $L$. By definition, the clothoid length is inversely linear to the curvature; thus, the length $L$ is simply clamped between a maximum length $L_{\max} = 3$ m (for consistency with the LPP) and inverse of $\kappa$ as:

$$L = \min \left( L_{\max}, \frac{1}{\kappa} \right).$$

The final FPP with its single prediction is demonstrated in Figure 3. Notably, the FPP approach neglects the virtual architecture in its prediction but is faster than the LPP despite the calculation of multiple derivatives as effectively fewer computational steps are required in the determination of a single prediction instead of many.

### 3.3 Predictive redirection

Conceptually, the predictive RDW entails a simple approach:

- it predicts a single path $T_{pred}$;
- $T_{pred}$ is redirected based on an action set $U$ consisting of multiple redirection techniques and different gains, resulting in $T_{red}$;
- a cost-based analysis of $T_{red}$ is used to identify the best redirection $\pi_{optimal} \in U$;
- $\pi_{optimal}$ is applied to the user.

### 3.3.1 State update

The action set $U$ of redirection techniques utilized in our approach consists of rotation gains, translation gains, curvature gains, and a combination of translation and curvature gains (Grechkin et al., 2016). Each gain $\pi \in U$ is only applied within its respective noticeability thresholds (Steinicke et al., 2009), as shown in Table 2. Naturally, resets are applicable above the respective rotational thresholds depending on the requirements determined for each reset. The specific process of injecting the particular redirection gains is included in the Redirected Walking Toolkit (Azmandian et al., 2016) and employed identically in our case. It is important to note that the size of the state space in which redirection is applied is manually limited by allowing only a single redirection action along the complete predicted path. Although the predicted path could potentially be divided into shorter segments, with each being subject to a separate evaluation, the computational demand grows exponentially with the size of the action set $U$, which would in turn linearly propagate with the number of segments that a path is divided into. Therefore, a finer segmentation of the path was rejected, and the state space was restrained in favor of faster iterations. The action set finally contains a null redirection gain and six different gain values per gain, i.e., the upper and lower noticeability threshold values (Steinicke et al., 2009) with a uniform distribution in between.

### 3.3.2 Redirection vector

In accordance with the performance comparison results of APFs in subsection 3.1, non-harmonic APFs are utilized (Bachmann et al., 2019; Thomas and Rosenberg, 2019), and a redirection vector $\vec{F}_{red}$ is defined. This redirection vector $\vec{F}_{red}$ is a total force vector and is the sum of all repulsive forces exhibited by the obstacles $i$ in the physical space $O$, as shown in Eq. (10):

$$\vec{F}_{red} = \sum_{i \in O} \vec{F}_{rep,i}$$

where the magnitude $\|\vec{F}_{red}\|$ denotes the total force acting on a specific place in the physical environment and is considered as its APF value.

The contribution of a single repulsive obstacle $i$ is formulated as in Eq. (11):

<table>
<thead>
<tr>
<th>Gain</th>
<th>Lower bound $L_{min}$</th>
<th>Upper bound $L_{max}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Translation</td>
<td>0.86</td>
<td>1.26</td>
</tr>
<tr>
<td>Rotation</td>
<td>0.8</td>
<td>1.49</td>
</tr>
<tr>
<td>Curvature</td>
<td>$-7.5$</td>
<td>7.5</td>
</tr>
<tr>
<td>Null redirection</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

In this work, we present two predictive approaches, PredRed LPP and PredRed FPP, which differ in their predictive components; thus, $T_{pred}$ originates from the respective LPP and FPP algorithms.
\[
\vec{F}_{\text{rep}} = \begin{cases} a_r \cdot \exp(-b_2 \cdot d_o^2) \cdot \vec{e}_o, & \text{if } d_o \leq d_a \\ 0, & \text{else} \end{cases},
\]

where \(a_r\) defines the maximum APF value generated by a single obstacle, and the constant \(b_2\) denotes the distribution width with respect to how quickly the APF value dissipates and approaches zero with increasing distance from the obstacle \(i\); \(d_o\) describes the Euclidean distance between a specific obstacle’s position \(p_i\) and the evaluated position \(p_{\text{eval}}\); \(d_a\) is the threshold range within the repulsive force that is considered to still contribute to the total force. Here, \(\vec{e}_o\) is the normalized direction vector from the evaluation position \(p_{\text{eval}}\) to the obstacle position \(p_i\), and is given as

\[
\vec{e}_o = \frac{p_i - p_{\text{eval}}}{\|p_i - p_{\text{eval}}\|}
\]

### 3.3.3 Cost function

The cost function is a crucial element in determining the best redirection among the redirected trajectories \(T_{\text{red}}\). Generally, minimizing the total cost \(J_{\text{total}}\) over all redirection actions \(\pi\) within the action set \(U\) results in the best redirection \(\pi_{\text{optimal}}\), as shown in Eq. (13):

\[
\pi_{\text{optimal}} = \underset{\pi \in U}{\arg \min} J_{\text{total}}(\pi)
\]

The overall cost function \(J_{\text{total}}\) thus consists of the sum of all individual costs \(J_i\) over the complete redirected path \(T_{\text{red}}\), which is evaluated for each data point from \(t_1, \ldots, t_N\), with \(N\) being the final point of the trajectory. To incorporate the increasing uncertainty along the prediction into the cost function, a discount factor \(\alpha = 0.8\) is implemented similar to that in literature (Nescher et al., 2014), as shown in Eq. (14):

\[
J_{\text{total}} = \sum_{t=0}^{N} \alpha^t \cdot J_i.
\]

The cost for each point is designed by separately considering the APF, the user’s current heading penalization owing to deviation toward the redirection vector, and the resets and redirection gains. The cost for the individual data point is thus given by Eq. (15):

\[
J_i = J_{\text{APF}} + J_{\text{Heading}} + J_{\text{Reset}} + J_{\text{Gain}}
\]

where \(J_{\text{APF}}\) denotes the APF value and is given by the magnitude of the redirection vector \(\vec{F}_{\text{red}}\):

\[
J_{\text{APF}} = \|\vec{F}_{\text{red}}\|
\]

Accordingly, the magnitude of the redirection vector directly translates the user’s proximity to the obstacles and thereby penalizes the positions in danger of collisions. Furthermore, \(J_{\text{Heading}}\) is given by the dot product between \(\vec{F}_{\text{red}}\) and current heading \(\vec{\theta}\):

\[
J_{\text{Heading}} = h_{\text{h}} \cdot \frac{1}{2} \left(1 - \frac{\vec{F}_{\text{red}} \cdot \vec{\theta}}{\|\vec{F}_{\text{red}}\| \|\vec{\theta}\|}\right)
\]

With this definition, the heading cost is limited between 0 and 1 as well as multiplied by \(h_{\text{h}}\), which is considered as the design parameter for heading penalization. This later offers the option to vary the weighting balance between the heading and APFs, with low heading costs to steer users toward open spaces rather than favoring positions closer, yet parallel to the boundaries with low APF costs. For the current implementation, \(h_{\text{h}}\) was chosen to be 1.

The resets are penalized through a binary decision of whether the evaluated data point lies within the tracking room boundaries or not, as shown in Eq. (18). Through this approach, collisions that unavoidably invoke a reset upon first impact are delayed as the collisions accumulate costs linearly with the amount of path lying outside the walkable space. Therefore, a late reset induces a lower cost in contrast to an early reset.

\[
J_{\text{Reset}} = \begin{cases} 1000, & \text{if outside tracking room boundaries} \\ 0, & \text{otherwise} \end{cases}
\]

Finally, the cost results from the different gains are formulated in \(J_{\text{Gain}}\). Accordingly, \(J_{\text{Gain}}\) and \(J_{\text{Heading}}\) were set to 0 for simplicity, but it would be reasonable to provide containers for these in the initial formulation of the PredRed implementation for later investigations. We aim to include psychometric functions (Neth et al., 2012; Steinicke et al., 2008) or similar means to account for the noticeable in deciding the redirection strength.

With all components elaborated, the two new predictive RDW algorithms PredRed LPP and PredRed FPP are complete. Along with these, three more conditions were implemented, namely NULL as well as the two reactive variations of the APF RDW steer-to-center (S2C) (Razzaque, 2005) and steer-to-gradient (S2G) (Thomas and Rosenberg, 2019; Bachmann et al., 2019). Although S2C has been established over the years as a simple yet powerful algorithm that is popular for its adequate performance comparisons in literature, S2G appears to be an obvious choice owing to its APF-based algorithmic proximity and inherently powerful premise. In both reactive approaches, the algorithms compare the current real user state to the redirection vector \(\vec{F}_{\text{red}}\) and apply the redirection that best closes the deviation between the two. In the case of S2C, \(\vec{F}_{\text{red}}\) is implemented by placing the coordinate system’s origin at the center of the tracking space and inverting the user’s position vector, which inherently forces \(\vec{F}_{\text{red}}\) to always point toward the center of the space. In the case of S2G, \(\vec{F}_{\text{red}}\) is simply calculated as shown in Eq. (10). NULL naturally refrains from applying any redirection while walking and only utilizes resets to prevent collisions. For all conditions, the reset algorithm was maintained consistently as reset-to-gradient (R2G) (Thomas and Rosenberg, 2019; Bachmann et al., 2019), which recalibrates the user by aligning their heading with \(\vec{F}_{\text{red}}\) via the reflex angle of the initial deviation. In our case, the reflex angle is specifically chosen over the acute and obtuse angles since it allows weaker rotational gains, consequently placing less strain on the user perceptions. Notably, applying R2G to a NULL redirector seems inappropriate at first since it also incorporates the potential influence of a second user, but we intended to maintain the conditions in addition to the redirectors consistent rather than implementing a simplistic alternative like the original 2:1-turn reset (Williams et al., 2006).

### 4 User study

To validate the newly presented PredRed redirectors, a user study was conducted to acquire relevant data. The participants
used a wireless HTC Vive Pro driven by two desktop towers, each with an i9-10900K and 64 GB of RAM as well as an NVIDIA GeForce RTX 3090, and handheld controllers were not provided. This setup ensured a steady frame rate of 90 fps and full resolution for both eyes. The system implemented SteamVR but the safety chaperones were deactivated to increase the presence of the users, with the only safety measure being a reset prompt that asked users to stop and perform a reset (see Figure 4A). Naturally, the reset direction is governed by the redirection vector and can either indicate clockwise or counterclockwise reorientation. The physically available tracking space was 5.5 m × 8.0 m, with a 0.2 m reset margin.

### 4.1 Study design

The participants were invited in pairs and explored separate yet identical virtual environments colocated in the same physical tracking space. The separation of the virtual environments was particularly chosen to avoid any bias from the users interacting with each other in VR (e.g., avoiding virtual collisions). Each pair of participants experienced only a single RDW condition to avoid learning or accommodation effects. All participants followed the same study protocols and filled a pre-questionnaire, were instructed before being exposed to the VR, and answered a post-questionnaire. The pre-questionnaire consisted of general demographic information, a self-assessment of their susceptibility to motion sickness, their experiences with VR systems, and a simulator sickness (SS) questionnaire (Kennedy et al., 1993). In the instructional part, the participants were introduced to the VR system, their task, and their expected behavior of collecting stars (see Figure 4B). They were further instructed to be especially responsive to the reset prompts, take short steps (since only their head was tracked), and avoid passing through virtual walls. The participants were aware that they shared a common tracking space, that they cannot see each other in the virtual environment, and that only their physical positions were exchanged between the systems to prevent collisions. They were not informed about the purpose of the study regarding RDW, so that the advance questions were unanswered. After receiving instructions, pairs of participants started their virtual experiences in opposite corners of the tracking space facing the center and aligned with the initial virtual corridor. Following the virtual task, they filled the post-questionnaire consisting of another round of the SS questionnaire and the standardized questionnaires on the simulation task load index (SIM TLX) (Harris et al., 2020) and cognitive absorption (CA) (Agarwal and Karahanna, 2000).

### 4.2 Study environment

The study environment consisted of seven rooms, each with distinctly different architectures varying from corridors and maze-like environments to local obstacles like pillars and mostly or even fully open spaces, as shown in Figure 5 (in order: Hallway, Yellow01, Yellow02, Red01, Red02, Blue01, and OpenSpace Forest). Although this delivered some variety to the participants to make the exploration more interesting, the rooms were also evaluated separately to highlight the performances in each of the architectural layouts. In addition to the aesthetics, the floor colors helped with orientation and provided some feedback regarding study progression to the investigators. The participants were asked to gather collectibles distributed throughout the environment by simply walking over them. Overall, the 27 stars that were to be collected were carefully distributed in the five rooms connected to the starting point (i.e., Yellow01, Yellow02, Red01, Red02, and Blue01), ensuring that the users explore the full environment without missing any corners or corridors. All the stars in a room were visible simultaneously, while the various rooms were connected by sliding doors that opened automatically after all the stars in a room were collected. The participants were always informed through an interface in the HMD regarding the number of stars they had already collected and that remaining to be discovered in a given room. The final area of the study was populated with trees and stones, suggesting independent exploration without a clear goal.

## 5 Results and discussion

In this section, we present and discuss the analytical results of the data acquired from the user study entailing the study population...
followed by the subjective and objective metrics. The video (Supplementary Video S1) displays a simulated top-down view of the tracking space using the recorded positions of two simultaneous study participants.

5.1 Study population

In total, 150 subjects participated in the user study (25.5 ± 5.5 years, 45 females). Since the participants enrolled in pairs, each condition was encountered 15 times, with an overall number of 30 recordings per condition. Among the participants, 31 wore contacts, 37 used glasses, and none of them experienced any remarkable issues with the VR system. The participants were recruited through university channels, which was reflected in the 138/150 participants who were currently studying. The complete study procedure roughly required an hour, for which the participants were compensated fairly. Even though the participants’ experiences with VR varied considerably (15 without VR experience, 103 below 20 h, 35 above), apart from the distinctly different navigation speeds, all participants collected all 27 stars each. Furthermore, although some of the participants considered themselves to be exceptionally susceptible to motion sickness, none of the study procedures were interrupted or aborted because of sickness.

5.2 Subjective metrics

The SS, SIM TLX, and CA questionnaires were filled out by the participants during the different study phases, and the results are clustered by redirection condition and summarized in Table 3. None of the participants aborted the study, which is confirmed by the fact that none of the collected delta values ΔSS between the pre- and post-exposure conditions indicate significant occurrence of SS. Furthermore, the SIM TLX scores (0–100) and CA (0–30) were all clustered around similar values without apparent advantages for any of the conditions, indicating that the new PredRed LPP and FPP methods can be integrated well with existing and proven algorithms. With the exception of presence and CA, lower values are deemed better for all conditions. Based on more qualitative feedbacks, the study participants notably complained that the NULL condition required them to spin a lot, which was hardly unexpected considering that some of the participants registered 100 or even more resets during their exposure time. On the other hand, the study participants at the lower end of reset counts, especially in PredRed LPP conditions, were often surprised with the size of the explored environment compared to the tracking space since they lost track of their real surroundings quickly. Furthermore, some participants realized and noted that they could feel the redirection, especially in the S2C and S2G conditions, but not in an overly disturbing sense.

5.3 Objective metrics

To assess the performances of different RDW concepts and steering algorithms, a popular measure for comparison is the mean distance between resets $d_{\text{reset}}$. Unlike the total number of resets, which was commonly used in early performance evaluations, $d_{\text{reset}}$ normalizes the number of resets over the total walking distance for each user and thereby better accounts for varying walking speeds, including stand still or other personal human walking traits like veering. On average, each participant covered 381 m during their exploration, but $d_{\text{reset}}$ was calculated for each participant separately based on their individually covered distance. Figure 6 shows the overall distribution of $d_{\text{reset}}$ against the different RDW conditions, and Table 4 presents the respective numerical mean values. Notably, in rare occasions, the participants who reset very quickly would overspin their initially indicated reset, instantaneously provoking a second successive reset. In such cases, these back-to-back resets were summarized into a single reset and applied to all conditions consistently.

Evidently, the newly introduced predictive RDW algorithm PredRed LPP managed to outperform the remaining algorithms overall. This is further emphasized by the one-tailed $t$-test on the normally distributed data, evaluating $d_{\text{reset}}$ in the presented order (PredRed LPP–PredRed FPP–S2G–S2C–NULL). The numerical results of the $p$-values are shown in Table 5, and a significance of $\alpha = 0.05$ was chosen from RDW literature. With this, we confirm that PredRed LPP showed statistically significant best performance ($p < \alpha$),
while PredRed FPP and S2G performed similarly ($p > \alpha$) even as they significantly outperformed S2C and NULL redirection ($p < \alpha$ in both cases). Noticeably, S2C showed no statistical superiority over NULL redirection. Given that only resets were employed in NULL redirection, this may indicate that continuous application of redirection is less powerful or less effective than usually agreed upon in literature, and we speculate that the resets may possibly have a much larger significance than commonly expected.

### TABLE 3 Results of the subjective questionnaires clustered by RDW condition: simulator sickness (SS), SIM task load index (0–100), and cognitive absorption (0–30). Aside from presence and CA, lower values are considered to be better.

<table>
<thead>
<tr>
<th>RDW Condition</th>
<th>Δ SS</th>
<th>Mental Demand</th>
<th>Physical Demand</th>
<th>Task Compl.</th>
<th>Stress</th>
<th>Distr.</th>
<th>Navig.</th>
<th>Presence</th>
<th>CA</th>
</tr>
</thead>
<tbody>
<tr>
<td>PredRed LPP</td>
<td>15.7</td>
<td>25.3</td>
<td>13.3</td>
<td>9.3</td>
<td>12.0</td>
<td>18.0</td>
<td>21.7</td>
<td>72.0</td>
<td>22.4</td>
</tr>
<tr>
<td>PredRed FPP</td>
<td>9.2</td>
<td>25.0</td>
<td>13.7</td>
<td>8.0</td>
<td>13.0</td>
<td>17.3</td>
<td>18.0</td>
<td>71.3</td>
<td>23.6</td>
</tr>
<tr>
<td>S2G</td>
<td>12.3</td>
<td>22.3</td>
<td>16.3</td>
<td>6.0</td>
<td>8.3</td>
<td>15.7</td>
<td>21.0</td>
<td>76.3</td>
<td>23.4</td>
</tr>
<tr>
<td>S2C</td>
<td>8.6</td>
<td>32.3</td>
<td>16.3</td>
<td>7.0</td>
<td>12.0</td>
<td>18.3</td>
<td>28.0</td>
<td>70.7</td>
<td>22.2</td>
</tr>
<tr>
<td>NULL</td>
<td>9.6</td>
<td>24.0</td>
<td>20.0</td>
<td>8.7</td>
<td>10.0</td>
<td>20.7</td>
<td>21.7</td>
<td>77.7</td>
<td>22.2</td>
</tr>
</tbody>
</table>

### TABLE 4 Results of the objective measure for each RDW condition over all rooms: mean distance between resets $d_{\text{reset}}$ including standard deviation.

<table>
<thead>
<tr>
<th>RDW Condition</th>
<th>$d_{\text{reset}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>PredRed LPP</td>
<td>5.75 ± 0.26 m</td>
</tr>
<tr>
<td>PredRed FPP</td>
<td>5.60 ± 0.27 m</td>
</tr>
<tr>
<td>S2G</td>
<td>5.56 ± 0.26 m</td>
</tr>
<tr>
<td>S2C</td>
<td>5.42 ± 0.20 m</td>
</tr>
<tr>
<td>NULL</td>
<td>5.28 ± 0.39 m</td>
</tr>
</tbody>
</table>

### TABLE 5 Results of a one-tailed t-test investigating the statistical significances of the respective algorithms based on $d_{\text{reset}}$. A significance level of $\alpha = 0.05$ is considered. The table is read from left to right, e.g., PredRed LPP vs PredRed FPP results in $p = 0.031$. Green indicates $p < \alpha$, and yellow is $p > \alpha$.

<table>
<thead>
<tr>
<th>p-value</th>
<th>PredRed FPP</th>
<th>S2G</th>
<th>S2C</th>
<th>NULL</th>
</tr>
</thead>
<tbody>
<tr>
<td>PredRed LPP</td>
<td>0.031</td>
<td>6.4E-05</td>
<td>0.013</td>
<td>2.1E-06</td>
</tr>
<tr>
<td>PredRed FPP</td>
<td>0.312</td>
<td>0.047</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td>S2G</td>
<td>0.056</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Furthermore, $d_{\text{reset}}$ was evaluated by considering the different architectural spaces separately (see Figure 7). On the left, the overall values are shown as references, and the rooms are ordered from left to right in consecutive order of exploration during the user study. Notably, especially in the initial hallway, PredRed LPP’s strength of integrating scene awareness was apparent. Even though the performance was not the best for each room, PredRed LPP often showed considerable advantage over the other algorithms; although it suggested an apparent weakness in the final open space, the
algorithm performed well for the other more open spaces in Yellow02 and Red02. PredRed FPP, on the other hand, while having only a slightly higher $d_{\text{Reset}}$ over S2G, appeared to struggle most with bent trajectories in guided environments (e.g., in Blue01 and Yellow01). Interestingly, S2C showed a particularly high $d_{\text{Reset}}$ in the straight hallway at the beginning but deteriorated drastically in the two yellow rooms.

6 Conclusion

In this paper, we introduced two new RDW concepts addressing challenges encountered in predictive RDW. These mainly consist of implementing simplifications like virtual constraints (e.g., mazes) to limit the choices of the predictive components, thus lowering the computational demand and ensuring real-time application, as well as applying prediction in colocated multiuser environments. We present the detailed implementations of the core elements and discuss how these are connected to the overall concepts forming the redirectors PredRed LPP and PredRed FPP. Both approaches combined cost-based evaluations correlating with a non-harmonic APF representation of the physical tracking space. The main difference between PredRed LPP and FPP was in the technical implementations of their respective path prediction algorithms. While LPP relied on multiple clothoid trajectories contained in a lemniscate shape, the application of a simple scene awareness to sort out infeasible trajectories, and a path similarity measure, FPP numerically approximated a single clothoid trajectory forecasting the user path based on their recent explorative behaviors.

Aside from the technical procedures, we designed and conducted a user study involving 150 participants. In addition to the two new concepts, we recreated three known RDW concepts from literature using the presented APFs: NULL, S2C (Razzaque, 2005), and S2G (Thomas and Rosenberg, 2019; Bachmann et al., 2019). We matched all five conditions with a consistent R2G reset strategy. For these five distinct conditions, we invited pairs of participants to obtain 15 pairs, with 30 individual recordings per condition. None of the participants aborted the user study due to sickness, and all participants completed the given search and collect task fully. Through recordings of the explorations, we showed that PredRed LPP outperformed the other conditions statistically significantly with regard to the mean distance between resets. Although PredRed FPP showed superior results over S2G, S2C, and NULL, it only showed statistical significant results over S2C and NULL. Furthermore, both PredRed approaches could be implemented well in locations with proportionally high amounts of open spaces without apparent spikes in their computational demands, other technical issues (e.g., dropping frame rate), or obvious deteriorations in the RDW performances.

7 Outlook

Both PredRed LPP and FPP algorithms introduce a new take on predictive RDW, enabling investigation of further opportunities. For example, in the current implementation, the second user was modeled as a simple, dynamic, and local obstacle whose influence on the redirection vector was equally weighted.
to the boundaries. A simple yet potentially powerful consideration would entail a priority system, which in its simplest implementation would contain a rigid order, in which some of the users receive precedence over others. Alternatively, since each user has their own velocity and prediction, incorporating a stronger weight along the expected motion axis or even full consideration of the predicted trajectory in the APF propagation would potentially improve the overall redirection strategy. This implies that the APF can be locally propagated to better reflect the effective future states of the environment in the planning iteration and sharing the propagated APFs with each other. Furthermore, as explained in subsection 3.3, instead of firmly locking the state space in favor of computational demand, segmenting the predicted path and allowing the full action set to be considered for each individual segment along the prediction would create a more elaborate redirection. Naturally, this requires careful integration into the cost function as changing the applied redirection gains in rapid succession can potentially become more noticeable and break a user’s presence quickly. On the prediction side, in the case of FPP, an additional integration of a system allowing scene awareness could create benefits with respect to accuracy and precision of prediction. This clearly imposes an algorithmic overhead and may most likely impair the computational demand slightly; however, since FPP is already less resource-intense, this should not pose a major issue. The complete procedure also entailed elaboration of many placeholder containers, such as $A_{\text{low}}$ in Eq. (1) to incorporate walking speed in the lemniscate prediction or heading cost $J_{\text{Heading},i}$ from Eq. (17) to address user alignment with the boundaries. Each of these placeholder containers, if calibrated properly, may again improve the overall performances of the new predictive systems, but further isolated investigations are necessary. As such, during calibrations of the placeholder containers, an ablation study could enrich understanding of the impacts of individual cost terms on the global cost function $J_{\text{total}}$. Regarding the resets, actively integrating the so-called predictive resets may potentially improve the redirection strategy considerably by preventing users from navigating into difficult situations, such as a corner of the tracking space. Otherwise, predictive resets could also take a user priority system into consideration and could be employed to actively balance the number of resets between the users or simply be integrated in a segmented evaluation connected to an unrestricted state space.

The algorithms presented herein have only been tested in virtually separated environments. Accordingly, including two users in the same virtual environment could potentially increase the users’ presence further, but we currently believe this to occur regardless of the applied RDW condition and therefore not affect the objective RDW performance measures, such as the mean distance between resets. Another interesting topic could be the incorporation of certain aspects of RDW alignment (Williams et al., 2021; Thomas and Rosenberg, 2020), which would eventually allow the users to physically interact with the real environment or even with each other.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical approval was not required for the studies involving humans because there was no personal information collected that could potentially be followed back to the individual participants. The studies were conducted in accordance with the local legislation and institutional requirements. All participants provided written informed consent to participate in this study.

Author contributions

CH: conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing—original draft, and writing—review and editing. NI: conceptualization, data curation, formal analysis, methodology, software, validation, visualization, and writing—review and editing. CHo: project administration, resources, supervision, and writing—review and editing. AK: funding acquisition, project administration, resources, supervision, and writing—review and editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This work was supported by the Innosuisse grant (no. 38431.1 IP-ICT) and Open Access funding by ETH Zurich.

Conflict of interest

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frvir.2024.1259429/full#supplementary-material


