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Towards realistic walk path simulation in automotive assembly lines: a probabilistic approach

Philipp Agethen[a,c,*], Felix Gaisbauer[a,c], Philipp Froehlich[a], Martin Manns[b], Enrico Rukzio[c]

[a]Daimler AG, Wilhelm-Runge-Str. 11, 89081 Ulm, Germany
[b]University of Siegen, Paul-Bonatz-Str. 9-11, 57076 Siegen, Germany
[c]Ulm University, James-Franck-Ring, 89081 Ulm, Germany

* Corresponding author. Tel.: +49-731-5052426; fax: +49-711-3052156294. *E-mail address:* philipp.agethen@daimler.com

Abstract

In the last years, automotive production planning has become increasingly time-consuming, since the trend towards mass-customization is currently leading to numerous possible assembly task-sequences within one assembly station. As a consequence of this development, walk paths for assembly operators in a manual assembly line may vary wildly from car to car. An increasing variety of routes, coupled with high requirements for efficiency and working conditions entails a growing demand for realistic walk path planning methods. In practice, walk paths are either planned with pen-and-paper methods or simulated using deterministic motion planning algorithms calculating a two-dimensional trajectory of the worker's Center of Mass. Both methods, however, do not consider gait and its influence on the actual walk path. Furthermore, by applying deterministic simulation approaches, the probabilistic nature of human motion is neglected. As a consequence, actual walk paths can significantly deviate from their corresponding plans. In order to overcome these limitations, this paper presents a two-dimensional motion planner incorporating fine grained information on human gait gathered from 600 000 samples of a probabilistic motion model. Those data points are drawn from a multivariate Gaussian Mixture Model based on real human motion capture data, thus guaranteeing natural human motions. By combining a global motion planner with this motion model, on the one hand, a realistic and collision-free trajectory can be computed in real-time. On the other hand, this novel probabilistic approach contributes to a better prediction quality of planning models by enabling production planning departments not only to calculate one valid walk path but to simulate all possible variants.

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Keywords: Production planning; Probabilistic walk path simulation; Motion capture

1. Introduction

In automotive industry, the trend towards product diversification [1] is currently leading to an increasing complexity for manual assembly planning departments since the vast majority of produced cars are unique in sum of their parts. As a consequence, walk paths of assembly operators may vary for each car within each production cycle. Therefore, the realistic simulation of human walking behavior within manual assembly lines is becoming increasingly important. In practice, however, walk paths are predominately planned in a bird's eye view using traditional pen-and-paper methods (i.e. spaghetti-charts). More recently, commercial production planning tools (such as IPO.Log [2] or ema [3]) are increasingly automating this process by simulating the two-dimensional trajectory of a worker's Center of Mass (CoM) using motion planning algorithms (i.e. [4,5]).

These methods aim at generating an optimal and collision-free path between a start and an end point while optionally taking into account physical restrictions (for instance maximum velocity, acceleration and angular velocity) of the human locomotor system. Generally, common two-dimensional motion planners have proven to be suitable for generating abstract, two-dimensional walk paths in assembly lines. However, these algorithms do not consider gait or the probabilistic nature of human motion and its influence on the walk path - as illustrated in Fig. 1. Within this picture, the straight red line depicts the abstract, two-dimensional walk

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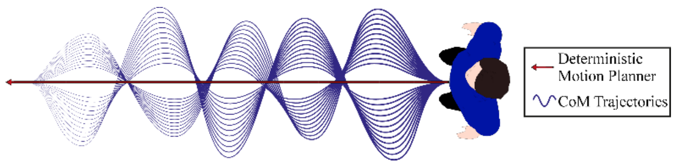

Fig. 1. Disparity between a global motion planner and real center of mass trajectory.

being generated using a deterministic motion planning algorithm. The set of n curved blue lines represent the range of possible CoM trajectory variants (motion corridor), being generated from n executions of the same walking task with identical start and end points. Note that the sinusoidal shape is stemming from the gait cycle whereas the motion corridor is a result of the human spatio-temporal motion variation (i.e. starting foot, stride length, foot contact points). When approximating walk paths using deterministic simulation approaches, this variance is neglected which leads to the problem that actual walk paths can significantly deviate from their corresponding plans [6].

In order to contribute to realistic two-dimensional motion planning, this paper presents a novel approach combining an arbitrary global motion planner (in this case a LazyTheta* [5] algorithm) with a probabilistic motion-model describing human gait variations in form of a matrix. The latter is generated from a motion synthesis model that was trained using real motion capture data. Using a discrete matrix representation consisting of 600 000 sampling points of left and right steps, realistic motion-sequences can be computed in a run-time efficient manner.

2. State of the Art

Various research has been carried out in the area of two-dimensional motion planning. Generally, these algorithms aim at generating an optimal and collision-free path between a start and end point. These approaches can be generally divided into global and local motion planners, whereby the former is used for application in which all obstacles are known a priori [7]. According to Gasparetto et al. [8] this group can be further subdivided into roadmap-techniques (i.e. [9]), cell decomposition (i.e. [4,5]) and algorithms using potential fields [8]. Other approaches use rapidly exploring random trees [10], genetic algorithms [11], interpolation methods [12] or neural networks as presented in [13].

In contrast, reactive local motion planners are modeling dynamic behavior while taking into account the desired characteristics and restrictions of the system to be simulated (i.e. human locomotor system). Various approaches have been used for this purpose, ranging from steering behaviors [14] over randomized models [15] to velocity obstacle algorithms (see [16,17]). Apart from the exclusive use of one presented categories, others combine global and local motion planners to a hybrid system, thus fusing both advantages [7].

While covering many important aspects of two-dimensional motion planning, none of these approaches generate a realistic trajectory, since human gait and its spatio-temporal variations in particular are neglected. As depicted in Fig. 1, however, the abstract walk path may differ from reality in terms of walk path length and shape.

Unlike the aforementioned deterministic algorithms, probabilistic approaches targeting human posture are recently receiving wide attention in various domains [18,19]. Generally, these statistical models contain an infinite number of motion variants thus enabling the generation of a rich repertoire of motions based on a finite number of input datasets. In contrast to deterministic approaches simulating human motion, statistical models are based on the assumption that human locomotor system comprises an infinite number of styles and postures. Moreover, it is assumed that different executions of one motion primitive show an intrinsic relationship, which may be approximated using statistical models [19]. Based on these assumptions, various approaches have been presented ranging from Hidden Markov Models [20,21], to Gaussian Process Dynamical Models [22]. Furthermore, multiple works (i.e. [23,24]) combine deterministic methods with statistical models.

Min and Chai [19] present a data driven approach, probabilistically modeling fully-articulated human motion based on a large number of motion capture recordings, hence synthesizing continuous style variant motions. Du et al. [25] adapted the approach to assembly workshop scenarios. Manns et al. point out the influence of quality to the effectiveness of the approach [26] and investigate motion capture effort for creating models that cover common shop-floor motions [27]. Results suggest considerable requirements in both motion quality and quantity for realistic full body motion data synthesis of shop floor data.

This representative sample of approaches illustrates the capability to holistically cover the full spectrum of human locomotion and its significant impact on common applications. For two-dimensional walk path simulation, however, data-driven models are not in scope of literature so far. Therefore, this paper bridges the gap between probabilistic approaches targeting fully-articulated human motion and two-dimensional Motion Planning.

3. Approach

This paper presents a method that combines a motion model describing human locomotion with a global motion planner. Using this method, production planners can generate statically distributed, realistic motions between two waypoints while avoiding obstacles. In order to generate such a model, a compact representation of all human motions has to be found, which is applicable to the context of automotive assembly lines. The approach follows the first part of Min and Chai [19], in which a latent space is derived, but considers the substantially larger motion variety that can be observed on assembly shop floors.

Initially, a holistic database of assembly-related, fully-articulated motions is generated using an OptiTrac motion capture system. Next, characteristic state changes for starting and ending frames are defined for different motion primitive types (e.g. *right stance* or *sidestep left*). These state changes mainly relate to contact situations of different joints - for example a left stance ends when the right foot loses floor contact. Afterwards, key frames are semantically annotated in the motion capture data using these criteria. In the case of walking, annotations include foot-joint contact with the floor. This information is employed to segment the motion trajectories into motion primitives.

Subsequently, similar motions are aligned to a canonical time line using dynamic time warping, in which spatial joint distances between different motion examples are minimized [28]. After conducting a z-transformation, the mapping between frames of the real and the canonical time line is represented with one cubic B-spline function per motion. A functional principal component analysis maps these functions into a latent space describing temporal motion variation.

The spatial motions in the canonical time line are transformed into joint angle space, where angles are represented as quaternions, so that singularities are avoided. Joint angle trajectories are approximated with cubic B-Splines so that each motion is represented as a spline curve in a space that has four times the number of joints dimensions (in the use case 232). Functional principal component analysis maps these splines into a second latent space representing spatial motion variation.

The two latent spaces of each motion primitive are then combined to a so-called *motion style* space S, where each motion is represented by a vector, from which it can be reconstructed. For any type of motion, the distribution of motion vectors forms clusters. It is now assumed that all points within a cluster represent valid motions [19]. Therefore, the clusters are generalized with Gaussian random distributions that form a Gaussian Mixture Model (GMM).

The GMM allows sampling of new vectors $s \in S$. Each vector s can be mapped onto a trajectory of all limbs of the human body during one motion primitive (e.g. step, grab or place). The trajectories normally are unique and do not match any recorded motion [19]. n samples of one motion primitive (e.g. one step) result in n different motion variants. The probability distribution of trajectories that are derived by concatenating these variants shall be called motion corridor. Fig. 1 sketches the idea of a motion corridor for multiple concatenated steps.

While the described motion model represents full-body skeleton motion distributions in both the spatial and the time domain, it encounters two practical drawbacks:

- The model and its results are complex. However, most of the contained information is not required for walk path simulation in automotive contexts.
- While deriving realistic walk paths from the probabilistic motion model is possible, results are far from robust, due to the limited quality, that motion capture in shop floor environments yields, and due to the high motion variability that is encountered on shop floors.

Therefore, the approach in this work employs the output of the spatial motion model for improving 2D walk path generation. In particular, motion variant samples from all motion primitives that are part of locomotion actions are employed: *Begin/end stance*, *stance*, *turning* and *sidestep* each left and right. Subsequently, 100 000 vectors s, each describing fully-articulated human motion, are sampled using the corresponding GMMs and mapped onto trajectories. In order to be compatible with state of art of automotive walk path assessments methods (i.e. [29]) only the information about the two-dimensional CoM position over time are taking into further consideration. Fig. 2 shows the result in form of a two-dimensional histogram containing 600 000 trajectory end points (CoM) for *begin stance left/right* (see $A_{L/R}$), *sidestep*

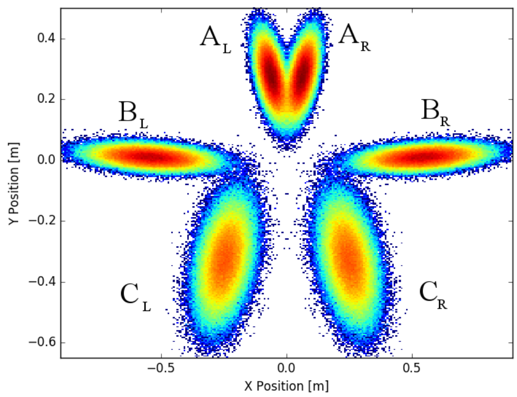

Fig. 2. 2D histogram with 300 bins of CoM end points being sampled from GMMs for motion primitive begin stance; begin stance left/right (AL/R); sidestep left/right (BL/R) and turning stance left/right (CL/R).

left/right (see $B_{L/R}$) and *turning stance left/right* (see $C_{L/R}$). Note that the start point of the body center is located in $[0\ 0]^T$.

Having created a rich repertoire of 600 000 samples for the mentioned motion primitives, next, this database is stored in a form of a two-dimensional array with the cell size of 5 mm. Consequently, each cell unites locomotion properties – namely trajectory, velocity profile and the histogram's corresponding probability – of all samples with the same end position in a range of 5 mm. By using this compact representation, the individual motion samples can be accessed run-time efficiently by loading the motion parameters from one cell.

In order to generate a trajectory consisting of more than one step, multiple appropriate sample vectors have to be concatenated, while taking into account the target, the obstacles and the shortest path. In order to obtain the shortest, collision-free result, the motion model is combined with a global motion planner creating an optimal reference path. By sampling vectors along this reference, collision-free motion can be guaranteed, whereas by incorporating local, statistically distributed gait information, a realistic CoM trajectory is achieved. In order to determine an appropriate motion primitive for each step, the motion model matrix is intersected with a series of lines being derived from the global reference trajectory. Since the end positions of left and right steps are normally not congruent with the center axis (equivalent to the reference path), the line of intersection is alternately sampled from two normal distributions modeling the intersection angle (mean values are defined to be ± 5°). The one-dimensional histogram resulting from the intersection contains a series of potential motion primitives (see Fig. 3), which still can result in a collision - depending on the scene environment. In order to exclude these motion primitives, all matrix cells which overlap with an obstacle are blocked for the respective gait cycle. If the result of this process does not contain an adequate amount of cells, new lines are sampled until valid data points are available. Finally, the specific motion can be determined from the one-dimensional histogram by means of probabilistic sampling or by selecting the most frequent value.

Since the shape and velocity profile of the final trajectory cannot be precisely predicted due to the method's probabilistic nature, the probability of collision-freeness is decreasing along the path since the uncertainty for each motion primitive is

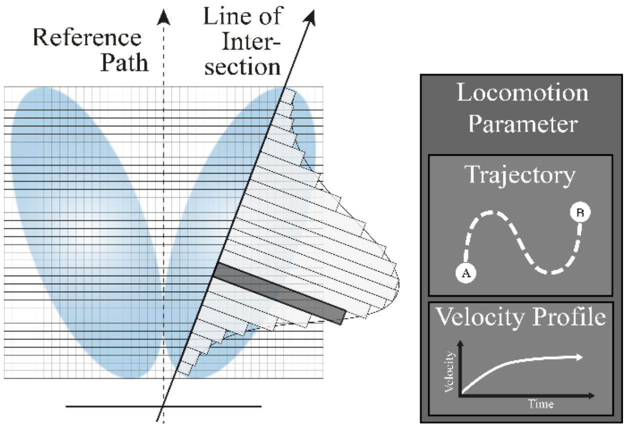

Fig. 3. Working principle of probabilistic approach: A precomputed two-dimensional matrix containing motion primitives is combined with a global motion planner to simulate human gait.

cumulated. Therefore, a new reference path is calculated and the above described sampling process is repeated whenever the distance between predicted and actual position is exceeding 0.5 m.

4. Evaluation

In order to gain insight into the performance and applicability of the novel motion planner, the proposed approach is compared in two scenarios with both a state of art algorithm and trajectories being gathered from a motion capture system, which serve as a baseline.

Participants: The experiment comprised of 16 participants, including 15 male and 1 female being aged from 19 to 59 ($\mu = 28$, $\sigma = 9.2$) with a height ranging from 1.70 m to 1.90 m ($\mu = 1.79$ m, $\sigma = 0.07$ m). The group included 13 students and 3 production planning employees. All participants were unpaid volunteers and naive to the purpose of the experiment. In order to not obstruct the walking style, participants wore their own clothing and shoes. None of the participants had vision or balance disorders that could alter the results of the experiment.

Apparatus: The experiment was conducted in a room with the dimensions of 7.0 m × 5.0 m × 3.0 m (length, depth, height). The experimental setup consists of a starting point (taped cross on the floor) and one locomotion target. In contrast to the ground-leveled starting point, the locomotion target was represented by a rolling cabinet (1.2 m × 0.4 m × 0.9 m). By using this box with the height of approximately one meter, participants were not forced to tilt their head downwards while focusing on a target near the ground. Furthermore, the person was not tempted to execute motion influenced, trying to place the foot during the last step onto a marked end point on the ground.

In the first scenario, no further obstacles were applied to the scene, thus allowing unrestricted walking. In contrast, in a second scenario, a box (1.5 m × 0.4 m × 1.5 m) was positioned at a distance of 1.5 m between the start and end point with its short edge being parallel to the straight line – as depicted in Fig. 4.

In order to capture the trajectory of each participant, the Center of Mass was monitored during the experiment. Following Auvinet et al. [30], a controller (200 g) of an *HTC Vive* tracking system (update rate 60 Hz) gathering information with six degrees of freedom was placed on the front side in center of the participant's hip (umbilicus). The controller was mounted using an elastic belt, being fastened around the person's hip. Subsequently, the CoM was individually derived for each participant from this tracking position as the extension of the controller's z-axis taking into account half of the torso depth and the distance between controller and skin.

Procedure: Generally, since walking in automotive assembly lines frequently takes place in assembly stations with edge lengths of only few meters, a straight line of 3 m, being defined by the start point and the box, was chosen as a representative use-case for both scenarios. Having positioned the target, obstacle and equipped the participant, next, the conditions of the experiment were orally explained to each person individually and ensured that the participant correctly understood the task.

Both scenarios included 3 min of walking between the start and the target point at self-selected speed. Having reached the target, the participant returned to start after standing still for 5 s. This procedure was repeated before repeatedly walking to the target. These two distinctive phases before and after each locomotion cycle subsequently served as distinctive landmarks to reliably distinguish between walking towards the target and returning to the initial position. Since linear walking without turning is in scope of scenario 1, only the former was considered for further investigation. All datasets were manually segmented offline in a post-processing step. Having finished the first scenario, the obstacle was applied to the scene and the identical procedure was repeated (scenario 2). During the whole experiment, participants were allowed to take breaks between trials in order to minimize the effects of exhaustion and lack of concentration.

Based on the recorded trajectories, the proposed approach was used to re-simulate both captured scenarios. For this purpose, first, the proposed motion model in combination with a LazyTheta* [5] (0.01 m cell size, 0.25 m clearance distance) was used to simulate (60 Hz refresh rate) the unrestricted motion between each captured start and end point. Based on the identical start and end points, second, a hybrid approach consisting of a global LazyTheta* [5] (0.01 m cell size, 0.25 m clearance distance) and a local RVO2 [17] (0.25 m clearance distance, $v_{max} = 1.36\ m/s$ [31]) motion planner was applied similarly to the identical scene. The same procedure was repeated for the collision afflicted scenario.

As the probabilistic algorithm is capable of generating arbitrary motions, trajectories between two consecutive executions might differ vastly in terms of the starting foot, foot contact positions and chosen motion primitives. Consequently, a pairwise shape comparison between a captured and a randomly simulated walk path would generate unreliable results - e.g. comparison of motions with left and right starting steps. Therefore, a series of 100 trajectories is subsequently simulated for each reference trail for both scenarios. Afterwards, the best fitting motion is additionally considered for further investigation thus taking into account the probabilistic nature of the novel approach.

Results: In total, an amount of 330 m straight and 530 m curved walking was recorded in both scenarios. Fig. 4 depicts the resulting motion corridors of the captured (see A1/2) and synthesized routes stemming from the presented (see B1/2) and state of art approach (see C1/2) for both scenarios 1 and 2. The images in Fig. 4 show a two-dimensional histogram with 250 × 60 bins of all walk paths in a bird's eye view. The point $[0\ 0.2]^T$ represents the starting point, whereas $[3\ 0.2]^T$ shows the walking target. For scenario 2, these points are located at $[0\ 0.1]^T$ and $[3\ 0.1]^T$. Fig. 4 confirms the assumption, that the presented approach is capable of generating variant-rich motion corridors for both scenarios, containing sinusoidal shaped trajectories. In contrast, the LazyTheta* and RVO2 algorithm are creating variant-free straight (see C1) or curved (see C2) paths due to the neglection of human gait. Note that their motion corridor's width is solely stemming from the captured variation of starting and ending points. The Chi-square distance (see [23]) between the A and B/C measuring motion corridor similarity underlines this findings. In scenario 1, the novel approach better covers the resulting 2D histogram distribution (score 39.71) than the state of art (score 73.00). These findings were confirmed for curved walking: 30.73 vs. 62.00. Moreover, Fig. 4 points out, that the simulated sinusoidal variance (width of motion corridor) of the novel approach is higher than the captured counterpart for straight walking, whereas curved walking shows contrary conditions. This circumstance can be traced back to the limited number of input motions, since the quality of results strongly correlates with the amount of input datasets - as pointed out by Manns et al. [26]. Despite this restriction, the presented approach outperforms the LazyTheta* and RVO2 algorithm in terms of motion corridor coverage using randomly sampled vectors.

Next, for pairwise comparing the shape of each synthetically generated trajectory with their captured counterpart, the best fitting trajectory (out of 100 samples) is utilized in the following. In order to analyze the shape similarity of the simulated walk paths with regard to the captured reference, a Procrustes analysis [32] is used. The results of this procedure can be seen in Table 1. For straight walking, the shapes of the novel approach's CoM trajectories match the recorded ones with a sum of squares of 0.77 m^2, whereas the LazyTheta* and RVO2 algorithm scores 1.15 m^2. Interestingly, the novel approach also outperforms the state of art in scenario 2, however, with increased shape error values (1.08 m^2 vs. 1.66 m^2). Consequently, the novel approach better predicts variance when walking along straight lines than in curved trajectories scenarios. Fig. 2 depicts the cause for this effect: The lower probability density at the side of the *stance* distributions (representing curved walking) is leading to lower variance in the generated trajectories.

Table 1. Results of the hybrid motion planner and the proposed probabilistic approach in relation to captured trajectories: Chi-square distance [33] between resulting motion corridors and Procrustes distances [32].

	Algorithm	Chi-square distance	Shape error [m^2]
Straight Line	LazyTheta* & RVO2	73.00	1.15 σ ± 0.46
	Novel approach	39.71	0.77 σ ± 0.22
Obstacle	LazyTheta* & RVO2	62.00	1.66 σ ± 0.74
	Novel approach	30.73	1.08 σ ± 0.40

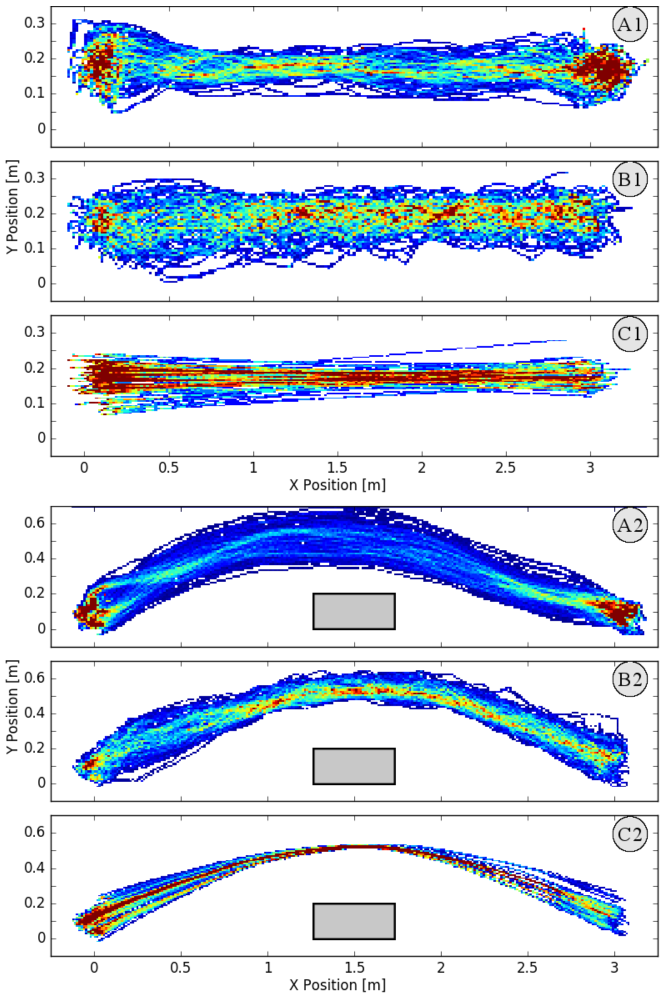

Fig. 4. Two-dimensional histograms of motion corridors for both, collison-free (1) and collision-afflicted (2) walking: A) Captured trajectories B) Novel approach C) LazyTheta* and RVO2.

Finally, each synthetically generated walk path is analyzed with regard to its length. Fig. 5 depicts the difference between the captured baseline and both, the state of art algorithm (green) and novel approach (blue). It becomes apparent, that the proposed method achieves more accurate results for both scenarios. In particular, the novel approach's mean error is located at 0.04 m in both cases. In contrast, the LazyTheta* and RVO2 algorithm constantly underestimates the walk path length by an average of 0.19 m / 0.21 m, ultimately leading to a systematical deviation between planned and actual walk path.

Summing up, both tested motion planners precisely match reality, however, the presented approach outperforms the state of art for walking along straight and curved lines in terms of trajectory length, shape and motion corridor similarity. On the other hand, the evaluation also shows, that the captured motion variance cannot be comprehensively covered yet due to limited data base – especially when considering curved routes. Nevertheless, the concept of coupling a statistical motion model with a global path planner proved to be suitable for increasing planning quality by more precisely predicting walk paths.

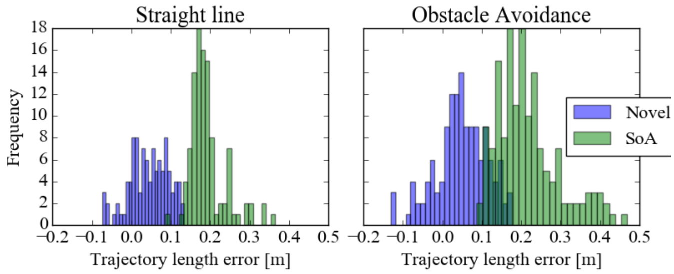

Fig. 5. Histogram with 25 bins of the length error between captured and synthesized walk paths: Blue) Novel approach; Green) LazyTheta* and RVO2.

5. Conclusion

In this paper a probabilistic two-dimensional motion planner is introduced, incorporating fine grained information on human gait gathered from 600 000 samples of a probabilistic motion model. By combining a global motion planner with this novel locomotion model, automotive production planners are enabled to realistically simulate walk path variants within an assembly line. The evaluation underlines the performance and potential of probabilistic motion planning. Future work will extend the presented model to consider a larger variety of motion primitives. Moreover, the impact of probabilistic walk path planning for automotive assembly simulation will be discussed in further publications.

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