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Using Marker-less Motion Capture Systems for Walk Path Analysis in Paced Assembly Flow Lines

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Abstract

In recent years, automotive industry is facing a turbulent environment with an increasing demand for mass-customization and shortened product life-cycles. For manual assembly, this trend has led to a rising planning complexity, since growing numbers of product variants are hitting mixed-model assembly lines. In this context, it is crucial for production planning to be aware of the actual state of an assembly line in order to identify inconsistencies between the situation in company-owned learning factories and the shop floor, especially when considering non-value-adding tasks (e.g. walk paths). However, a feedback loop for walk paths linking the assembly line with the planning department is not established in practice. Consequently, discrepancies between planned and real processes remain largely unknown since they only become apparent through production disruptions. In order to provide production planning with an objective tool for walk path assessment, this work proposes a novel tracking approach, being able to reconstruct operators' motion within an assembly line. Based on a distributed depth camera array, a scalable and marker-less tracking system is presented that can be applied in productive environments. An in-depth evaluation underlines the performance of this novel approach and assesses the overall path accuracy. Finally, the proposed system is set up in an automotive final assembly line during operation. The gathered data is investigated regarding planning inconsistencies during operation.

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Keywords: Production planning; Monitoring; Motion capture; Automotive assembly

1. Introduction

Manual assembly process verification aims to achieve an optimal production process preparation through which efficient, ergonomically viable and robust processes are defined [1]. In practice, these processes are defined during the ramp-up phase in several production preparation workshops. These are typically conducted in company-owned learning factories which provide a "realistic manufacturing environment" through "the adoption of new manufacturing knowledge and technology" – according to the definition of Abele et al. [2].

Rising variant complexity of production sequences coupled with simplifying assumptions of planning models (e.g. abstraction of walk paths ignoring operator drift) lead to a decreasing reflection of reality in process plans. Consequently, real production processes fall short of expectations stemming from the outcome of tests performed in learning factories. Since the real situation at the shop floor is hardly ever compared to the original plans after their deployment, these inconsistencies often remain unidentified. Similarly, not all optimization potentials can be fully grasped in the learning environments. A feedback loop as depicted in Figure 1 – linking the assembly operator with the relevant planning stakeholders – is a valuable tool to help overcome these drawbacks.

Furthermore, by comparing shop floor data and the capabilities of current planning methods and models to depict this data, improvements for future methods and models can be derived. At the same time, the applicability of knowledge gained from learning factories can be reviewed.

This paper presents a novel approach for marker-less walk path recording in order to compare actual walk paths with their corresponding planned ones. The proposed tracking system consists of a distributed depth camera setup and can be used in a manual assembly line during operation.

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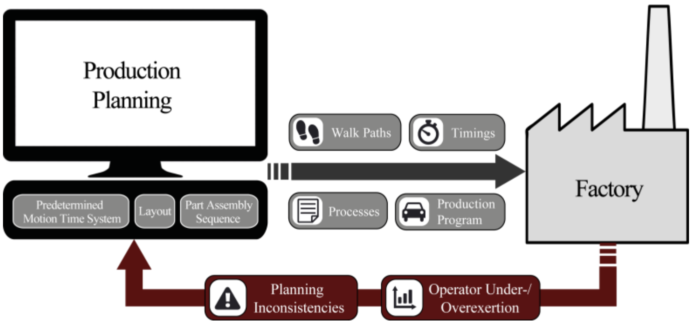

Figure 1: Proposed feedback loop between shop floor operations and planning departments.

The remainder of the paper is structured as follows: First, an overview of current methods for planning walk paths is given. Second, the state of the art of motion capture techniques is reviewed and requirements for such systems on the specific use case "walk path assessments" are derived. On this basis, a marker-less tracking system is proposed, being tailored to the identified needs. Finally, the overall technical performance and applicability of the novel approach is evaluated both in laboratory conditions and in operating final assembly line work places. The paper concludes with a holistic assessment and outlook on further optimizations.

2. Walk paths in paced mixed-model assembly flow lines

Automotive assembly is typically carried out on a series of connected assembly lines, consisting of continuous conveyor belts that carry cars through assembly stations at a constant speed. The system is therefore continuously and strictly paced. In this case, unless the conveyor stops due to a disruption in the assembly process, the time that a car spends inside a station is fixed and defined as cycle time [3]–[5]. This represents the available mean time for an assembly operator to work on a car, assuming that operators are assigned to stations and do not move along with the cars. On the other hand, the assembly operations to be carried out on a certain car at a certain station can vary with each customer order, especially when considering mixed-model assembly lines. An actual sequence of cars ("production program") may have a mean total assembly time per car that fits into the accumulated cycle time of all available stations. However, inside that sequence there might be subsequences of cars that exceed the available cycle time at a station, whilst others have an assembly time below the mean [5], [6]. Therefore, when planning an assembly line, it is crucial to not only look at the production program average, but also at the momentary peaks.

In reality, the point in time at which an assembly operator starts to work on the next car is not exactly synchronous with the pace of the flow line, but "floats". For example, on one occasion the operator might start working on the next car only ten seconds after the car has entered his station because he was held up with the previous car, on another occasion he might be able to start ten seconds before, when the car has not yet entered his station. The term drift is used to describe this effect [6]. The drift at a certain cycle results from a variety of variables, a major one being the accumulated task times of the preceding cars up to that moment. Accounting for drift in assembly planning is especially difficult, because the amount of drift at a station depends on the sequence of the production program, which is typically not known in advance.

When assessing the efficiency of a planned assembly line, in the spirit of lean production, often the ratio of value-adding and non-value-adding task times is regarded. The non-value-adding portion is usually comprised to a large extent by walking. Thus, when optimizing an assembly line, minimizing walking distances is important. In practice, walk paths are often planned with pen-and-paper methods, such as spaghetti charts. The time needed for walking activities is usually determined using predetermined motion time systems (PMTS) and mainly depends on the traveled distance [3].

For the sake of feasible modelling and planning effort, walk paths in process plans are usually static and do not reflect any drift situation. The typical planned situation is that the car is in the middle of the station. It is apparent that the more drift occurs at an assembly station, the more plans will deviate from reality. This can lead to overexertion of assembly operators as well as plans overestimating assembly line capacity. With the current trend of increasing product variance hitting mixed-model assembly lines, practitioners are starting to pay more and more attention to the impact of drift on assembly line performance and line balancing.

One possibility to account for drift-related walk paths is to perform simulations of assembly plans and production programs using station layout-based digital planning tools such as IPO.Log (see *www.ipoplan.de*). However, actions of real assembly operators can deviate significantly from the simulation, as is depicted in section 5. Frequent reasons are plan inconsistencies and the operator optimizing his work methods on his own.

3. State of the art techniques for walk path assessments

In order to improve the reliability of learning environments and to benefit from self-optimization processes, it is crucial to compare the predetermined plans with the real situation at the shop floor. Since the domain of manual assembly focusses on human work, the main subject of such an evaluation is operators' motion, which needs to be captured precisely.

Tracking systems are the enabling technology for reconstructing human movements. This includes Motion Capture (MoCap) techniques using various physical effects ranging from spatial scan procedures like e.g. time of flight and phase-difference sensing over inertial sensing to mechanical linkages [7], [8].

Currently, in the automotive industry MoCap technology is frequently used for virtual assembly scenarios such as virtual training, maintenance and virtual process verification tasks. In practice, typical assessment scopes are production-oriented product optimizations, ergonomics, time planning or process verification [9]–[11].

3.1. Marker-based Motion Capture systems

Optical marker-based tracking systems consist of multiple fixed infrared cameras, being positioned on the edges of the desired tracking frustum, called outside-in camera arrangement. The integrated camera modules emit modulated infrared light so that optical retroreflective markers can be detected within the scene. These rigid bodies are applied to the human body, so that movements can be traced in the scene. This technology is able to track huge interaction volumes with a high accuracy in position and orientation. High initial total costs are decreasing significantly, since they are deployed in a vast variety of use cases [12].

Another frequently used MoCap technology utilizes inertial measurement units (IMUs), combining magnetic, accelerometer and gyroscope sensors which are providing relative position and orientation updates (attitude and heading). This technology is deployed within various industrial use cases [13], [14]. These sensors offer fast update rates and an easy installation process. Due to missing external reference, small measure errors cumulate to an angular and positional drift over tracking time.

In contrast to the already mentioned properties and advantages of marker-based tracking, such systems go along with several drawbacks: Operators have to be equipped with a so-called marker suit that consists of multiple rigid bodies, which are applied on the whole body. This procedure takes 10 to 15 minutes and it cannot be ruled out that the cumbersome suit could affect the operator's movements.

3.2. Marker-less Motion Capture systems

Marker-less optical capture systems that are able to track the motion of characters without interfering with the scene are still an ongoing research topic [15]–[17]. They inherit big advantages of the non-intrusive measurement way. Industrial use cases profit from lower setup times, no anthropometry calibration, no additional danger of damaging products and the user is able to wear his regular working clothes.

Two different clusters of marker-less optical capture technologies can be found in literature: Depth camera and RGB camera-based systems. Using common infrared, greyscale or RGB camera systems, there are multiple approaches to realize marker-less optical capture systems for MoCap data.

One example for an multi-view MoCap system was presented in the paper and patent by Stoll et al. [18], which is commercially available as the Captury Studio software tool (see *www.thecaptury.com*). This system is already able to track subjects at interactive speeds, but rely on a color model (i.e. cloth and skin) that have to be initialized laboriously with a set of training data for each person. Moreover, highly specialized systems for performance analysis in professional sports like Prozone (see *www.prozonesports.com*) are used to track movements and distances covered by players [17]. With the advent of consumer-graded, low-cost depth cameras, new MoCap systems are pushing into the market. Kinect v1 and v2 enabled gamers to marker-lessly interact with virtual environments. Being based on a structured light and time of flight approach, these systems are able to detect distinctive points of the human body, in order to reconstruct its skeleton [19]. Many industrial use cases have been presented using this approach, such as ergonomic assessments ([20]–[22]), maintenance [23] and training [24].

3.3. Applicability within industrial environments

Having discussed the current state of the art of MoCap technology, requirements for a tracking system, being able to analyze walk paths within the industrial environment of an assembly line, will be provided and matched to the technical specifications of commercially available products. The major requirements for such a system are:

- Technical applicability in industrial environment
- No negative influence on productivity during capturing
- Protection of operator privacy
- Portability/Scalability
- Fast setup (system & user tracking)
- Tracking volumes encompassing entire workplaces
- Medium requirements on precision (better than 100 mm)

First, marker-based optical outside-in tracking systems, such as A.R.T (see *www.ar-tracking.com*), VICON (see *www.vicon.com*) or OptiTrack (see *www.optitrack.com*) are intrusive. Since it cannot be ruled out that the protruding markers damage the car's surface or affect the operator's productivity these systems do not meet the needs of an industrial factory environment.

Second, IMUs lack positional stability and magnetic sensors suffer from factory environments, such as jamming interferences or material absorption of geomagnetic field.

Commercial marker-less, multi-view approaches using RBG cameras (e.g. Prozone or Captury Studio) are highly specialized systems and apply use case optimized algorithms. Video surveillance approaches such as FXPAL (see *www.fxpal.com*) are collecting personalized data that can be linked to a certain operator. Consequently, these systems infringe labor agreements of most automotive companies and therefore cannot be used in regular assembly lines. In addition, single Kinect approaches are limited in their tracking space and consequently do not fulfill the spatial requirements of an automotive assembly station of at least 6 m × 4 m.

Therefore, currently there is no MoCap system presented in literature or as a commercial product which meets all the above mentioned requirements.

4. Marker-less Motion Capture for walk path assessments

The determination of human walk paths in an assembly flow line has not yet been in the scope of literature. Therefore, a use case driven implementation of a marker-less, non-intrusive, tracking system that can be set up quickly in productive factory environments is presented.

4.1. Multi Kinect tracking

The presented method utilizes the distributed camera approach presented in the publication of Otto et al. [25] and consists of multiple Kinect cameras that are observing one or more work places of interest. In order to prevent the system from collecting personalized data and thus protecting the operator's privacy, each RGB sensor is covered with a small cap. Consequently, the information being used by this approach is solely based on the depth sensors reconstructing anonymized skeletal data.

The tracking data gathered by the Kinects are polled by the so called fusion server that synchronizes the local clocks. Furthermore, to establish a common world coordinate frame within the system, this computer calculates the extrinsic transformations between the cameras via an extended iterative closest point algorithm [25]. After determining a valid registration, the MoCap data from different Kinects are merged by a heuristic-based algorithm combining them in a meaningful way [25]. This tracking system operates at approximately 30 Hz refresh rate and is interconnected via a 5 GHz wireless network, in order not to jam otherwise utilized industrial bandwidths.

By generating fused skeletal data from the distributed depth cameras, the system is able to track the operator's motions continuously within an area that can be scaled up to several workplaces and stations. Generally, to cover a typical automotive assembly line section of 6 m extensively, a tracking setup would utilize four to five sensors which are located at the edges of the production line and are facing outside-in.

4.2. Walk path reconstruction

In order to reconstruct the walk paths, the fused skeletal data are utilized to determine the operator's center of mass (COM) in each frame (see Figure 2). Following Gabel et al. [26], this distinctive point is chosen to be the center of the hip, spine and shoulder joints. Since walk paths in assembly planning are generally created in a two-dimensional bird's eye view, the COM is subsequently projected on the floor plane to be compatible with the target data. For this purpose the proprietary Kinect Software Development Kit (SDK) is used to obtain a rough estimation of the underlying floor plane.

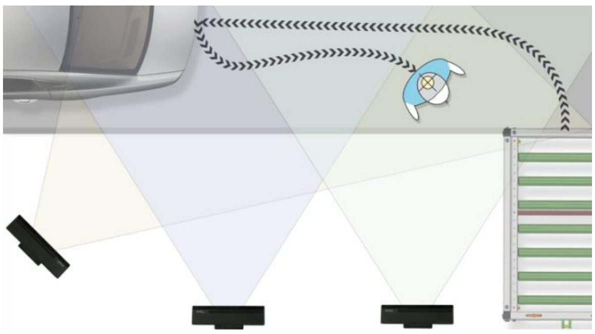

Figure 2: Typical setup of registered Kinect sensor array for walk path reconstruction throughout a whole station.

Subsequently, based on the two-dimensional COM, the change in position and time between two consecutive frames is computed. The walk path of an operator is finally reconstructed by linking the resulting vectors to a concatenated trajectory.

4.3. Evaluation of path accuracy and validity

To gain insight into the accuracy of the walk path reconstruction in combination with the concatenated registration process, several experiments have been carried out.

Experimental setup: In each case, a marker-based tracking system consisting of 16 ARTtrack2 cameras was used as the baseline due to its high positional accuracy of 0.42 mm. Since the user is moving in an upright posture during the whole evaluation, it can be reasonably assumed that the COM corresponds to the center of the subject's hip. Therefore, this distinctive point was defined to be the center of two optical markers, attached on both sides of the hip. The three-dimensional point was subsequently processed by the reconstruction method, mentioned in chapter 4.2. Finally, both tracking systems were aligned by placing an ART marker on the main Kinect, closing the transformation chain between the two coordinate frames. During all experiments six Kinects were used, being evenly arranged in two straight lines on both sides of an 8 m × 5 m tracking area.

Design of experiments: In three different scenarios, a single user was walking at approximately 3 km/h in the common tracking space along three predetermined path: A straight line with the length of 4.5 m, a circle (Ø 4.5 m) and a lemniscate (external dimensions of 4.5 m × 2.0 m). Each scenario included 10 repetitions.

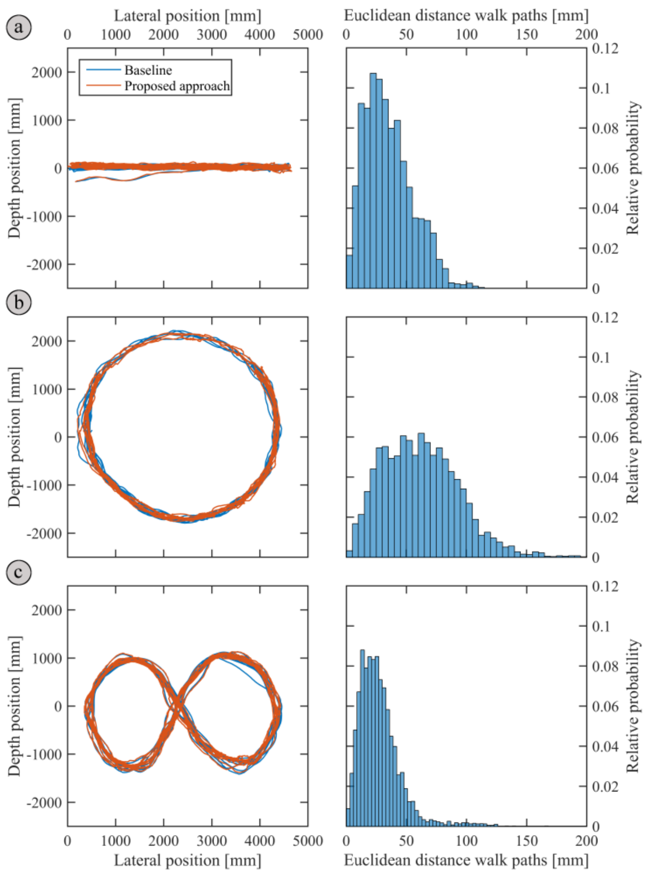

Figure 3: Technical evaluation of generated walk paths: Proposed approach vs. A.R.T. baseline. Left: Bird's eye view of walk paths comparison, Right: Histogram of Error Distribution; (a) Straight line; (b) Circle; (c) Lemniscate.

Results: Figure 3 depicts the results of the three experiments. The left side shows the walk paths for the three scenarios in a two-dimensional bird's eye view. The blue line represents the walk path of the high-precision ART camera system, whereas the orange trajectory is reconstructed by the novel tracking approach. Additionally, the right half illustrates the distribution of the overall error, being defined to be the Euclidian Distance between each corresponding COM pair.

Within scenario a) the mean error was 35.0 mm, with a standard deviation of 19.8 mm, whereas in c) the two values approximately doubled. The lemniscate experiment scored similar to the straight line (see Table 1).

Table 1: Overall error between the proposed marker-less approach and the marker-based tracking system.

Scenario	Straight Line	Circle	Lemniscate
Mean Euclidean Distance	35.0 mm	62.2 mm	27.5 mm
Standard deviation	19.8 mm	32.2 mm	17.7 mm

Considering that the resolution of walk path plans in MTM1, i.e. the PMTS with the highest modelling detail, is “one human step” (which depending on the carried weight ranges between 0.60 m and 0.85 m) [27], the tracking accuracy of the proposed marker-less approach is deemed sufficient for the purpose of comparing planned and real work paths.

5. Practical evaluation of assessment method in automotive final assembly line

Additionally to the presented technical evaluation, the proposed method is also evaluated towards its investigative power, optimization potential and its practical applicability in real shop floor environments.

5.1. Experimental Setup

The system has been set up in a productive mixed-model assembly line. Three Kinect Sensors have been set up at the border of the station (see Figure 2). The sensor array has been facing the conveyor belt from the edge of the production lane at a distance of 1.5 m to the car body. Whereas the system observed a whole station, only one certain workplace within this station has been evaluated during one work shift. The three analyzed work tasks, which had to be conducted successively, accounted for approximately 50 % of the processes that had to be carried out within one cycle of 120 s in this particular workplace. The plan defined these tasks as:

- Fetching a paper-based card and scanning it for documentation of safety critical parts.
- Fetching a corded screw-driver and screwing two times at the left side of the chassis.
- Screwing two times at the right side of the chassis and returning the screw-driver.

Approx. 2.5 h of Motion Capture data have been recorded from one single operator that carried out all tasks during the shift. All captured data were segmented and aligned to the actual production program in a post-production step.

5.2. Results and discussion

On-site evaluation showed that walk paths could be reconstructed inside the whole observed work place with comparable results to the laboratory evaluation (see Figure 3).

Due to the unobtrusive working principle and the usage of anonymized skeletal data, no negative effects to the productivity could be identified. Operators’ privacy was hardly affected. Moreover, the evaluation revealed that the proprietary Kinect SDK occasionally suffers from false-positive skeletal recognitions, i.e. when moving car chassis are detected as human skeletons. However, the vast majority of the flawed data can be filtered out in the post-processing step both automatically and manually. In summary, it can reasonably be stated that all organizational requirements defined in section 3.3 are fulfilled. Additionally, the system is proved to be reliably working within operational environments since the outcomes are comparable to the technical evaluation in the previous section.

Figure 4 underlines this assumption by depicting four representative examples of the captured, filtered and segmented data. This floor-plane projection shows the bird’s eye view on the walk path trajectories of real human operators. The grey transparent line represents the preplanned ideal walk path analysis generated by production planning in advance. Thin colored lines represent the operator’s captured walk paths of four exemplary, consecutive cycles.

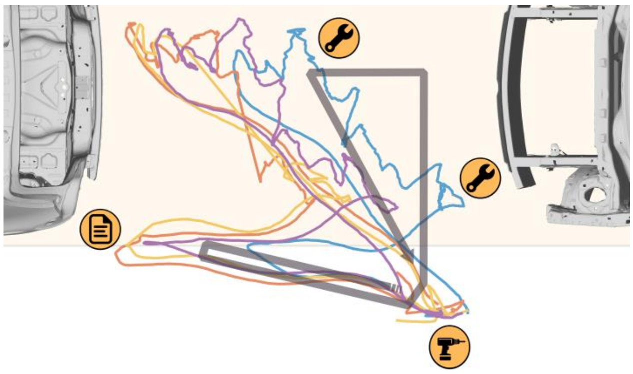

Figure 4: Planned (thick) vs. captured (thin) walk paths recorded in a real production environment. Points of Interest: Screwdriver and scanning station, documentation card, 2x screw points on body chassis.

Although the main focus is on proving the applicability of the proposed approach, observing the work place for multiple cycles reveals that the operator has had the possibility to reach an average negative drift of -0.99 m, meaning he is able to achieve tasks faster than cycle time during the observed period. Additionally, operators self-optimize the preplanned processes for their own work place. In Figure 4 this process can be seen where the operator fetches the documentation card without returning to the screw-driver station, effectively shortcutting the planned walk paths.

Current walk path planning methods often use static simulation routines. The movement of conveyor belts and moving working points are not represented in planning data. This leads to spatial inconsistencies which can be identified in the results of Figure 4 as well: During the first screwing task no movement of the operator and the product has been considered, in contrast to the second screwing task.

This evaluation shows differences between preplanned walk paths and reality, although the gathered results cannot be considered to be generally applicable since the preliminary analysis only covers one participant at one workplace in a timeframe of 2.5 h. Despite these limitations, by assessing only one work place, already multiple effects caused by static planning methods and simplifications can be revealed. According to the plan, the operator has to cover an overall distance of 7.2 m per cycle, whereas the analysis reveals that due to self-optimization the real walk path has an average length of 6.34 m.

6. Conclusion

This paper presents an approach for reconstructing walk paths within assembly flow lines in order to identify inconsistencies and limitations of current planning methods and plans stemming from company-owned learning factories. Providing a possibility to uncover and learn from planning mistakes, stakeholders are enabled to improve the productivity and quality whilst preventing the operators from overexertion. Furthermore, since the walk paths document how employees optimize processes on their own, knowledge about optimization potentials is transferred to the planning department and learning environment. Both evaluations have shown that the system is technically and practically able to be used for walk path assessments in real shop-floor environments.

For future work, an investigation of stations on a long-term basis in order to optimize the planning quality with a statistically significant basis is proposed. Moreover, automatic segmentation of assembly processes and determination of key figures (e.g. drift, walking distance) based on MoCap data would enable a comprehensive use within several stations. Finally, an extension of use cases from walk paths to a holistic ergonomic assessment is planned.

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