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Procedia CIRP 41 (2016) 945 – 950

www.elsevier.com/locate/procedia

48th CIRP Conference on MANUFACTURING SYSTEMS - CIRP CMS 2015

Measuring motion capture data quality for data driven human motion synthesis

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Abstract

In automotive industry, market demands shorter life cycles and individualized products. For manual assembly, this trend leads to more frequent planning of an ever increasing number of process variants. In order to ensure planning quality, virtual verification of manual production is crucial for efficient process optimization. However, virtual verification is not established in practice because available simulation tools require prohibitive manual modeling effort for human motions of acceptable quality. For automating the modeling process, data driven motion synthesis approaches are promising candidates that –however– require high quality input data for acceptable synthesis results. Therefore, objective motion capture data quality measures for data driven human motion synthesis are sought.

This work proposes and tests a principal component analysis (PCA) and a Shannon entropy based quality measure. Both measures evaluate post-processed data and thus consider motion capture hardware in combination with a post-processing tool chain.

The measures are tested for selectivity and validity using two low cost and two high cost motion capture systems. They differ in selectivity for high and low cost motion capture systems. Both measures correctly predict motion synthesis quality in tests with treadmill walking. Therefore, they can be employed for testing if a motion capture system is suitable for data driven motion synthesis that relies on PCA for input dimension reduction. Further research on robustness of the measures against motion variation is proposed.

Peer-review under responsibility of the scientific committee of 48th CIRP Conference on MANUFACTURING SYSTEMS - CIRP CMS 2015

Keywords: Digital production planning; Digital human simulation; Motion capture; Quality measure

1. Introduction

In automotive industry, there is an ongoing trend to shorter life cycles and individualized products [1]. This market-driven development to larger product variety (s. [2]) has partly led to a reduction in end-assembly automation in high cost countries such as Germany [3]. In order to ensure product quality and production efficiency, the resulting manual assembly processes have to be planned and verified carefully with prototypes before the actual start of production. This approach –however– contradicts to increased planning frequency.

Furthermore, the increasing number of product variants leads to an equivalently increasing demand on prototypes for product verification which drives planning cost (c. [4]).

Therefore, virtualizing verification of manual assembly processes is considered a competitive advantage. In physical production verification a group of process experts examine workers, who conduct the planned tasks in workshops. Issues in various fields such as process times, ergonomics and process quality are documented and solutions are found, discussed and chosen.

A straight forward approach is to replace workers and physical prototypes with a simulation expert and simulations. In field tests at Daimler this approach led to an acceptable number of identified issues within the process.

However in the workshop, the simulation model was fixed because changes required a day of re-modeling. This limitation hindered trying out new ideas and prevented solution generation. Only few solutions or process improvements were derived in the field tests.

Peer-review under responsibility of the scientific committee of 48th CIRP Conference on MANUFACTURING SYSTEMS - CIRP CMS 2015
doi:10.1016/j.procir.2015.12.068

Modelling effort with state of technology tools such as Delmia V5 Human or Tecnomatix Jack was one week for a worker process in order to get simulation quality that is acceptable for experts.

Approaches to reduce modeling and re-modeling time with partly automated planning tools such as EMA [5] have been conducted. However, field tests at Daimler showed that for a majority of processes simulation quality from these tryouts was considered too unrealistic by process experts [6]. Another approach is to directly record motions within process verification workshops [7]. This approach has been successfully tested in practice. While motion quality meets requirements, verification requires time consuming manual recordings for each considered product variant.

Therefore, automating the modeling process with realistic and variant-rich motion synthesis is considered a missing enabler for virtual production verification.

2. Related Work

2.1. Motion synthesis

Generation of human motions can be manual, semi-automated or fully automated. In context of this work, only fully automated approaches are taken into account. Wright and Jordanov differentiate [8]:

- Analytical approaches that explicitly model state equations of motion
- Central pattern generators that employ representations of the biological innate locomotion e.g. as systems of oscillators
- Neural networks mainly relying on kinematic or kinetic sensory variables as inputs
- Hidden Markov Model techniques that observe motion patterns and then reproduce them
- Rule based systems that comprise generalized state based methods

Furthermore, Gaussian process networks, which are able to generate infinite motion variations with a semantically interpretable, statistical model, have been presented e.g. by Min et al. [9] and Glardon et al. [10].

Data driven motion synthesis approaches, which rely on motion capture data, share the issue that such data is structured, i.e. consists of consecutive frames with information about multiple joints' positions. Concatenating this data normally reduces efficiency of the before-mentioned algorithms because of the curse of dimensionality (c. [11]). Besides ignoring parts of the skeleton, dimension reduction has been achieved by regarding poses and their transitions in two separate models (e.g. in [12]) or by using consecutive frames at a time and compressing them into low dimensional vectors. In the latter case, a popular approach is to use dynamic time warping [13] in order to separate space and time variations and the employ principal component analysis (PCA) [14] on both results (c. [9,15]).

PCA derives a linear projection of a high dimensional input space into a space of lower dimensionality so that the explained variance is maximized. Therefore, its effectiveness for dimension reduction is mainly influenced by the way how input data is distributed in input space. Obviously, motion capture artifacts such as jitter should affect variance. Skeleton data representation also can introduce artificial variance e.g. from joint angle singularities or meaningless quaternion rotations (c. [16]). Therefore, motion capture data quality after post-processing is relevant for successfully applying PCA based motion synthesis.

2.2. Motion Capture Systems

To generate plausible and variant-rich human movement via statistical motion synthesis, it is crucial to capture high precision quality training data. Therefore, commercial, state of the art motion capture systems are evaluated. Motion capture systems are commonly employed to digitalize human movement in different environments [17]. Rolland et al. present a taxonomy of motion capture and tracking systems classified by their physical principles of operation [18]:

- Time of flight (e.g. ultrasonic or light)
- Spatial scan (e.g. optical outside-in cameras)
- Inertial sensing (e.g. gyroscope and accelerometer)
- Mechanical linkages
- Phase-difference sensing
- Direct-field sensing
-

In order to create a high quality database and having controlled capture situations, optical outside-in tracking systems are the prevalent technology for human motion capture. Commercial optical tracking systems offer markerless and marker-based skeletal reconstruction.

Comparing commercial, marker based tracking systems, the price for the same tracking volume differs by factor of 10, while tracking accuracy of single markers are comparable at a fraction of a millimeter [19]. However, single marker accuracy does not necessarily provide insight into how well the resulting skeleton motion is suited for data driven motion synthesis approaches.

2.3. Motion Capture Quality Measures

Welch and Foxlin [20] formulate their vision of an ideal tracking system as tiny, self-contained, complete, accurate, immune to occlusions, robust, tenacious, wireless and cheap. Motion capture systems can either be compared by their hardware/software specifications or by data output quality.

Vendors of tracking systems typically provide information on hardware specifications of their tracking system, but only few on recognition and post-processing algorithms or on final motion data quality (s. Table 1). However, post processing has significant influence on motion data quality.

Known measures for analyzing motion capture output quantify the jerkiness, frequencies, smoothness [21] and variance [15] of human movement

Table 1. Choice of motion capture system specifications following [20].

Performance Parameters	Hardware Parameters	Software Parameters
Spatial distortion	Data-returned (3DoF, 6DoF)	Marker-based / markerless tracking
Spatial jitter	Error-proneness (e.g. interferences)	Post-processing algorithms
Stability or creep	Resolution	Skeletal hierarchy
Latency	Update rate	Output Formats
Latency-jitter	Tracking space	Real-time operation
Dynamic error	Durability	

Biomechanical, anthropometric models such as RAMSIS [22] and Dynamicus [23] provide methods for measuring plausibility of a captured movement. Such measures allow recognizing and suppressing unrealistic movements. Additionally, angular velocities and accelerations and jerkiness can be used to detect unrealistic movements. Frequency domain and differential equation analysis of motion capture data can be used for plausibility evaluation as well.

Furthermore, to validate smoothness of motions, Rincon-Montes compares four algorithms which are called "logarithmic dimensionless jerk metric", "mean arrest period ratio", spectral arc-length metric" and "peak metric"[21]. As result of this survey the "spectral arc-length metric" of Balasubramanian [24] is found to be the "most convenient computable tool".

However, it remains unclear how existing quality measures on motion capture systems and data can be applied so that they deliver information on suitability for data driven motion synthesis. Therefore, a quality measure for statistical motion synthesis is sought.

3. Two measures for motion capture data quality with focus on data driven human motion synthesis

3.1. Objectives

This work suggests and investigates two method-driven measures for motion capture data quality. Quality is considered with special focus on data driven motion synthesis algorithms that are based on principal component analysis.

3.2. PCA based motion capture quality measure

For the principal component based motion capture quality measure, walking on a treadmill is chosen as a well-understood example motion.

The captured motions are cut into the segments right stance and left stance. A step starts with the frame, when the foot loses contact to the floor plane and stops when the opposite foot leaves the floor plane.

Motions are represented as a skeleton tree structure with fixed bone lengths and a set of frames where each frame consists of skeleton root node position and orientations of each skeleton node. In order to avoid singularities in Euler or exponential map representations (c. [15]), quaternions are employed for orientations. Since quaternions are over-specified with 4 values for 3 degrees of freedom, they are aligned so that their distances are minimized throughout all motions of a joint.

The cut motions are aligned by letting each motion start at a skeleton root node position of (0, 0, 0) and then minimizing Euclidian joint position distances in all frames. Right and left stances are separated, and dynamic time warping is applied on each following the methodology proposed by Kovar and Gleicher [25]. The result is the spatial domain, i.e. a set of spatial trajectories on a canonical timeline that has the same number of frames for each motion and the temporal domain, i.e. a time value list per cut motion that maps each frame of the canonical timeline to an actual point in time.

In principle, the next steps can be applied to both the spatial and the time domain. However, since preliminary tests show no impact of the time domain on PCA results, only the spatial result, i.e. the motion in the canonical timeline is employed in the proposed measure.

The spatial data in the canonical timeline is preprocessed by first concatenating all frames, then centering the motion and finally normalizing variation of each value. Next PCA is applied. Instead of using the standard method for deriving an appropriate number of principal components, the number is fixed to 10. Using ten principle components is an empirical value the quality measure is the amount of variance that is explained by the resulting 10 principal components for the input data, e.g. right stance takes or left stance takes.

3.3. Shannon entropy as motion capture quality measure

Shannon entropy [26] is examined as a second measure for motion capture quality. Input data are the aligned input vectors from section 3.2. For each dimension of each joint, the number of bins is derived by multiplying the maximum value with 1.5 times the number of recorded steps at and rounding up. When following the measuring principle in section 3.4, the multiplication factor is 300. Next values for each joint dimension are sorted into the bins. The bins are concatenated and used as input for calculating the Shannon entropy, which acts as motion capture quality measure.

3.4. Measuring principle

In order to get reproducible and intersubjective results, the measure is accompanied with a measuring principle that describes how input data shall be gathered.

Motions should be uniform, well defined and reproducible. Since this is difficult to achieve with humans acting freely, walking on a treadmill is chosen, which controls speed and eliminates curve walking.

Treadmill walking is not comparable to normal walking but is more uniform (c. [15]). However, motions should show variation. Therefore, treadmill velocity is varied: 100 steps are recorded at 4 km/h and 100 steps at 6 km/h.

The recorded data is post-processed into a Biovision Hierarchy (BVH) file [27]. In order not to imbalance results with retargeting, the native skeleton of the respective motion capture system is employed for BVH generation. Manual optimization with post-processing software has to be minimized. Acceptable interactions are starting recommended actions in post-processing software such as gap filling.

While the latter restriction can be relaxed when measuring different post-processing toolchains, all actions have to be documented and stated in order to get comparable results.

4. Evaluation

4.1. Tested Motion Capture Systems

Four different commercial motion capture systems are used to capture human gait data. These are all optical outside-in tracking systems. Three of them use retro-reflective markers suits to reconstruct skeleton structure, whereas one ("CapturyStudio") uses algorithms to non-obtrusively and markerlessly reconstruct human movement. Still, the user's clothes have to be trained first. The specifications of each motion capture system are given in Table 2.

Table 2. Motion capture systems used for experimental dataset.

Properties	Vicon Bonita 10	A.R. Tracking ARTrack5
Number of cameras	18	18
Resolution	1024x1024 px	1280x1024 px
Framerate	250 Hz	150 Hz
Tracking procedure	Marker-based	Marker-based
Post-processing SW	MotionBuilder & Blade	ARTHuman
Properties	OptiTrack Flex 13	Captury Studio PointGrey Blackfly
Number of cameras	18	8
Resolution	1280x1024 px	808x608 px
Framerate	120 Hz	50 Hz
Tracking procedure	Marker-based	Markerless
Post-processing SW	Motive:Body	CapturyStudio 0.1

For each motion capture system, hardware, software and post-processing pipeline are set up according to the proposals of the vendors or integrators. System output is directly converted to the BVH format.

For Captury motion capture data, CapturyStudio version 0.1 was used. The current version 1.0 is likely to exhibit different results but has not been available for the tests.

4.2. Design of Experiments

The PCA efficiency measure and Shannon entropy measure will be tested on the following quality criteria:

1. Selectivity
   Given an appropriate measurement principle, the PCA efficiency and Shannon entropy measures are able to separate distinct results for different systems.
2. Validity
   The hypothesis for validity is that motion capture systems, which yield larger results on the quality measure, are better suitable for statistical motion synthesis. Therefore, the found rank order of measure will be checked against results from motion synthesis.

For each capture system, 100 steps are captured at 4 km/h and 100 steps at 6 km/h. The actors are not given any instructions on their walking style. Identical actors have conducted the recordings on the same treadmill for OptiTrack, A.R.T and Captury motion capture systems. Because of availability for Vicon system recordings, a different actor and treadmill is employed.

Left and right stances are examined separately in order to gain insight into the variation within each system's recor–dings. We assume that for the examined measure to be selec–tive, the variation between left and right stances of one system must be smaller than the variation between different systems.

In order to verify the hypothesis of validity, a motion synthesis model for walking is set up following Min. et al [9]. Results are visually evaluated and ordered by quality.

Additionally both quality measures are compared to "spectral arc length metric". The hypothesis is that the novel quality measures are better suited for prediction of quality for statistical motion synthesis than the compared ones.

4.3. Results

Fig. 1 depicts the results of the cumulated explained variance for the four motion capture systems. On average, the A.R.T. (98.99 %) system yields the highest explained variance followed by Vicon (98.69 %), OptiTrack (98.15 %) and Captury (94.20 %).

In order to indicate how well the measure distinguishes a system, the measures for left and right stance are calculated and divided by the difference between the average measure of the system and the average measure of the next system. A.R.T., Vicon and Captury show differences in results between left and right stances that are more than three times smaller than the distance to the closest system.

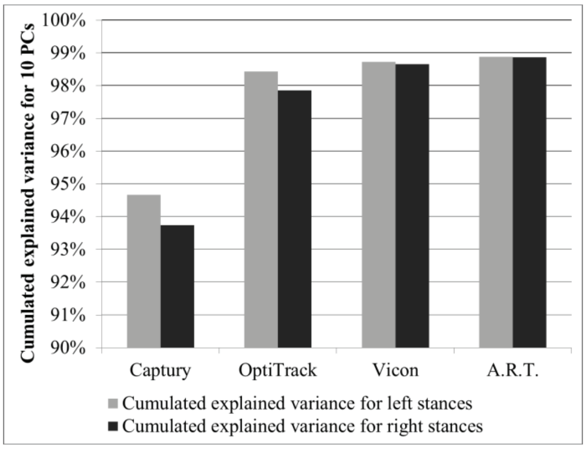

Fig. 1. Results on the cumulated explained variance at ten principle components of walking motion capture data of four different mocap systems.

Motion synthesis models for left and right stances have been constructed for Captury, OptiTrack and Vicon. Motion synthesis quality for the Vicon data is comparable to the results previously published by Min et al. [9].

The resulting motions have been rated naturally looking and of high quality. Captury based synthesis has not yielded motions of acceptable quality, because limbs movements are highly show unrealistic joint angles and jerkiness. OptiTrack system based motions are situated in between which means jerkiness is occurring less often and joint angles are more realistic. Therefore, motion synthesis quality order is Vicon better than OptiTrack better than Captury. This result corresponds to the PCA efficiency measure.

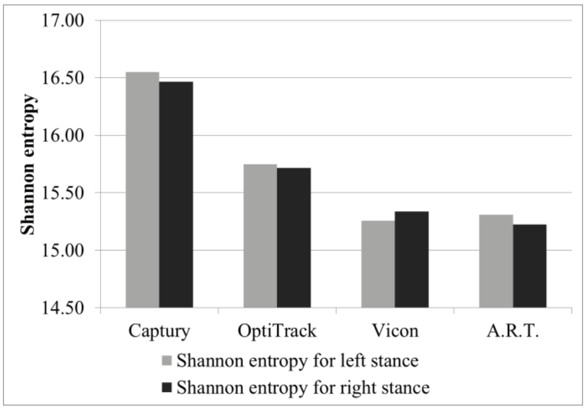

Fig. 2. Results on Shannon entropy for walking data captured with four different systems distributed over 300 bins.

Shannon entropy calculates the uncertainty contained in the motion data. Higher values indicate a higher average amount of information. Fig. 2 depicts the results for the Shannon entropy. Entropy is averaged for left and right stance results. On average, the A.R.T. (15.27) system yields the lowest entropy followed by Vicon (15.30), OptiTrack (15.73) and Captury (16.51). The same system rank order as for the PCA efficiency measure can be recognized. However, lower Shannon entropy does not always go along with higher PCA efficiency. While right stances yield lower PCA efficiency than left stances, they show lower Shannon entropy for OptiTrack and Captury.

Vicon, OptiTrack and Captury show differences in results between left and right stances that are more than eight times smaller than the distance to the closest system. Between Captury, OptiTrack and Vicon, Shannon entropy differentiates stronger than PCA efficiency measure. Vicon and A.R.T. cannot be clearly differentiated.

5. Discussion

All tracking systems have been set up according to the integrator's recommendation for optimal results. Therefore, the experimental setups vary by their sensing technology, camera arrangement and tracking volume, e.g. comparing the markerless tracking system Captury to common marker-based systems different levels of accuracy could be expected. It is not possible to draw conclusions on the resulting data quality of the four motion capture systems, just by comparing hard–ware and software specifications as depicted in section 4.1.

Due to the usage of a treadmill, a small tracking volume is utilized, thus penalizing large area tracking systems at constant sensor resolutions. During the capture sessions, two different actors with similar proportions have been recorded. Additionally, according to Tilmanne [15] treadmill walking does not correspond to regular walking style but all experimental data has been recorded on a treadmill and therefore is uniform. In spite of the mentioned differences in experimental setups, motion segments still can be declared as comparable raw data.

Post-processing pipelines of all tracking systems differ in skeletal hierarchy and degree of optimization (gap filling and low-pass filtering). The PCA efficiency measure penalizes skeletal hierarchies with higher joint number due to multiple variations in orientations for each joint. The impact of this effect has to be further investigated. Retargeting of motion data would harmonize skeletal hierarchy but weaken discriminative power of PCA efficiency measure and therefore reduces selectivity and validity.

The upper bound of PCA efficiency measure declares 100% of the cumulated explained variance. As discussed by Min et al. [9], 99 percent of original variations is considered to be a good value for synthesizing natural movement variations whereas Tilmanne and Dutoit presented other levels: Leaving 80% variance in PCA the synthesized motion is "visually significantly impoverished". "Taking into account 90% of cumulated percentage of information[…], gave data reconstruction that was very difficult to differentiate from the original data by the human eye."[15] Lower results show less cumulated explained variance. Comparing similar motion types for different systems, lower values can be interpreted as unnecessary variance induced by spatial jitter or jerkiness.

Lower cumulated explained variance can also be explained by intrinsic non-linearities due to the angle-based representations in skeletal hierarchy (c. [28]). Tilmanne and Dutoit state that "PCA is a strictly linear algorithm and cannot be applied on quaternions as they do not form a linear space" [15]. The proposed approach addresses this issue by aligning quaternions. In the experiments, no effect of different quaternion rotations on the measures could be found after alignment.

According to the design of experiments, both efficiency measures are positively evaluated on selectivity and validity. In comparison to measures such as spectral arc length measure or jerkiness, the two proposed measures concentrate on the overall effect on the result rather than the reason for quality loss. Both measures indicate well how suitable resulting motion capture is for the tested data driven motion synthesis approach.

Before choosing an appropriate motion capture system, PCA efficiency measure and Shannon entropy can show differences in tracking system data quality for data driven motion synthesis. Both quality measures can be used without extensive manual effort. Therefore, their applicability is considered as easy.

6. Conclusion & Outlook

The proposed motion capture data quality measures are considered a good indicator regarding validity and selectivity. The measures predict suitability of a motion capture system and post-processing pipeline for data driven motion synthesis approaches that rely on PCA for dimension reduction. They are clearly better suited than technical specification by motion capture equipment vendors. Besides the measures, a measurement principle has been proposed that has proven to ease applicability and ensure reproducibility of results.

Further research is required to investigate how robust the proposed PCA efficiency measure and Shannon entropy are - especially regarding motion variation. Therefore, additional test series with different motions have to be carried out.

Acknowledgements

This research activity was partially supported by the research project INTERACT - Interactive Manual Assembly Operations for the Human-Centered Workplaces of the Future that has received funding from the European Union Seventh Framework Programme (FP7, Grant Agreement No. 61107).

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