Movement Analysis in Laparoscopic Surgery Training

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Abstract

Analysis of surgeons' and novices' movements in laparoscopic surgery and especially in their training has become a novel field of application for motion capture technology. This paper defines emerging problems, relates to theoretical foundations necessary to solve them, and presents elementary approaches. For a final implementation and realization of the described training system extension, there are eventually lots of options to choose from. For these options this work aims to provide a rich spectrum, especially when it comes to the feature extraction. A specific solution approach is explained and practically tested to some extent in order to demonstrate and partially validate the methodology.

1. MOTIVATION

In surgery training, up to date, there are only two common ways of objectively determining the causes of mistakes and poor performance. By precisely monitoring the operations in a computer assisted surgery trainer, the supervisor might be able to exactly describe and point out what the trainee did wrong with the surgical instruments. Those mistakes are mostly caused by insufficient hand-eye coordination, which is still to come in course of the training process. The other way of giving reason for poor performance might be to compare the body posture and manual techniques of the trainee during an operation to the ones of experienced surgeons. Proctering trainees' body postures and explaining how they could improve turns out to be not that easy, even for highly experienced surgeons. The problem is further compounded since the operations are not usually recorded and the only examples of optimized posture and movement are those the expert can demonstrate. This is an inefficient use of the expert surgeon's time. At this point, applying motion capture technology could make a change.

Sampling body motion of surgical trainees and professional surgeons in operation training, and then applying appropriate methods of pattern classification to significant motion characteristics (or in terms of pattern recognition referred to as calculated *features*) could help to cast both the ideal body posture and the most successful instrument handling techniques for surgeons into figures. On this basis the objective computer aided assessment of surgical trainees could be advanced and the efficiency of their training could be improved.

2. PROBLEM DEFINITION

Given motion capture data (MCD) of trainees' and expert surgeons' body movement and posture, one can follow three branches of applications.

Branch 1 could be the observation of the single trainee's progress in training. Here the aim would be to find the most significant features which change over time as the surgical trainee constantly succeeds in the performed operations. These most significant changing features consist of two classes which are defined in the following.

Definition of Changing Motion Feature Classes (CMFC)
Regarding to how they change over time, there are two classes of motion features $CMFC_d$ and $CMFC_i$. $CMFC_d$ includes the features which **d**irectly change over time, *because* the trainee succeeds and his or her hand-eye coordination and skills improve (for example, the velocity). Assume a trainee who improved handy-eye coordination during some training sessions can now perform a certain task quicker than before. This would be the perfect reason for an increased velocity feature of the new MCD and could be used to

reconfirm a good assessment for the performed task. However suggesting that other trainees who perform worse (with a lower velocity feature) should just increase the speed of their motion cannot be considered as constructive advice and would probably corrupt their performance even more instead of leading to their success.

$CMFC_d$ basically **d**epends on the trainee's training progress and skills.

$CMFC_i$ includes the features which can be easily changed **i**ndependently of time or training progress without obvious risk of compromising performance. The reason they change over time, but in a much more **i**ndirect way is due to the fact that trainees steadily learn how to improve their performance by optimizing operation techniques and so features change too. These features depend on how the trainee decides to carry out certain motions and techniques or how how the trainee changes the body posture. When it comes to certain tasks which require their own special techniques trainees work with the principle of trial and error. Whether he or she carries out correction moves too fitful or too smooth or whether the elbow should rest against the hip, be uplifted in the air or hover in between during a certain task - problems like these are solved and optimized by the trainee during training sessions over time, by experience. Of course trainees also needs to gain their own personal experience, but comparing features of $CMFC_i$ would give them some direction which could probably help them to shorten their trial and error time.

Branch 2: By comparing two or more trainees with similar experience ($CMFC_d$ features), the differences in performance are likely to be explained by $CMFC_i$ features. Hence, differences in body motion data can be used to find $CMFC_i$ features.

The only big source of fuzziness (or dispersion) might originate from the individual trainees' general talent for surgical tasks or they might have trained their manual skills or hand-eye coordination previously elsewhere. Most of the dispersion in $CMFC_i$ could be caused by different approaches for handling the instruments, for certain manual techniques and body posture among the trainees. Inside this set the features belonging to trainees with better performance assessment have to be discriminated from the one with worse results. A model describing the significant differences could then help the trainees to improve their approach, similar as in branch 1.

Branch 3: In branch 3 trainees' motion features are contrasted with those of expert surgeons. The aim is to assemble a model to assess trainees and provide suggestions for improvement. This is similar to the other branches, but the significant difference here is the meaningfulness of expert surgeons' $CMFC_i$ features, which could serve as a much more reliable source of suggestions for improvement. On the other hand the challenge of separating $CMFC_i$ from $CMFC_d$ features could be much harder to solve with experts' MCD.

In the following the problem definition is presented for branch 3.

2.1. Primary problem: Assessment

Given the MCD of a subject performing a laparoscopic exercise a previously trained classifier has to decide whether he/she is novice or expert. For the classifier's training a training set is needed. The training set has to be refined from the raw MCD by feature processing prior to the training process. During the training process the classifier has to learn the distribution of the data components labeled as either *expert* or *novices* and classify them into each group. After the training, when MCD of a new subject are provided and the feature processing completed, the classifier has to be able to estimate the most likely group to which the subject belongs.

2.2. Secondary problem: Suggestion for improvement

More desirable but also harder to elaborate are suggestions for the improvement of surgical trainees performance. The efficiency of the trainees' training only improves, when the feedback also tells them how their motions differ from the one of an expert and how they could change their body posture and manual techniques in order to perform better. For this purpose the calculated features have to be separated into $CMFC_i$ and $CMFC_d$. Only features included in $CMFC_i$ should be compared between experts an novices and serve as reference point for suggestion for improvement.

2.3. Problem summary illustration

For a more sophisticated depiction of the problems the diagram in Figure 1 illustrates the data and feedback flow of the desired implementation and supports the disambiguation of both problems referring to the definition of Changing Motion Feature Classes (CMFC). The initial block is the one that represents the **subject**. During the surgical training session the subject physically handles instruments in order to perform laparoscopic tasks. How well he or she does basically depends of his or her surgical skills. Accordingly, the motion of the instruments and the subject's body differ among the subjects. The next functional blocks represent the data that are acquired from that motion. One block for the **instrument data** from the surgery training system's motion tracking system and another block for the **motion capture data** from the motion capture (mocap) sensors attached to the subject's body. Each type of data is analyzed separately at first, but then in a more advanced approach the analysis can be improved by combining the data. This is why the **analysis** block shares the data flows. The suggestion for improvement benefits from the correlations between the instrument data and the MCD, so that certain parameters can be individualized for the suggestion procedure. The instrument data might even serve as a baseline for any further suggestions. For instance, if the assessment of the instrument data indicates the subject is an expert with little room for improvement, then the suggestions should take that into account. In this case the system would have to be deterred from stating or implying, that the expert performs like a novice, even if his or her MCD look alike in terms of classification. The results of the Analysis are stored as **suggestion for improvement** data (from $CMFC_i$ features) and **performance assessment** data (from $CMFC_d$ features and instrument data/features), which are represented by corresponding functional blocks. Finally, both are visually presented to the subject as his or her training feedback.

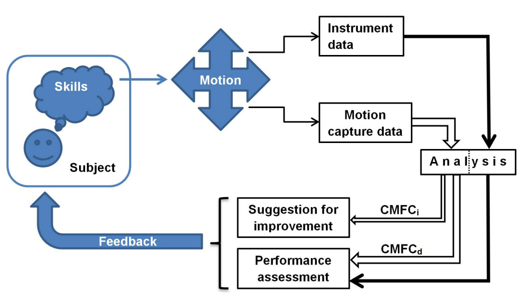

Figure 1. data and feedback diagram

3. RELATED WORKS

The most relevant works related to this paper are "Objective Evaluation of Laparoscopic Surgical Skills Using Waseda Bioinstrumentation System WB-3" [4] and its previous versions [5] [7]. In their research the team of Zhuohua Lin, Student Member, IEEE, Munenori Uemura, Massimiliano Zecca, Member, IEEE, et. al. concentrates on an appropriate application of Waseda Bioinstrumentation Systems. These Sensor Systems are basically consisting of Inertial Measurement Units (IMUs) and are connected to a PC via a CAN BUS. Their most significant advantage might be their low weight of 2.9g each. However, they are tethered, which results in some additional weight and increases the risk of a negative impact on the measurements through subjects being bothered by the cables. The research efforts are focused on the problem of surgical skill assessment. The classification approach is based on Linear Discriminant Analysis (LDA). Although LDA is a relatively simple classification method, the rates of correct classification of expert surgeons and novices in the two latest papers reach 93.75% (total) each.

However, this paper aims to support wide approach variations by introducing wireless, less invasive hardware and a broader set of extractable features. It also proposes the approach for a methodology which might advance surgical training by generating suggestion for improvement based on the detection of significant aberrations of novices' from experts' MCD and supported by the combination with conventional assessment data from instrument tracking.

4. THEORETICAL FOUNDATIONS

In the following a set of references to the basic theory is provided. Generally speaking, it is a summary of the knowledge required for understanding the application of classification methods to MCD in the context of surgical training.

4.1. Computer Assisted Surgery Trainer (CAST)

CAST is a computer aided system developed in its third generation (CAST III) by Prof. Rozenblit, PhD (Model Based Design Laboratory, University of Arizona). CAST includes a real life operation space, which is virtually simulated and visualized by tracking the surgical instruments' movements. It serves as the basis of our study and tests.

4.2. Body posture and manual techniques

When it comes to certain surgical tasks which require their own a special techniques trainees basically work with the principle of trial and error. There are practical problems to solve which are difficult to describe. These questions might serve as examples:

- "Are the correction moves during a path tracking task carried out too fitful or too smooth?"

- "Should the elbow rest against the hip, be uplifted in the air, or hover in between during a certain task?"
- "What is the ideal distance between body and surgical instruments?"

Expert surgeons have learned to solve problems like these by experience before they even have to think about it [3].

4.3. Features and Classification Methods

The most relevant classification methods, which might be chosen from for the classification of the MCD are: Support Vector Machines (SVM), Decision Trees (DT), Artificial neural networks (ANN), Bayesian Networks, and Clusters Analysis.

The amount of motion data captured by the sensors and recorded by the mocap software is quite extensive. At the Yost Engineering 3space sensors' maximum 60 frames per second can be recorded. So several thousands of frames gather quite quickly. For MCD there are two options for the feature extraction:

1. either the feature is calculated for the entire scope of the sample or
2. it is derived from the measurements by consecutively dividing them into windows

The window size is quantified by the number of frames included and can either vary from window to window or be a fix parameter. The increment represents the number of frames a window is shifted forward compared to its predecessor window. A division has to be determined prior to the feature extraction process. Then, for each window, the selected feature can be calculated [2]. A window division of the sample (second option) can be generally recommended if it is assumed that the observed feature changes over time, for reasons which are directly induced by conditions also changing over time. If such a change can be linked to a certain point in time or an event (such as the passing of a corner point), the window increment should be equal 100% of the predecessor window size, so that the windows do not overlaps in this point. If none of the windows overlaps the division can be considered a partition.

Example: For a mocap sample recorded from a surgeon performing a simple path tracking task it can be useful to establish a partition of windows, of which each is covering one of the path sections in between the corner points. This is because from each corner point to its successor the path direction changes and the surgeon might adjust his or her instrument handling technique to the new direction (see Figure 2).

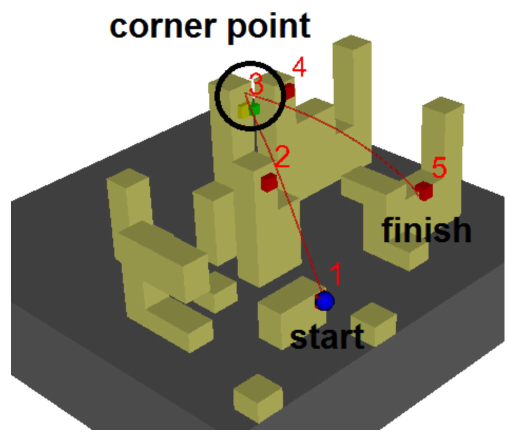

Figure 2. Example for a path with one corner point

However, it has to be taken into account, that each window extends the feature space by one dimension. At some point, the number of dimensions could be too high for the selected classifier. This could lead to the curse of dimensionality and ruin the resulting model's capabilities.

There are two different types of measures for the captured motion - **angular (also referred to as rotational) and three dimensional (absolute coordinates)** - with three orders of derivation each, which the features can be calculated for:

order\type	**angular**	**3D**
zeroth order	absolute angle	displacement
first order	angular velocity	translational velocity
second order	angular acceleration	translational acceleration

The first order derivatives equate with the quantitative intensity and the second order derivatives with the quantitative dynamic of the motion. For the angular metrics either one of the three rotation axes have to be selected or a combination of angles have to be assembled and transformed into an appropriate mean value (e.g. arithmetic mean), depending on the purpose. In the following, some of the many features conceivable for the application to MCD are introduced. They are dedicated to serve as the base for the feature extraction processes during the classification testings in Section 6 [2]. Each feature has to be implemented in MATLAB. As an example for the combination of the three values from the degrees of freedom to a mean value, a MATLAB function `MeanOfThree` is used to calculate the arithmetic mean for the value triples. The **cumulative displacement** represents the total distance a moving object traveled.

It's value for N measurements $x_1 \dots x_n$ is given by

$$CumDisp\,(x) = \sum_{i=1}^{N-1} \left| x_i - x_{i+1} \right|$$

Obviously it should be calculated for the absolute angle (zeroth order) only.

The **mean absolute value (MAV)** represents the average absolute value of a given derivative metric [2]. It's value for N measurements $x_1 \dots x_n$ is given by

$$MAV\,(x) = \bar{X} = \frac{1}{N} \cdot \sum_{i=1}^{N} \|x_i\|$$

The **Root Mean Square**, also known as the quadratic mean, measures the average magnitude of a given derivative metric and is calculated using [6]:

$$RMS\,(x) = \sqrt{\frac{1}{N-1} \cdot \sum_{i=1}^{N} x_i^2}$$

Generally speaking, both RMS and MAV commensurate with the motion activity, if applied to first or second order derivatives.

The **variance (VAR)** is a measure of how much the measurements of the given derivative metric differ between each other [2]:

$$VAR\,(x) = \sigma^2 = \frac{1}{N} \cdot \sum_{i=1}^{N} (\bar{X} - x_i)^2$$

where $\bar{X}$ is the average value of x, defined as:

$$\frac{1}{N} \cdot \sum_{i=1}^{N} x_i$$

The **zero crossings (ZC)** feature counts how often the difference of the given derivative metric is changing its sign (crossings zero) within a window. As an example: If applied to the angular velocity (first order), it quantifies the changes in direction, from "clockwise" to "counterclockwise" and vice versa. The feature is calculated as follows, with a threshold T to reduce noise [1]:

$$ZC\,(x) = \sum_{k=1}^{N-1} g_{ZC}\,(x_k)$$

with

$$g_{ZC}\,(x) = \begin{cases} 1 & \text{if } \left(x_k \cdot x_{k+1} < 0\right) \wedge \left(\left\|x_k - x_{k+1}\right\| \geq T\right) \\ 0 & \text{else} \end{cases}$$

The zero crossings feature may not be applied to the absolute angle (zeroth order), because it represents no meaningful information about the data set.

5. SOLUTION APPROACH FOR A STUDY AND TESTING

This section explains what would be necessary for an appropriate study and conducts a preliminary test of the methodology. For a meaningful study expert surgeons have to be recruited and perform exemplary operation tasks in order to sample MCD, which can then serve as a statistically relevant baseline for pattern recognition. For an initial proof of concept, however, some numbers can be reduced. The number of surgeons could stay between one and two, the number of observed upper limbs to one, applied sensors per arm between two to four (hand and lower arm first, then upper arm and chest), and the number of considered features per sensor between two to four (e.g. cumulative displacement, average velocity, variance of velocity and average acceleration).

Applied Theory: For an initial testing of the methodology a subset of the theory introduced in Section 4 is selected. As classifier a Artificial Neural Network is trained in MATLAB. The following features are calculated for the data samples: Cumulative Displacement, Mean Absolute Value of the angular velocity, Mean Absolute Value of the angular acceleration and the Variance of the angular velocity.

Hardware set: The applied motion capture sensor set consists of three wireless inertial measurement units (IMU) and one wireless USB dongle. The first two sensors are attached to the upper arm and lower arm using the straps. The third sensor is attached to a short fingered glove, which is comfortable to wear while handling the surgical instrument during motion capture sessions. In order to acquire some preliminary data, the motion of two novices has been captured during a short and easy path tracking task with three samples each. In the following the three applied sensors are called S_1 for the shoulder, S_2 for the elbow, and S_3 for the wrist. The one subject is abbreviated with A, the other one with B. The recorded samples were numbered enumeratively, so there are six samples: `a1.bvh`, `a2.bvh`, `a3.bvh`, `b1.bvh`, `b2.bvh`, `b3.bvh`

Setup: The third generation Computer Aided Surgery Trainer (CAST III) served as a platform for the path tracking task. It was configured for the operation with the right hand (single-arm), which the mocap data has been captured from.

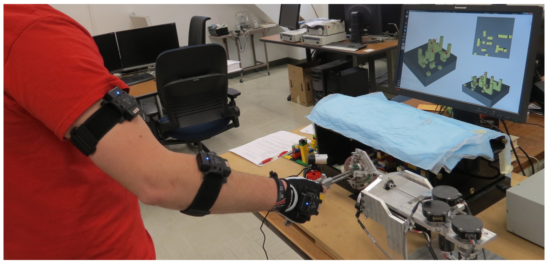

Figure 3. handling the instrument with sensors attached

Task: As a basic surgical task for the novices the Visualization Toolkit was configured to show a path in the virtual operation space, which had to be tracked with the instrument. At the start of each sample the instrument was held in checkpoint 1. Mocap recording and tracking the path were started simultaneously. Then the path has to be followed via point 2 to corner point 3 and from there to final point 5 (point 4 is offside) without losing contact. Contact means that there is an intersection between path section and the cube which represents the instrument end. As soon as final point 5 was reached recording was stopped. The subjects were standing straight, eyes front to the computer screen, which showed the operation space visualization.

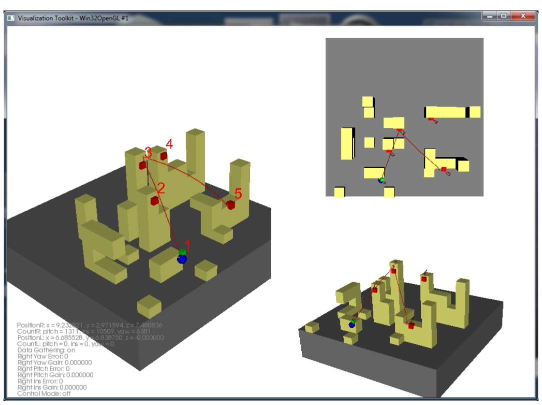

Figure 4. path tracking task

6. ANALYSIS AND RESULTS

For the analysis the figures from the recorded `.bvh` files were saved as a separate `.txt` file and then imported into MATLAB as matrices `a1, a2, a3, b1, b2, b3`. After calculating the Cumulative Angular Displacement feature for `a1` the data recorded for S_1 turned out to be faulty. In most of the samples the initial angle values almost don't change over time. So the first three columns were deleted in all samples and features were calculated only for S_2 and S_3 using the previously implemented MATLAB functions `CumAngDisp`, `MAV_AngVel`, `MAV_AngAcc` and `VAR_AngVel` as well as `MeanOfThee` for the calculation of the arithmetic mean of channels X, Y and Z.

	`CumAngDisp`		`MAV_AngVel`	
	S_2	S_3	S_2	S_3
`a1`	134.9666	129.7836	0.0857	0.0824
`a2`	116.3062	117.0620	0.0967	0.0973
`a3`	113.9635	114.1560	0.0826	0.0828
`b1`	124.7340	113.4774	0.1478	0.1345
`b2`	113.1551	112.7726	0.1130	0.1127
`b3`	137.3885	150.2262	0.1296	0.1417

	`MAV_AngAcc`		`VAR_AngVel`	
	S_2	S_3	S_2	S_3
`a1`	0.1009	0.0973	0.0099	0.0095
`a2`	0.0996	0.1015	0.0099	0.0102
`a3`	0.1088	0.1078	0.0125	0.0116
`b1`	0.1624	0.1346	0.0247	0.0141
`b2`	0.1285	0.1140	0.0125	0.0146
`b3`	0.1791	0.1786	0.0162	0.1609

These feature values represent the input data, with which the Neural Network was trained in the next step. They were saved as `inputs.txt`.
Before the training process can actually start, the class labels have to be provided, too. For this purpose an 8-by-2 matrix, encoding subject A with `1` in the upper half of the second, subject B with `1` in the lower half of the first column and else `0`, was written into `targets.txt`.
At this point, work with the Neural Network Pattern Recognition Tool could begin. The two `.txt` files were imported. After determining the number of hidden neurons, as well as the percentages of validation and test data, the network can be trained and retrained again and again, coming up with different output Mean Square Error rates each time and low classification error rates most of the times (Figure 5).

7. CONCLUSION AND FUTURE WORK

This paper proposed the idea of applying motion capture technology and pattern recognition to surgical

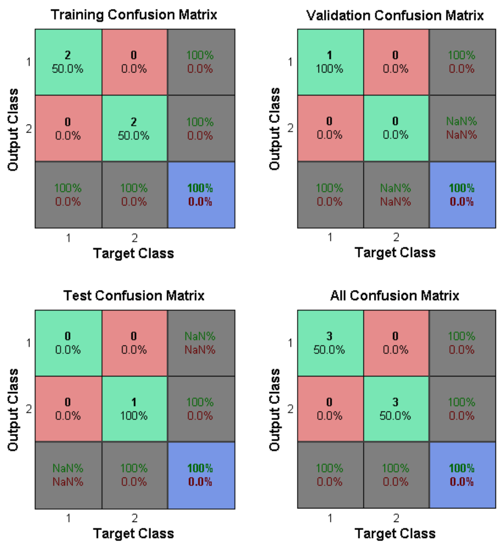

Figure 5. NN - example for confusion matrices

training. Three different branches of application have been pointed out, of which branch 3 was followed in the sequel. An appropriate problem definition including a breakdown into subproblems as well as a problem illustration has been presented. An overview of the theoretical foundations has been given which are essential for the development, implementation, and realization of an extension for laparoscopy training systems. This allows for the affirmation of the system's performance assessment and for the suggestion for improvement by analyzing their motion and body posture. A broad variety of possible approaches, concepts, and designs have been introduced, which can be followed to a final implementation and realization. The paper especially focused on the feature extraction process with its large set of available motion features. The combination of the choice of a suitable classification algorithm and the selection of the optimal feature subset is the key for successful classification. An exemplary implementation was presented applying a subset of the theoretical foundations. Finally this approach was practically tested by applying three motion capture sensors as a preliminary demonstration of the methodology.

In future work, this implementation has to be applied to a statistically relevant number of samples. This means an extensive study has to be conducted, recruiting a sufficient number of novices or surgical trainees and especially expert surgeons, which are quite difficult to get hold of. After these samples have been captured, the methodology from Section 6 can be put to the test. At first, the primary problem of performance assessment has to be tackled, beginning with the training of a reliable expert/novice classifier. Clearly, we will have to design a meaningful experiment which will objectively measure movement characteristics. We plan to leverage our existing platform (CAST) to accomplish this goal.

For a more effective training, the rotational measurements can be translated into three dimensional coordinates using forward kinematics. For these dimensional data the features can be calculated the same way as for rotational data. But since they have a different meaning regarding the carried out motion, adding them to the set of training data might improve the classifier. After such a classifier has been found, the performance assessment aspect can be explored in a more sophisticated way, evaluating significant features and utilizing them for the affirmation and extension of already existing assessments.

When this subproblem has been solved, the secondary problem can be faced. Features of $CMFC_i$ have to be separated from $CMFC_d$ in order to solve it. This seems to be a challenging task, because the meaning of single features have to be interpreted and put into perspective of the body posture and the way manual techniques are carried out. Only if $CMFC_i$ features can be identified and interpreted, can suggestions for improvement be given to the trainees through their training feedback.

When this challenge is mastered, the whole procedure can be expanded to a larger set of motion capture sensors. The set of three motion capture sensors for one upper limb could be extended to six (or seven) sensors for both upper limbs (and head), to a set covering the upper part of the body or even to a whole body set.

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BIOGRAPHY

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Tobias Haug received his BS in Computer Science at the Universität der Bundeswehr München and is currently writing his MS Thesis at the University of Arizona, until July 2014. His research interests are motion capture technology and pattern recognition.