Whole Hand Modeling using 8 Wearable Sensors: Biomechanics for Hand Pose Prediction

Christopher-Eyk Hrabia
TU Berlin
Berlin, Germany
c.hrabia@gmail.com

Katrin Wolf
TU Berlin
Quality & Usability Laboratories
Berlin, Germany
katrin.wolf@acm.org

Mathias Wilhelm
TU Berlin
DAI Labor
Berlin, Germany
mathias.wilhelm@dai-labor.de

ABSTRACT

Although Data Gloves allow for the modeling of the human hand, they can lead to a reduction in usability as they cover the entire hand and limit the sense of touch as well as reducing hand feasibility. As modeling the whole hand has many advantages (e.g. for complex gesture detection) we aim for modeling the whole hand while at the same time keeping the hand's natural degrees of freedom (DOF) and the tactile sensibility as high as possible while allowing for manual tasks like grasping tools and devices. Therefore, we attach motion sensor boards (accelerometer, magnetometer and gyroscope) to the human hand. We conducted a user study and found the biomechanical dependence of the joint angles between the fingertip close joint (DIP) and the palm close joint (PIP) in a relation of DIP = 0.88 PIP for all four fingers (SD=0.10, R^2=0.77). This allows the data glove to be reduced by 8 sensors boards, one per finger, three for the thumb, and one on the back of the hand as an orientation baseline for modeling the whole hand through. Even though we found a joint flexing relationship also for the thumb, we decided to retain 3 sensor units here, as the relationship varied more (R^2=0.59). Our hand model could potentially serve for rich hand-model-based gestural interaction as it covers all 26 DOF in the human hand.

Categories and Subject Descriptors

H5.2 [Information interfaces and presentation]: User Interfaces. - Input Devices and Strategies.

General Terms

Algorithms, Design, Human Factors.

Keywords

Biomechanics; Gesture; Glove; Hand model; Wearable.

1. INTRODUCTION

Gestural interaction is an important research topic because human-computer interaction has, for many years, not been limited to desktop environments, and within research concerning interaction in mobile scenarios and within smart environments, many questions have yet to be answered. We address the field of input technologies for mobile interaction in ubiquitous computing
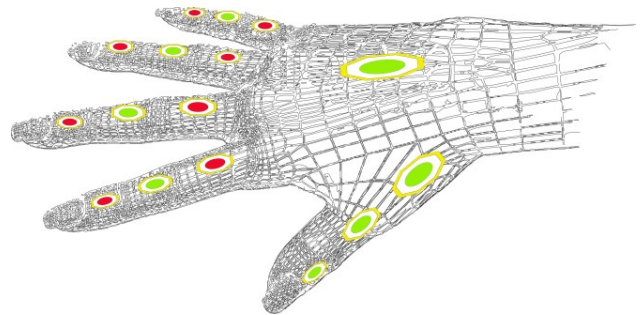
Figure 1. Our initial whole hand model based on 16 motion sensor boards mounted on the green and red marked positions. Applying bio-mechanics allows the hand to be modeled using just the 8 green marked sensor positions shown.

and investigate how wearable sensors extend the design space of free hand gestures, by which is meant those gestures that are not currently detected with sensors integrated with mobile devices (such as capacitive screens or inertia sensors).

Optical sensors and cameras are widespread for free gesture detection through augmenting environments [Wilson 2010, Harrison 2012] although less frequently used for mobile scenarios as these techniques are limited in mobility. More recently, researchers attached cameras to users' bodies [Bailly 2012] that required a stable camera focus on the hand performing the gesture, although this approach can be limited by occlusion if users hold devices, such as phones or tablets. The *Magic Finger* interface [Yang 2012] is attached at the fingertip and detects movements on and above a given surface. Optical sensors have some limitations, such as light-dependency, occlusion, computing efficiency and form-factor. Our device overcomes these problems, because the recognition is achieved by the use of cheap and tiny sensors that require less computing power such as Inertial Measurement Units (IMU) or Magnetic Angular Rate and Gravity-Sensors (MARG). In contrast to *Magic Finger* [Yang 2012] that is a camera attached on the fingertip, we developed a gesture-based input device that allows for rich gestural input but does not limit the rich human sensitivity of touch. Therefore we attach motion sensors on top of the finger.

In order to be able to interpret highly complex hand gestures, our aim is to detect the whole hand with any finger configurations while the possibility of holding devices shall be given. This goal could be reached through attaching a sensor at every finger

segment and an additional sensor at the back of the hand (see Figure 1). We do not use cameras, as occlusion usually limits gesture detection for free hand scenarios. Being aware of a lack in usability if users have to wear 16 sensors per hand, we investigated the relationship within the orientation of finger segments for each finger, by considering biomechanics. Taking biomechanics into account actually limits the DOF of humans' hands because each finger joint has just one degree of freedom. Others [Wu 1999] have found that there is a stable linear relationship between the flexion angles of both joints for each finger. In a user study we tested whether the flexion relationship of Wu *et al.* [Wu 1999] can be confirmed with our input interface using 16 wearable motions sensor boards. Moreover we introduce an approach of applying biomechanics that allows the whole hand configuration to be predicted through using just 8 instead of 16 sensor boards. We conclude with exploring the emerging gestural design space when using our interface approach and show that using 8 wearable sensors allows for a rich free-hand gesture vocabulary that is not limited through occlusion and which does not limit the sense of touch or the mobility of the user.

2. RELATED WORK

Here we give an overview on wearable sensors for hand movement detection and hand configuration modeling. Moreover, we are discussing approaches that aim to predict the configuration of the hand based on biomechanics and intra-finger joint dependencies.

2.1 Wearable Sensors

For detecting hand or finger gestures, glove-based devices have been used and explored for decades [Dipietro 2008]. Glove-based devices, mostly using bend-sensors and accelerometers, are able to fulfill the requirement of reliable recognition and allow a detailed virtual model of the human hand to be represented, however they lack usability, as they restrict tactile feedback and are not suitable to wear in everyday use. Another limitation of gloves might be that they usually not fit to small hands. We experienced some accuracy problems due to the sensors not staying in their recommended position in cases where the users' fingers are slim.

Another type of interface enables gesture input without augmenting the hand or finger, but instead attaching the interface at the wrist. The *GestureWatch* [Kim 2007] allows simple direction based gestures to be executed by the hand with the use of proximity sensors, but has only a limited gesture design space and requires both hands for interaction. *GestureWrist* [Rekimoto 2001] allows for body-centric pointing with three different handed gestures. That interface has a limited gesture design space, because the device is measuring the hand capacitance that allows only for the recognition of very simple hand shapes (such as body-centric pointing: up-, down-, and to the side) with three different hand configurations: stretched index finger, stretched index and middle finger or with clenched fist. *Digits* [Kim 2012] is an inner wrist mounted depth-camera combined with an IMU, which enables precise finger-gesture tracking due to extensive use of inverse kinematics in conjunction with biomechanics. But like all computer-vision based approaches *Digits* suffers from strong limitations due to both occlusion and motion beyond its field of view. These limitations pose particular difficulties for everyday mobile interaction outside of controlled environments, such as executing gestures while holding another device.

One solution to the occlusion problem is to use motion sensors rather than a camera. Fukumoto and Tonomura [Fukumoto 1997]

augmented each finger and the wrist of one hand and have shown with *Body coupled FingeRing* that accelerometers can be used for simplified keyboard-less typewriting as they do not distinguish between different letters per finger. However, Fukumoto and Toromura found an interesting solution for wireless sensor connection to the wrist-worn microcontroller by using the skin for conduction; their gesture vocabulary is very basic as they had not interpreted more detailed gestures than tapping with different fingers. *UbiFinger* [Tsukada 2002] enables pointing at locations and objects in the environment through infrared light, and allows simple gestures (such as turning a volume knob or pushing a switch) to be recognized, based on bend and acceleration sensors that are attached to the index finger. ,

Taking advantage of biomechanical constraints of the human hand would allow for an advanced hand model to be built with only a limited amount of sensors. Our work also uses accelerometers, but because they sometimes lack information details and can suffer from drift-based errors, our interface also contains gyroscopes and magnetometers. This combined sensor approach actually allows a more detailed gesture vocabulary and even permits the modeling of the whole hand, as is described later in section 5.1.3.

Nenya [Ashbrook 2011] uses a ring-type device that includes a strong permanent magnet, as well as a wrist-device with a magnetometer for recognizing the rotation of the ring relative to the wrist. The magnetic ring has the advantage of not requiring a power supply; however the technology only allows one ring to be fitted per hand, thereby strongly limiting the gesture design space. Moreover their user study shows that this device is only suitable for two-hand usage.

Our aim is to enable complex gesture detection that is not limited to a controlled environment. Therefore we wanted our device to be able to provide rich information on hand configuration in a manner similar to data gloves, while simultaneously keeping hand augmentation to a minimum, in order to maximize usability.

Our goal therefore is to build an interface that can potentially be integrated into jewelry, such as rings, wristbands, and watches. This means that we must reduce the number of sensors used (when compared to data gloves), which will potentially lead to a loss of information. Information that would have been supplied by a greater range of sensors is, in our approach, gained through the application of biomechanics.

2.2 Biomechanics for Hand Modeling

Much research in investigating biomechanical constraints is done for realistic hand modeling, e.g. in computer vision. This work covers mainly inter-finger and intra-finger constraints.
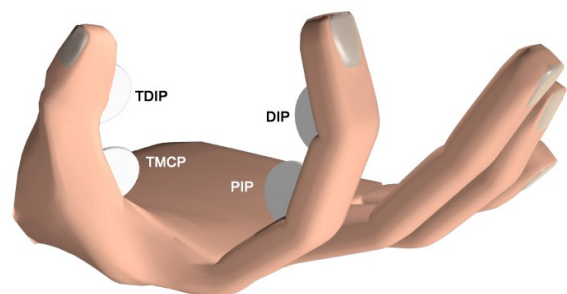

Figure 2. Joint notation and angular relationship between upper finger joint DIP and mid finger joint PIP as well as upper thumb joint TDIP and mid thumb joint TMCP.

As one of our aims is to be able to predict the tilt angle of a particular finger-segment based on the tilt angle of another segment on the same finger, we first present and discuss explorations of intra-finger constraints.

Each single finger joint has just one degree of freedom (DOF). Several researchers [Fahn 2005, Cobos 2007, Wu 1999] investigated whether or not a linear angular relationship might exist between the two upper joints of one finger, the distal interphalangeal (DIP) and proximal interphalangeal (PIP) joint (see Figure 2). They identified an approximate relation of DIP ≈ 2/3 PIP of joints within the same finger. The thumb differs in anatomy from the other fingers and a linear angular relationship for the joints of the thumb was defined by Cobos *et al.* [Cobos 2007] as an appropriate angular relation of thumb distal interphalangeal joint (TDIP) ≈ ½ thumb metacarpophalangeal joint (TMCP).

We felt that the relationship between the angles of the joints ought to be checked for our interface because of the following three reasons: 1) in the study mentioned above, neither the gender or the total number of participants is reported; 2) Secondly they consider the relation is an approximated result; 3) the data is detected through gloves, which, as outlined above, can produce data errors due to a bad fit, particularly for users with small hands.

Fahn and Sun [Fahn 2005] actually reduced the numbers of sensors in their glove. They used magnetic induction and were able to model the expressiveness of ten DOF while using five sensors. Our approach uses a combination of accelerometers, gyroscopes, and magnetometers and aims to model the hand with the full set of 26 DOF [Vardy 1998].

3. METHOD

The proposed appropriate joint flexion relationships of DIP ≈ 2/3 PIP within the same finger and of TDIP ≈ ½ TMCP for the thumb have been found through the study of biomechanics.

Similar to Fahn and Sun [Fahn 2005], identifying an exact linear relationship (rather than an approximate one) would allow for interpolation of one finger joint from the other. Due to this relation it would then be possible to reduce the amount of hand-attached sensors used for measuring the hand configuration. In contrast to Fahn and Sun, our interface would allow for reducing the number of sensors to eight instead of five, but with the advantage of retaining the full set of 26 DOF [Vardy 1998] instead of the ten DOF that Fahn and Sun could provide.

For checking the angular joint relationship proposed by Wu *et al.* [Wu 1999], Fahn and Sun [Fahn 2005] for finger joints and for the joints of the thumb that was proposed by Cobos *et al.* [Cobos 2007], a user-study was conducted with 19 participants in order to check the relation of the linear angular relations of joint flexion from previous work (as well as the precision) because the proposed related were mentioned to be approximated values:

H1: The linear angular relation of joint flexion is: $\angle DIP = \frac{2}{3} \angle PIP$ for the index, middle, ring, and little finger with an error < 5%.

H2: The linear angular relation of joint flexion for the thumb is $\angle TDIP = \frac{1}{2} \angle TMCP$ with an error rate < 5%.

As the finger joint flexibility might depend on the hand orientation or wrist tilt angle [Spalteholz 1861], we are moreover questioning:
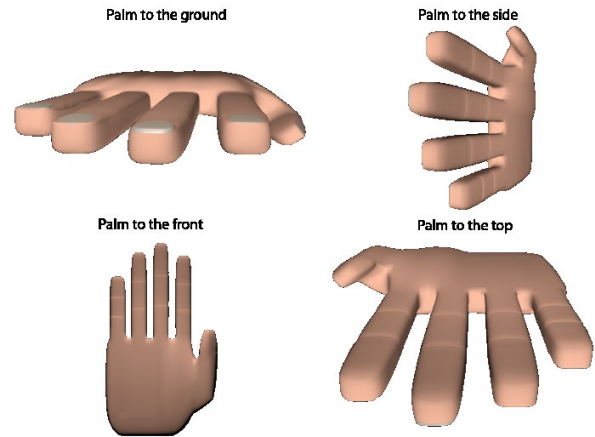

Figure 3. Hand orientations in which positions the participants were asked to flex their fingers.

Q1: Are both angular relationships stable for four different hand orientations?

Q2: Are both angular relationships stable for both, left and right hand?

3.1 Design

Dependent variables were the measured angle between the finger segments neighboring the DIP, PIP, as well as the TDIP and TMCP joints of all fingers. Independent variables were hand orientation, finger, and hand. The hand orientation had four stages: palm facing down, palm to the side, palm raised, and palm facing up (see Figure 3). The joint angles were measured for all participants for all four fingers and the thumb of both hands, while flexing the thumb and fingers. The flexion was measured for each finger separately twenty times. Therefore we had a within 4x2x5 design with twenty repeated measurements per participant.

3.2 Participants

We invited a heterogenic group of participants regarding gender, age, and body size. 19 participants, 11 male and 8 female, between 20 and 70 years (mean=40, SD=16) volunteered in our experiment. Their height ranged between 160 and 190 cm (mean=175, SD=7) and one was left-handed.

3.3 Apparatus

Our apparatus is a hand-augmented sensor interface that transmits motion data to a PC, in order to serve as a basis for modeling the human hand based on motion sensor data. For modeling the hand, we developed software that generates a hand model but also logs the raw sensor data, which allows for the analysis of hand motions, such as finger joint flexion angles and motion paths.

We propose using four multiplexed MARG (Magnetic Angular Rate Gravity) – sensors that contain acceleration sensors and magnetometers in combination with gyroscopes for joint orientation tracking.

3.3.1 Hardware

Our apparatus consists of four sensor sticks[1] with nine degrees of freedom through a gyroscope (ITG3200), an accelerometer (ADXL345), and a magnetometer (HMC5883L) which

---

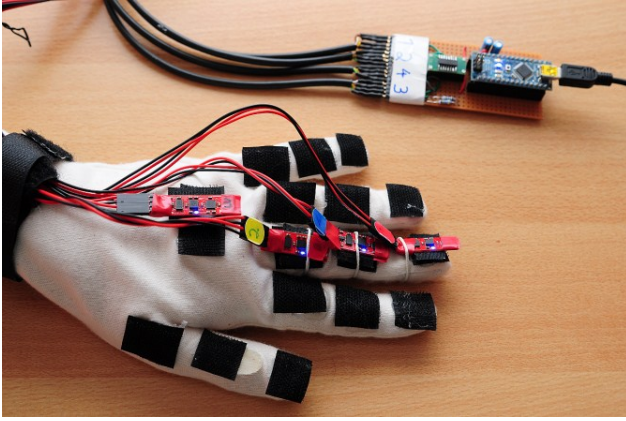[1] SparkFun Electronics Item Nr. SEN-10724.

Figure 4. Hardware interface with 4 sensor sticks attached to the middle finger and the palm

communicate over an I2C interface with a wrist-worn Arduino Nano V3 (see Figure 4) together with an I²C-Switch for multiplexing several sensors. The Arduino is attached to the PC-Application with a USB-Serial-Interface. After shortening the sensor sticks to a size of 30 mm, they were small enough to attach them to each single finger segment for modeling the whole finger. The sensors were attached on gloves and, for a better fit, we secured each sensor with an elastic band. This prevented unwanted sensor movements that did not refer directly to finger movements. The current prototype is powered through a USB connection to a PC. For future versions it is intended to use batteries, in order to provide additional freedom.

3.3.2 Data processing
The apparatus is capable of tracking the configuration of single finger joints with over 30Hz in real time.

The microcontroller software is only responsible for the logging of the raw sensor data. All further processing is done at a higher level in the PC-Application. To do this, a Java-based PC-Application fuses the raw sensor data from the accelerometer, gyroscope and magnetometer. Mahony's [Mahony2008] complementary filter extended with a magnetic distortion filter by Madgwick [Madgwick2010] is used in order to fuse the sensor data and calculate a three dimensional orientation. In order to remove the influence of drift and noise of the MARG-sensors from the calculated joint orientations, an extended error correction technique is applied to the orientation values, by using a biomechanics based hand model. The result of the hand model based error correction feeds back into the complementary filter algorithm.

3.3.3 Hand Model
Based on an initial calculated joint orientation calculation, the extended hand model error correction mentioned above is executed. The error correction checks for plausibility and takes the possible DOF (see Figure 5) and motion radius (see Figure 6) of each joint into account.

Figure 5 gives an overview of the DOF for each finger joint. All fingers without thumb are mapped in the same way, with one DOF for both upper joints and two DOF for the base joint. The thumb has also either one DOF for both upper joints, but three DOF for the saddle joint. The whole hand has 3 DOF, too.

In Figure 6 the possible motion radius for thumb and index are shown [Fahn 2010, Lin 2000, Wu 1999]. All other fingers are mapped like the index finger. For simplification of the figure the
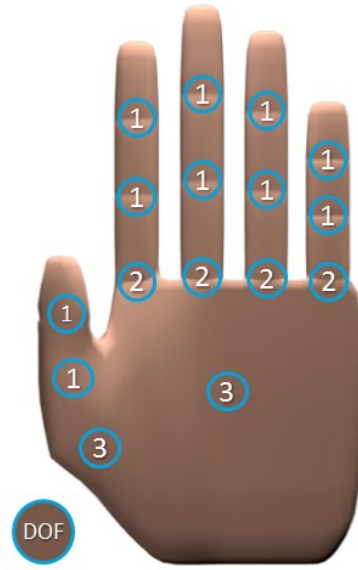

Figure 5. DOF for each joint

overflexion of all fingers is not shown. While recording, one sensor stick is always attached to the back of the hand and serves as a reference orientation for the whole hand. The reference is used to calculate the finger orientation relative to the palm. Three sensor boards can be worn at each individual segment of a finger, which allows the position and orientation of every segment (and therefore the entire finger) to be modeled 16 sensors would provide sufficient data for modeling the whole hand at once. As we wish to detect the measurements finger-wise, we also attach three sensors to the finger whose motion we want to track.

3.4 Measurements
Our apparatus captured the raw sensor data from four sensor boards at a rate of 30 Hz. The data is stored in a relational database. Each board delivers the x-, y-, and z-values of the accelerometer, the gyroscope, and the magnetometer, respectively. For ensuring that the measurements were not influenced by tiredness, we used the SMEQ questionnaire for measuring perceived task load. The questionnaire was answered twice by all participants, (i.e. once for each time after completing the tasks with a particular hand).
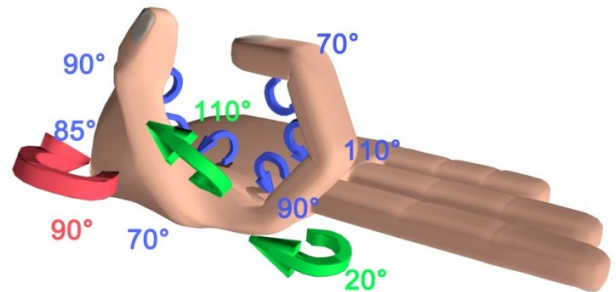

Figure 6. Motion radius for each joint of thumb and index finger

3.5 Task

With the motion sensors attached, the participants were asked to move their fingers from a starting point of complete stretching to complete flexion with twenty repetitions. For each set of 20 repetitions, only one finger at a time was measured in order to simplify the experiment setup and to keep finger feasibility limitations to a minimum. Participants were asked to use all fingers in the task in order to overcome the problem of motion dependence between individual fingers as a result of shared sinews and ligaments between fingers.

Procedure

Each participant executed the same task. The flexion of the fingers was first shown by the instructor and afterwards practiced by participants a number of times until we were certain that the instruction had been clearly understood. The order in which fingers were measured was permutated across all participants, in order to eliminate the influence of tiredness.

4. RESULTS

The data was checked for normal distribution with a Kolmogorov-Smirnov-Test. The angular relationships between the fingers were calculated with linear regression analysis. We tested with ANOVA whether the hand, the hand orientation, the finger or the participant had a significant influence on the angular relationship of joint flexion.

These linear angular relationships between the two upper finger joints DIP and PIP and upper thumb joints TDIP and TMCP, which are determined with a linear regression analysis over the whole dataset for each finger and thumb, are show in figure 7 and lead to the regression equations that are presented underneath.

Little finger: $\sphericalangle DIP = 0.79 \sphericalangle PIP; R^2 = 0.63$

Ring finger: $\sphericalangle DIP = 0.88 \sphericalangle PIP; R^2 = 0.78$

Middle finger: $\sphericalangle DIP = 0.87 \sphericalangle PIP; R^2 = 0.76$

Index finger: $\sphericalangle DIP = 0.88 \sphericalangle PIP; R^2 = 0.77$

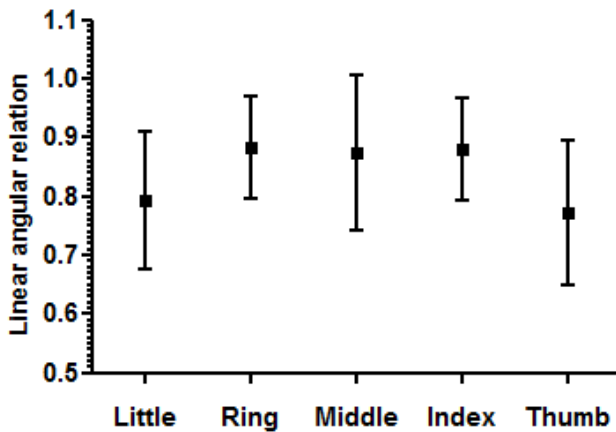*Thumb:* $\sphericalangle TDIP = 0.77 \sphericalangle TMCP; R^2 = 0.59$

Figure 7. Angular relationship between two upper finger joints DIP and PIP based on coefficient of linear regression analysis over entire dataset per finger for little (ß=0.79, SD=0.12), ring (ß =0.88, SD=0.09), middle (ß =0.87, SD=0.13), index finger (ß =0.88, SD=0.09), and thumb (ß =0.77, SD=0.12)

The used finger has only a significant influence on consideration of all five fingers together ($F_{4,545235}$=3.523, *p*=0.007). The factor finger is not significant without the thumb ($F_{3,4406955}$=1.432, *p*=0.234), therefore it shows, that only the thumb has a different relationship. Hence it follows the relationship for all fingers without the thumb.

All Fingers without thumb: $\sphericalangle DIP = 0.86 \sphericalangle PIP; R^2 = 0.74$

Index, ring and middle finger: $\sphericalangle DIP = 0.88 \sphericalangle PIP; R^2 = 0.77$

The ANOVA showed, that neither hand orientation (*Q1,* see Figure 3) ($F_{3,545235}$=0.043, *p*=0.984) nor whether the left or right hand (*Q2*) was used ($F_{1,545235}$=0.202, *p*=0.653) had a significant influence on the angular relationship between the two upper finger joints. That means the linear angular relationships above can be taken for both hands in all tested hand orientations: palm raised, palm facing the ground, palm facing up, or palm to the side.

The linear angular relationship between the two upper finger joints, which was proposed in *H1* to be $\sphericalangle DIP = 0.67 \sphericalangle PIP$, is based on our whole aggregated dataset different: $\sphericalangle DIP = 0.86 \sphericalangle PIP$ with a coefficient of determination (R²) of 0.74 and SD = 0.11. Because the angular relationship of the index finger might be affected by noise of sensor board movements, as described in the discussion, we also calculated the angular relationship without the little finger that is $\sphericalangle DIP = 0.88 \sphericalangle PIP$ and shows an expectable slightly higher coefficient of determination (R²) of 0.77 with a standard deviation of SD = 0.10. Thus, we argue that the angular relationship of 0.88 is representable for each, even for the little finger those data were affected by noise.

In contrast to the assumed angular relation of *H2* for the thumb of $\sphericalangle TDIP = 0.5 \sphericalangle TMCP$, our data showed a linear angular relationship of $\sphericalangle TDIP = 0.77 \sphericalangle TMCP$ with a coefficient of determination (R²) of 0.59 and SD = 0.11.

The evaluation of the user surveys reveal, that the participants did not feel increased effort over the experiment execution time ($F_{1,36}$=0.093, *p*=0.762).

Finally the determined linear relationships between the upper finger joints for all fingers were integrated into our hand model. Hence the results were reviewed with qualitative comparison on the recorded finger movements with sensors on all limbs and without sensors on the tip by the use of the real-time visualization of our developed software.

5. DISCUSSION

In this section we discuss our results on the linear angular relationship between the upper and mid joints of the fingers and the thumb. Furthermore we show how our found angular relation of the finger joints serves for improving the initial hand model of our apparatus. Finally we show how the hand model, which covers all 26 DOF of the human hand, could serve as a gestural design space and how that design space allows the gesture repertoire of the existing gestural input devices we introduced in the section on related work, to be greatly extended.

5.1.1 Linear angular relationship

The results of our user study expose a significant difference to both hypotheses; the first hypothesis based on the related work from Fahn and Sun, and Wu *et al.* [Fahn 2005, Wu 1999] who proposed a relationship of $\sphericalangle DIP = 0.67 \sphericalangle PIP$ for the finger joint. The second hypothesis based on Cobos *et al.* [Cobos 2007] proposed an angular relation of $\sphericalangle TDIP = 0.5 \sphericalangle TMCP$ for the

joints of the thumb that is different from ours. As mentioned above, the researchers did not provide much detail on how they determined the linear angular relationship. This makes it difficult to suggest why our results differ from angular relationship found and reported by them. The authors did not give information about the instructions given in the task with respect to how to flex the fingers, nor did they provide information about the age, gender or height of the participants. Moreover just one angular relationship was given for all fingers, which furthermore was described to be appropriate. We suggest that the authors perhaps noticed some experiment limitations, e.g. data gloves tend to slip a bit out of position while flexing fingers, and were aware about the fact that the relationship can be identified more exactly in future work.

Therefore, we suggest that our results give a more accurate relationship of the two upper finger joints ($\sphericalangle DIP = 0.86 \sphericalangle PIP$, $R^2=0.74$), because we were able to attach single sensors tightly to the specific finger segments and consider different hand sizes with flexible sensor positioning. This safety against sensor slipping is not given for data gloves, because most of them use bend sensors for determining the bending angles.

The comparable low coefficients of determination for the measurement of the thumb ($R^2=0.59$) and the little finger ($R^2=0.63$) might have different reasons. The little finger suffered from the non-appropriate size of our sensors boards, which leads to collision between the boards and therefore produced more data noise for the little finger. Hence we suggest the results for the little finger would be more accurate if sensor boards that are shorter than the little finger segments are used. Assuming that the little finger has the same biomechanical constraints than the other three fingers, we re-calculated the linear angular relation without that digit and got a new angular relation of $\sphericalangle DIP = 0.88 \sphericalangle PIP$ that improves our results because the new formula has a slightly increased R^2 of 0.77 and lower standard deviation of 0.10.

For the thumb we assume the attachment of the sensor board for the saddle joint was more difficult and less tight compared to the others. We assume, however, that our results for the thumb are still more precise than former work on this topic due to the sensors being tightly attached to the upper two thumb joints. However we recommend a repeat of the study for the thumb with a slightly adjusted setup for the lowest thumb joint. A possible solution could be to stick the sensors directly onto the skin.

In general we were able to prove that neither the hand orientation or pose (Q1) nor the used hand (Q2) have an influence on the linear relationship between the two upper finger joint angles. This implies, that the results can be used for general-purpose and therefore allow for an improvement of the hand model.

5.1.2 Hand model improvement
We are able to eliminate the need for attached to the fingertips, by using the linear angular relationship between the two upper finger joints for the four fingers without the thumb. The relationship we found allows the amount of sensor-boards necessary for a full featured hand model to be reduced by 4, shown in Figure 8. This could have a high impact on usability, because, compared to data gloves and also to our initial setup, the fingertip would not be augmented at all and therefore the sense of touch would not be limited, something with implications for the usability of the interface in everyday life.

Again through considering biomechanics, it is possible to save additional 4-5 sensors. This is possible due to the single DOF for the two upper finger joints and the limited freedom of movement, shown in Figure 6.
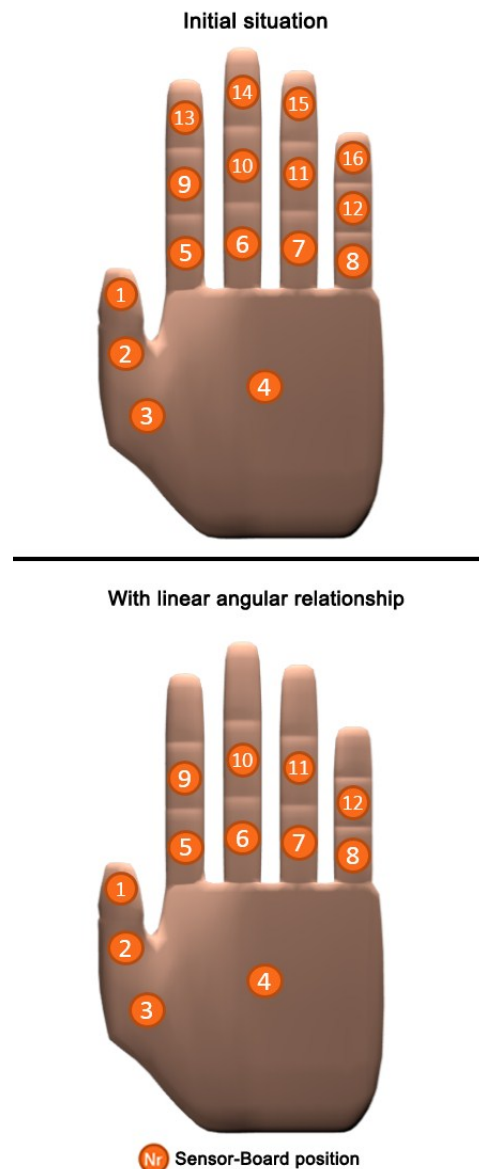

Figure 8. Possible reduction of necessary sensors for detecting a full featured hand model by the use of the linear angular relationship between DIP and PIP joints.

Therefore we are able to interpolate the state of the base joint from the orientation of an upper joint by using a carry from the upper joint to the base joint, when the upper joint has reached its movement bounds. For example if the PIP joint with one DOF allows a maximum flexion angle of 100°, but the measurement from the motion sensors gives a flexion angle of 130°, measured between the middle limb of the finger and the palm. The flexion out of the movement bounds of 30° can be carried to the finger base joint together with the information of the second DOF, which is not available at all on the PIP joint. This method of interpolation is illustrated in Figure 9 using the example of the index DIP and PIP joint.

This approach operates particularly well for the four fingers without the thumb, because it seems like the PIP joint is used more often in common conditions. But like all interpolation
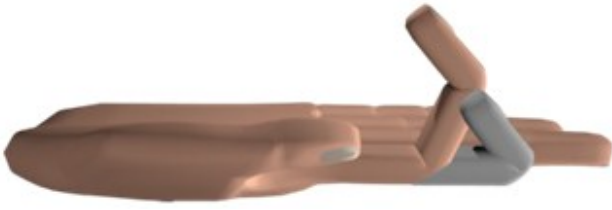
Figure 9. Example interpolation of PIP joint state by the use of a carry from the DIP joint

methods, this approach has a loss of precision, which leads to a somewhat unnatural looking finger motion for a dynamically generated hand model visualization. The reason is, that the single joints of the finger are moving in sequence and not like naturally observed at the same time. Indeed this approach still provides rather accurate information about continuous finger motion, which would only lack on gestures based on the relative joint relationship on single fingers.

Based on the linear angular relationship of the two upper joints and an interpolation of the base joint it is possible to use a sensor board setup like that shown in Figure 10. This setup gives suitable precision and still allows for a wide range of gestures even though as a result of the interpolation less accurate feedback is given, than that provided by the setup shown in Figure 8.

It is important to note, that we have kept all sensors on the thumb, although it would be possible to apply a sensor reduction based on presented results and methods. However, conditioned on the high importance of the thumb for gesture interaction, we recommend the shown configuration for a high precision hand model, until we complete further research on the thumb.

The presented hand model for wearable sensors allows for a precise and graded tracking of the human hand. Through the highly increased usability and the independence of environmental conditions this qualifies for everyday interaction.

5.1.3 Gestural design space

The gesture vocabulary that is covered by the related work is very limited: *Nenya* [Ashbrook 2011] recognizes finger ring rotation relative to the wrist as a 1D parameter. *GestureWatch* [Kim 2007] allows only for pointing whilst *GestureWrist* [Rekimoto 2001] allows for body-centric pointing with three hand configurations. *UbiFinger* [Tsukada 2002] allows for simple gestures, such as turning a volume knob or pushing a switch whilst pointing, *Body coupled FingeRing* [Fukomoto 1997] detects a tapping fingers or thumb and therefore has a gesture vocabulary of five binary finger states per hand, namely whether each finger is tapping or not. Data gloves are able to detect whole hand motion with all 26 DOF, but as we doubt that glove interfaces fulfill the usability requirements of everyday usage, we aim for augmenting the hand as little as possible. Fahn and Sun [Fahn 2005] were reducing the number of sensors to five and could provide ten DOF of the hand movability. The mentioned interfaces do not allow for recognizing a gesture vocabulary sets that considers complex hand and finger movements. But as shown in the *microgesture taxonomy* [Wolf 2011], the gestural design space that considers those finger movements that are ergonomically feasible is much more complex than those movements that the interfaces mentioned above could detect. Therefore a gestural interface that is able to detect gestures out of the continuous movements of the whole hand in 26 DOF

would be an important contribution to the field of ubiquitous gestural interaction.

In contrast to the related work our interface provides the motion data that is needed for recognizing 26 DOF and would therefore potentially allow for a complex gesture vocabulary, such as continuous and relative movements in detailed graduation, to be recognized. Our proposed interface provides rather accurate information about continuous finger motion, which only lacks gestures based on the relative joint relationship on single fingers but will still detect any hand movement that is part of the microgesture vocabulary proposed by Wolf *et al.* [Wolf 2011] and is actually able to detect whole hand movements of all 26 DOF [Vardy 1998] that are feasible. Therefore our proposed hand model (which considers biomechanics) could be used for providing motion data for gestural interactions in everyday life in manifold environments, like smart living, automotive, smart office and other mobile application.
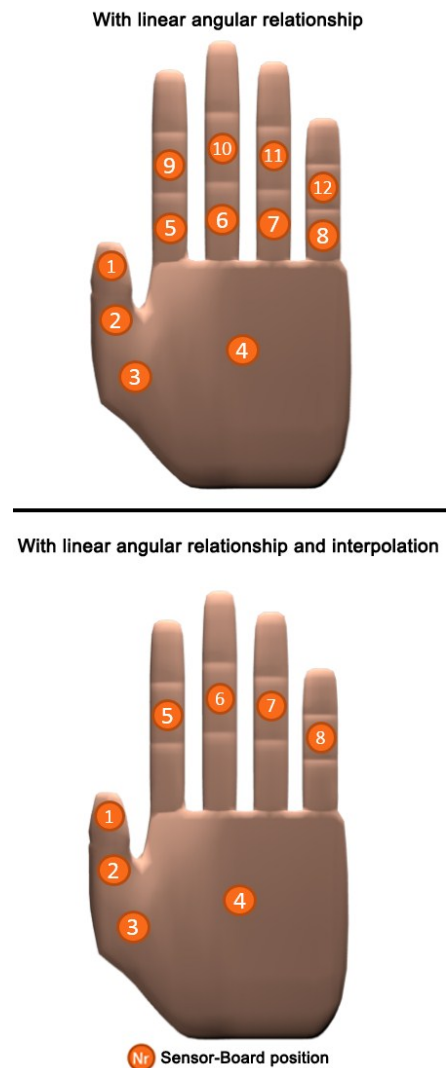

Figure 10. Possible reduction of necessary sensors for detecting a full featured hand model with reduced precision by the use of the linear angular relationship between DIP and PIP joints and interpolation with movement bound carry.

6. CONCLUSION

We presented a new approach for precise modeling of the whole hand with wearable motion sensors by applying anatomic relationships.

Our user study regarding the linear angular relationship between the two upper finger joints of all fingers showed new and more precise results than former work in this field. It points out a relationship of $\sphericalangle DIP = 0.88 \sphericalangle PIP$ for all four fingers and $\sphericalangle TDIP = 0.77 \sphericalangle TMCP$ for the thumb, which were different to our assumptions that refer to angular relationships defined by others. Moreover we were able to show, that our results are generalizable hence we proofed there is no dependence on the hand orientation (Q1) or used hand (Q2).

Based on the found linear angular relationship it is possible to reduce the number of sensors for a full featured hand model by four sensor-boards on the finger tips. This reduction avoids augmenting the fingertip, which leads to better tactile sensitivity in the fingertips and therefor a much better usability, especially in daily use. Moreover, a new approach for interpolation of the finger base joint by the use of movement bounds and carry calculation allows an additional sensor reduction of one sensor per finger. Thereby that makes possible to track the whole hand with all fingers with only 8 motion sensors. Thus the thumb is still fully attached with motion-sensors and we aim for few as possible sensors per finger, we aim to work on better sensor fixation for the lowest thumb sensor in future work. That would again reduce the amount of required sensors by two and allow for modeling the whole hand based on six sensor boards.

Our new developed hand model and motion sensor setup allows for hand and finger tracking with graduated and precise results to enable the recognition of a rich gesture set including continuous and relative movements of the whole hand independent of environmental conditions.

Although the used sensor-boards are already small enough to fit on an individual finger segment, a further reduction in size is necessary to integrate them in unobtrusive items like rings. Another question which has to be answered in the future is a small wireless energy supply for the finger attached sensors. Both would enable our vision of unobtrusive, wearable, ring shaped devices which can be used as input device in all smart environments in everyday life.

7. REFERENCES

[1] Ashbrook, D., Baudisch, P., White, S. 2011. Nenya: subtle and eyes-free mobile input with a magnetically-tracked finger ring. In *Proc. CHI 2011*, 2043-2046.

[2] Bailly, G., Müller, J., Rohs, M., Wigdor, D., Kratz, S. 2012. ShoeSense: A New Perspective on Hand Gestures and Wearable Applications**.** In *Proc. CHI 2012*, 1239-1248.

[3] Cobos, S., Ferre, M., Sánchez-Urán, M.A., Ortego, J. 2007. Constraints for Realistic Hand Manipulation. In *Proc. Presence 2007*, 369 – 370.

[4] Fahn, C.S., Sun, H. 2005. Development of a Data Glove with Reducing Sensors Based on Magnetic Induction. In *Proc. IEEE Vis. Image Signal Process 2005*, 501 – 512.

[5] Fahn, C.S., Sun, H. 2010. Development of a Fingertip Glove Equipped with Magnetic Tracking Sensors. In *Sensors 2010*, 1119-1140.

[6] Fukumoto, M. and Tonomura, Y. 1997. 'Body coupled FingeRing': wireless wearable keyboard. In Proc. *CHI 1997*, 147–154.

[7] Dipietro, L., Sabatini, A.M., Dario, P. 2008. A Survey of Glove-based Systems and Their Applications.*Trans. Sys. Man Cyber Part C* 38, 4, 461-482.

[8] Harrison, C., Ramamurthy, S., Hudson, S. E. 2012. On-Body Interaction: Armed and Dangerous. In Proc. *TEI 2012*, 69-76.

[9] Kim, J., He, J., Lyons, K., Starner, T. 2007. The gesture watch: A wireless contact-free gesture based wrist interface. *Wearable Computers,* 15-22.

[10] Kim, D., Hilliges, O., Izadi, S.,. Butler, A. D., Chen, J., Oikonomidis, I., and Olivier, P. 2012. Digits: freehand 3D interactions anywhere using a wrist-worn gloveless sensor. In *Proc. UIST 2012*, 167-176.

[11] Lin, John, Wu, Ying und Huang, T. S. 2000. Modeling the constraints of human hand motion.In: Proc. HUMO 2000, 121,

[12] Madgwick, S.O.H., Harrison, A.J.L., Vaidyanathan, A. 2011. Estimation of IMU and MARG orientation using a gradient descent algorithm. *IEEE International Conference Rehabil. Robot*, 1-7.

[13] Mahony, R., Hamel, T., Pflimlin, J.: Nonlinear J. 2008. Complementary Filters on the Special Orthogonal Group. *IEEE Transactions on Automatic Control, 1203-1218*.

[14] Nielson, M., Störring, M., Moeslund, T.B., Granum, E. 2003. A Procedure for Developing Intuitive and Ergonomic Gesture Interfaces for Man-Machine Interaction. *Technical Report CVMT 03-01, CVMT, Alborg University 2003*.

[15] Rekimoto, J. 2001. GestureWrist and GesturePad: Unobtrusive Wearable Interaction Devices. In *Proc. Wearable Computers*, 21-27.

[16] Spalteholz, W. 1861. Hand-atlas of human anatomy.

[17] Tsukada, K., Yasumura, M. 2002. Ubi-Finger: Gesture Input Device for Mobile Use. In *Proc. APCHI 2002*, 388-400.

[18] Vardy, A. 1998. Articulated Human Hand Model with Inter-Joint Dependency Constraints. *Computer Science 6752, Computer Graphics, Project Report,* 1-13.

[19] Wilson, A. and Benko, H. 2010. Combining Multiple Depth Cameras and Projectors for Interactions On, Above and Between Surfaces. In *Proc. UIST 2010*, 273-282.

[20] Wolf, K., Naumann, A., Rohs, M., Müller, J. 2011. Taxonomy of microinteractions: defining microgestures based on ergonomic and scenario-dependent requirements. In *Proc. INTERACT 2011*, 559-575.

[21] Wu, Y., Huang, T.S. 1999. Capturing Human Hand Motion: A Divice-and-Conquer Approach. In *Proc. IEEE Int'l Conf. Computer Vision*, 606-611.

[22] Yang, X.D, Grossman, T., Wigdor, D. and Fitzmaurice, G. 2012. Magic Finger: Always-Available Input through Finger Instrumentation.*In Proc. UIST 2012*, 147 – 156.