Ubiquitous Human Motion Capture using Wearable Micro-sensors

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I. Introduction

Motion capture serves as core technology in a wide spectrum of applications, such as interactive digital media (games, mixed reality, interactive learning, animation and film special effects), medical care and rehabilitation, athletic training, and navigation. It has attracted lots of research interests in the last two decades. The existing human motion capture techniques are mainly based on optical system, which are are extremely expensive and lack of portability; furthermore, it is a big challenge to capture human motion in real time because of a huge amount of data to be processed.

With the rapid advances of micro-inertial sensors, human motion capture using micro-inertial sensors (mainly accelerometers and gyroscopes) has attracted a lot of interests. Unfortunately, inertial sensors are always subject to drift problem. To overcome this problem, magnetic sensors [1] or ultrasonic sensors [2] are employed to provide compensative information, but they may be interfered by the environment. In this extended abstract, we present our work in progress on human body motion capture using only wearable mirco-inertial sensors without any other compensative sensors. Firstly, a novel error model for inertial sensors is given to deal with sensor drift. It can represent the slowly varying bias error of inertial sensors adequately; Secondly, for any two body segments connected by a joint, they move together and constrain each other by the muscle and anatomical constraints. Given all the body segments are connected by joints, the motion parameters of body segments should be constrained to each other. We propose to extend current Dynamic Bayesian Network (DBN) definition and add undirected sub-graph to DBN, called Extended Dynamic Bayesian Network (EDBN), to model the constraints; thirdly, there are huge uncertainties of body segments' movement, including movement models, process noise and measurement noise. Any body segment can maneuver or keep still, so it is impossible to use only one model to represent body segment behaviors. Furthermore, different segments should behave differently. Here we propose to use multiple models to describe the behaviors of each body segment and incorporate the multiple models in the framework of EDBN.

II. Methods

A. Drift Modeling

Wearable micro-inertial sensor are very cheap, and suffer from low-frequency bias. The time variation of the bias is attributed to thermal effects based on that the device gradually heats up during operation. The bias can taper off to a negative or positive value depending on the ambient temperature. To develop an error model for the inertial sensors, their output are recorded over long periods of time when subjected to zero input. We found that the mean value gradually increases with time in an exponential fashion. We propose to use the following drift model: $\varepsilon_m(t) = C_1 e^{t/T} - C_2$, where C_1, C_2 and T for tunable parameters. For any inertial sensor, C_1, C_2 and T have different values.

The residuals δ are defined as the differences between he fitted model and original readings. We found that the distribution of δ is approximate Gaussian in a long period, and the energy of auto-correlation function $R(\tau)$ of δ concentrate around zero; consequently, the residuals can be well approximated by a white, zero-mean gaussian process, and the model is adequate to fit the experimental data.

The differential $\dot{\varepsilon}_m(t)$ equals $\varepsilon_m(t)$ plus a control variable, so it can be discretized using the backward difference method. After that, sensor errors are augmented as state variables, and estimated in the Extended Dynamic Bayesian Network.

B. Extended Dynamic Bayesian Network

The body motion structure can be well represented by a Dynamic Bayesian network (DBN), which is an ideal mathematical framework for human body motion capture and analysis [3]. Since any body segment can not move independently, motion parameters for a body segment should impact on other body segment motion parameters. Given that there are many segments with a human body and many motion parameters to be estimated simultaneously, those parameters should be constrained with each other. Existing DBN is directed graph and cannot represent a mutual relationship, so extension of Dynamic Bayesian Network (DBN) is a necessity. Here we propose to add undirected sub-graph to DBN, called Extended Dynamic Bayesian Network (EDBN), to model the constraints. The constraints are then modeled by a simple Markove Field.

Another big challenge for human motion capture is that the movements of human body segments are with huge uncertainties. Any body segment can maneuver and keep still, so we propose to use multiple models to describe the behaviors of body segments and incorporate the multiple models in the framework of EDBN, as shown in figure 1. In the figure, only upper limb motion estimation is presented for simplicity. This network can be easily extended to whole body motion

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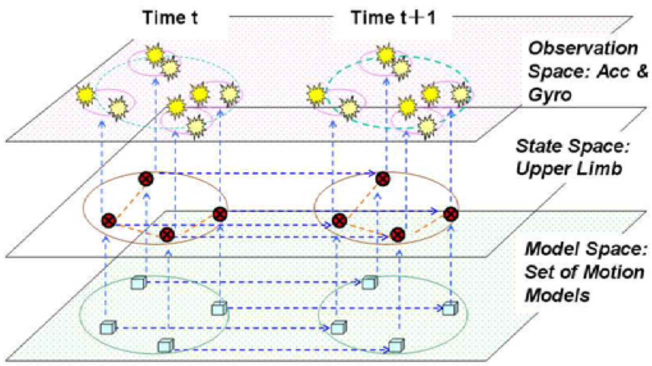

Fig. 1. Extended Dynamic Bayesian Networks representation for upper limb motion estimation. Here we only take should, upper arm, forearm and hand into consideration; consequently, there are four nodes at state space, and each node represents one segment. According to human skeleton structure of a upper limb, the four nodes are connected by undirected arcs.

estimation by adding some nodes at state space and model spaces. The undirected arcs are decided by the skeleton structure.

III. Preliminary Results

In the current stage, we have applied the proposed method to estimate human upper-arm and forearm motion. A subject is asked to do the following task: the upper limb moves inward to the body together, forearm moves upward while the upper arm keeps still, and then reverse the movements to recover the initial posture. The entire action is repeated three times. Figure 2 clearly shows the human upper limb motion capture result of one trip of the movements. As we can see from the figures, the 3D human motion animation moves simultaneously with that of the subject. The sequence of movements include screwing of forearm, which is nearly impossible to estimate with a single optical sensor. As we can see from the figure, our proposed system can estimate the screwing accurately. The prototypical system has been tested extensively by various movements of upper arm, by comparing the reconstructed 3D avatar with the video of the real arm movements, it shows that our proposed upper limb motion capture algorithm works well with reasonable motion estimation accuracy.

Figure 3 shows the comparative results of reconstructed human upper limb. After the entire action repeated three time, the upper limb recovers the initial posture. Figure 3(a) indicates the result without constraint, while Figure 3(b) shows the results with the constraints. It is clear that the results the constraint is not reasonable. The constraint can makes the estimation more reasonable.

IV. Conclusions

We have presented our work in progress on Human Body Motion Capture using wearable mirco-inertial sensors only. Novel drift model are proposed to deal with inherent bias problem of inertial sensors, and Extended Dynamic Bayesian Network (EDBN) are employed to model the constraints among human body segments. Given the uncertainties of human movements, multiple models are proposed to describe the behaviors of each body segment in the EDBN. The future work will be on consummating our current work. More comprehensive experiments will be further studied to evaluate our proposed method.

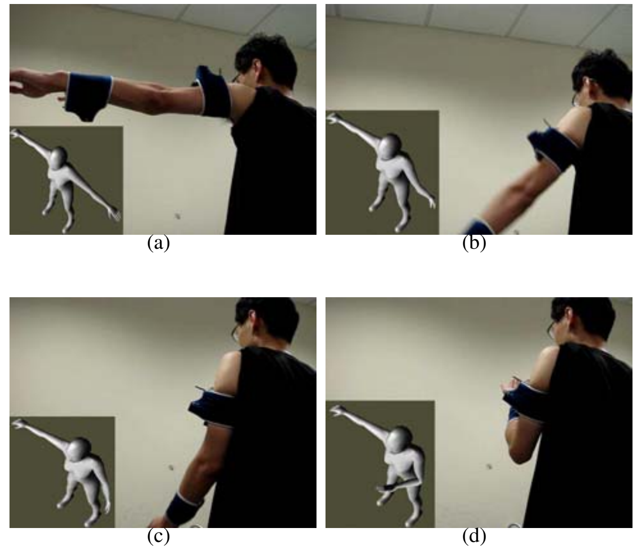

Fig. 2. The upper limb motion capture results

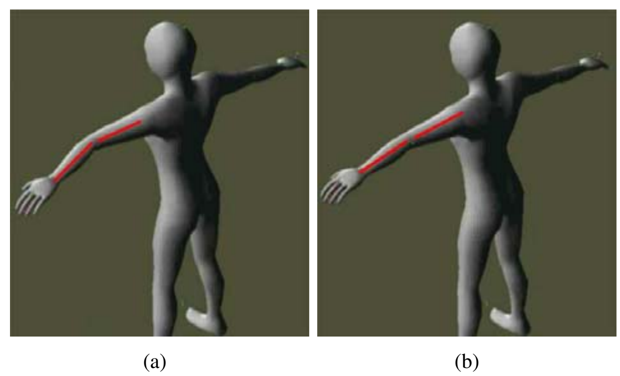

Fig. 3. The comparative results of reconstructed upper limb

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References

[1] X. Yun and E. Bachmann. "Design, Implementation, and Experimental Results of a Quaternion-Based Kalman Filter for Human Body Motion Tracking". *Robotics and Automation, IEEE Transactions on*, 22(6):1216–1227, 2006.
[2] D. Vlasic, R. Adelsberger, G. Vannucci etc. "Practical motion capture in everyday surroundings". *ACM Transactions on Graphics (TOG)*, 26(3), 2007.
[3] Murphy, K.P. "Dynamic Bayesian Networks: Representation, Inference and Learning". *PhD thesis, UC Berkeley*, 2002.