Towards Recognizing Tai Chi – An Initial Experiment Using Wearable Sensors

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Abstract. Inexpensive wearable sensors are well-suited for the automatic recognition of many activities occuring in everyday life. But what about fast and involved movements such as those occuring in athletic sports? We tackle this question by studying the feasibility of using body-worn gyroscopes and acceleration sensors to recognize Tai Chi movements. To this end, we conducted an initial experiment with eight sensors each affixed to four different persons who repeatedly performed three distinct Tai Chi movements. The resulting data confirm that standard thresholding and pattern-matching techniques should suffice to automate the analysis and recognition of the movements. Moreover, the data also seem to allow for distinguishing between certain levels of expertise and quality in executing the movements.

1 Introduction

Video analysis and motion capturing are standard tools in professional sports to monitor and improve athletic performance by fine-tuning the quality of movement. Cutting-edge systems with high-quality sensors hardly suffice to fulfill these professionals' needs. Quite often, trainers and other experts still process the recorded data by hand. The whole setup and procedure are not only expensive and time-consuming but also error-prone in the sense that the effectiveness of the analysis depends on the humans doing it. Hence, the large-scale use of similar analyses for the masses (i.e., hobbyists and spare-time practitioners) requires a different approach.

We envision to employ inexpensive wearable sensors to achieve this, preferably tiny gyroscopes and accelerometers worn by people on their bodies (e.g., integrated into their clothes). Such body-mounted sensors provide a cheap alternative for motion capture while letting users move and roam about freely independent of any additional infrastructure. This opens up a wide range of potential applications in rehabilitation, advanced consumer sports equipment, and emergency services such as fire brigades. Whether the above applications can actually be implemented depends on the ability of data processing algorithms to compensate for inaccuracies inherent in inexpensive wearable sensor system. The inaccuracies result from the limited resolution and sampling rate of the sensors, variations in sensor placement, dynamic sensor displacement during user motion, and other sources of noise (e.g., environmental magnetic fields or temperature-related sensor drift). The challenge in algorithmic design is to find features that are sensitive to the relevant motion characteristics and at the same time insensitive to the inaccuracies mentioned before.

As an initial investigation towards such processing algorithms for athletic sports, we conducted an experiment described in Section 3 capturing Tai Chi movements with wearable gyroscopes and acceleration sensors to test the feasibility of our vision. Section 4 discusses and analyzes the experimental results, proving to be very promising indeed. Based thereon, it certainly seems worthwhile trying to automate at least some parts (if not all) of an expert analysis for Tai Chi movements.

Tai Chi is of special interest because clinical studies show it helps to reduce the probability of falling, especially for the elderly [10] and patients with chronic conditions [2]. Furthermore, even experts find it hard to quantify and judge the quality of Tai Chi performances.

2 Related Work

By now, many independent researchers have demonstrated the suitability and excellent further potential of body-worn sensors for automatic context and activity recognition, e.g., [1,3,6,8,11,12]. The available scientific literature reports about successful applications of such sensors to various types of activities, ranging from the analysis of simple modes of locomotion [11] to more complex tasks of everyday life [1] and even workshop assembly [7].

We do not know of any scientific publications about computer aid and support specifically for Tai Chi. For similar fields of martial arts in general and Kung Fu in particular, some interesting related research even seems to be currently ongoing. In [4], wearable pressure sensors integrated into body protectors help to control and decide the counting of points for Taekwando. Supposedly helping children with their Kung Fu education, [9] introduces some kind of computerized toy ball. Focusing on Kung Fu, [5] presents a video capturing system for artificial and augmented reality games of martial arts. The work emphasizes the specific gaming aspects of the application and suffers from the usual drawbacks of video-based approaches, i.e., high sensitivity for lighting conditions and demanding requirements on equipment and infrastructure.

3 Experimental Setup

Our initial Tai Chi experiment featured four different persons as test subjects (see Section 3.4) and three kinds of basic Tai Chi movements as test actions

Fig. 1. Test subjects wearing wired sensor boxes while performing

(see Section 3.3). For every subject, we recorded five distinct performances of each movement resulting in 15 data sets per subject and 60 data sets overall for the whole experiment. The sensor data stem from eight wearable boxes (see Section 3.1) affixed to the test subjects' arms, legs, feet, hip, and neck (see Figure 1 and Section 3.2).

3.1 Hardware Details

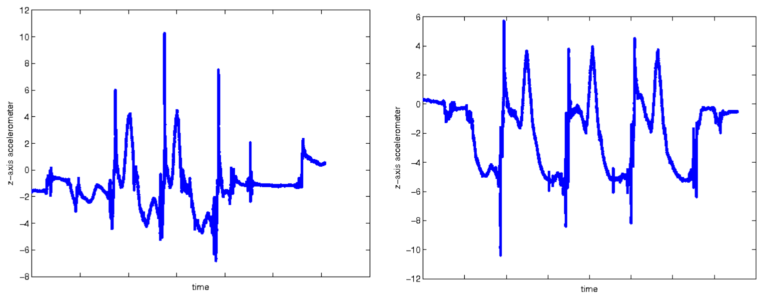
We used the *XBus Master System (XM-B)* manufactured by XSens (`http://www.xsens.com/`) as the global sensor control, wired by cable to eight boxed *MT9 sensors*. Each such MT9 houses a 3-axis accelerometer, a 3-axis gyroscope, and a 2-axis magnetometer (not used by us). To directly collect the complete sensor data on some permanent external storage, we linked an *oqo* mobile computer (`http://oqo.com/`) to the XBus master unit via a wireless Bluetooth connection streaming the captured data in real time.

3.2 Sensor Placement

We discussed good locations for placing the sensors with a Tai Chi expert and finally decided on the following (one MT9 each):

- right and left upper arm (ca. 2 cm over the ankle),
- right and left lower leg (directly above feet),
- right and left knee (directly above knee cap),
- neck (on shoulder height), and
- rear hip (on backbone origin).

All MT9 sensor boxes were oriented with their cables pointing skywards when the test subjects stood still and relaxed. Then, the x-axes of the acceleration sensors pointed down towards the ground while their y- and z-axes pointed horizontally. The XBus master unit is also affixed at the hip. To strap and keep everything tight in place, we use flexible bands which work very well here according to our experience.



(a) amateur (b) expert

Fig. 2. Data from the z-axis of the accelerometer attached at the left foot.

3.3 Tai Chi Movements

The basic forward and backward movements of the first form of Tai Chi served as the test actions for our experiment. The English translations of the names of these three movements read as follows.

1. Parting the Horses Mane
2. Brush Knee Step Forward
3. Repulse the Monkey

3.4 Test Subjects

Two of the four test subjects participating in the experiment are reputable Tai Chi experts and instructors actually teaching the art. The other two are amateurs with roughly equal levels of limited experience and skills in Tai Chi. Of the two amateurs, one has some background in professional dancing that the other lacks.

4 Experimental Results

Subsequently, we discuss our initial analysis of the data gathered by the experiments outlined in the previous section.

Inspecting the accelerometer and gyroscope data, it shows that the peaks in the signal of the experts have approximately the same length and over the five measurements the signal is smoother and more periodical than in the amateur's data. An example for this is depicted in Figure 2. Figure 2 shows the z-axis accelerometer data of the left foot sensor for amateur and expert during one measurement of the 'Parting the Horses Mane' movement. Especially, the mentioned periodicity appears to be easy recognizable using signal processing or machine learning techniques. Also, the number of events where the absolute sum of the foot gyroscopes is smaller than 0.1 (close to zero) is much less with the experts than the amateurs. This could be a hint for pauses and choppy movement. The neck and hip movements are much faster with the experts.

One of the principles of Tai Chi is that the total consumed energy is supposed to be as small as possible. Therefore, we calculated the squared angular velocity,

Subject	squared angular velocity	standard deviation
expert	794	41
amatuer 1	836	35
amateur 2	1130	100

Table 1. The squared angular velocity (in $(\text{rand/s})^2$) and its respective standard deviation calculated from the gyroscope sensors on the hip

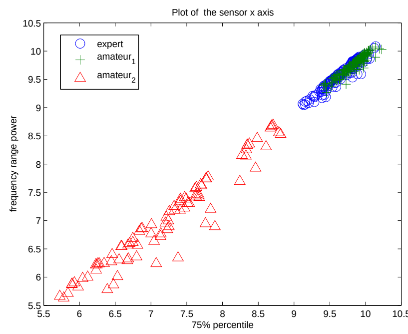


Fig. 3. 75% percentile plotted against the frequency range power from the neck accelerometer x-axis

w^2 in $(\text{rad/s})^2$, as indication for the rotational energy, defined by $E_{rotational} = \frac{1}{2}Iw^2$. As Table 1 neatly underlines this principle of Tai Chi using the data we gathered. The expert has the least rotational energy consumption, followed by the amateur that has experience in dance and finally the other amateur. Yet, one needs to gather more data of a more diverse population to see if this effect is not simply an artifact.

For further analysis, we used a 100 sample sliding window over the data and calculated around 20 features. As depicted in Figure 3, two of these features, the 75% percentile and the frequency range power of the accelerometer x-axis at the neck , are plotted against each other. It is easy to recognize that these features seem to separate the second amateur from the expert and the first amateur. Training a K-nearest-neighbour (KNN) clustering algorithm with these two features, results in a 76 % correctly classified instances using 10 fold cross validation, see Table 2. Using those two features and the root-mean squared (RMS) to train another KNN to classify two different Tai Chi movements leads to 85% correctly classified instances using a 10 fold cross validation (see Table 2. Yet, the later classification is test subject dependent. The results seem to be promising. Yet, to be sure that the features and relationships discovered are no artifacts, we will need to conduct more experiments.

5 Conclusion and Future Work

As the manual analysis of the data showed, there is some evidence that an automated evaluation of Thai Chi can work. Therefore, our preliminary results

a	b	c	← classified as
93	55	0	a = expert
42	127	0	b = amateur 1
0	0	88	c = amateur 2

a	b	← classified as
735	165	a =Parting the Horses Mane
150	950	b = Repulse the Monkey

Table 2. Confusion Matrices for the two KNN classifications (respective 76% and 85% of samples corretly classified)

look promising. It is also possible to generate automated, meaningful classifications from a very small subset of the data, as seen in Table 2. We will continue to conduct more experimental trials with diverse Tai Chi practitioners, expert, intermediary and amateur, to get a statistically representative data set.

References

1. L. Bao and S.S. Intille. Activity recognition from user-annotated acceleration data. In F. Mattern, editor, *Pervasive Computing*, 2004.
2. Wang C., Collet J., and Lau J. The effect of tai chi on health outcomes in patients with chronic conditions: a systematic review. *Arch Intern Med.*, 1:188–189, 2004.
3. Ozan Cakmakci, Joelle Coutaz, Kristof Van Laerhoven, and Hans-Werner Gellersen. Context awareness in systems with limited resources.
4. Ed H. Chi, Jin Song, and Greg Corbin. "killer app" of wearable computing: wireless force sensing body protectors for martial arts. In *UIST '04: Proceedings of the 17th annual ACM symposium on User interface software and technology*, pages 277–285, New York, NY, USA, 2004. ACM Press.
5. Perttu Haemaelaeinen, Tommi Ilmonen, Johanna HoeysniemI, Mikko Lindholm, and Ari Nykaenen. Martial arts in artificial reality. In *CHI '05: Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 781–790, New York, NY, USA, 2005. ACM Press.
6. N. Kern, B. Schiele, H. Junker, P. Lukowicz, and G. Tr̈oster. Wearable sensing to annotate meeting recordings. In *Proceedings Sixth International Symposium on Wearable Computers ISWC 2002*, 2002.
7. P. Lukowicz, J. Ward, H. Junker, M. Staeger, G. Troester, A. Atrash, and S. Starner. Recognizing workshop activity using body worn microphones and accelerometers. In *Pervasive Computing*, 2004.
8. J. Mantyjarvi, J. Himberg, and T. Seppanen. Recognizing human motion with multiple acceleration sensors. In *2001 IEEE International Conference on Systems, Man and Cybernetics*, volume 3494, pages 747–752, 2001.
9. Heberlein Markus, Hayashi Takafumi, Nashold Sarah, and Teeravarunyou Sakol. In *CHI '03: CHI '03 extended abstracts on Human factors in computing systems*, New York, NY, USA.
10. Wolf S., Sattin R., and Kutner M. Intense t'ai chi exercise training and fall occurrences in older, transitionally frail adults: a randomized, controlled trial. *J Am Geriatr Soc.*, 1:188–189, 2003.
11. L. Seon-Woo and K. Mase. Recognition of walking behaviors for pedestrian navigation. In *Proceedings of the 2001 IEEE International Conference on Control Applications (CCA'01) (Cat*, pages 1152–1155, 2001.
12. P. H. Veltink, H. B. J. Bussmann, W. de Vries, W. L. J. Martens, and R. C. Van-Lummel. Detection of static and dynamic activities using uniaxial accelerometers. *IEEE Transactions on Rehabilitation Engineering*, 4(4):375–385, Dec. 1996.