Using Wearable Sensors for Real-time Recognition Tasks in Games of Martial Arts – An Initial Experiment

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***Abstract*— Beside their stunning graphics, modern entertainment systems feature ever-higher levels of immersive user-interaction. Today, this is mostly achieved by virtual (VR) and augmented reality (AR) setups. On top of these, we envision to add ambient intelligence and context awareness to gaming applications in general and games of martial arts in particular. To this end, we conducted an initial experiment with inexpensive body-worn gyroscopes and acceleration sensors for the Chum Kiu motion sequence in Wing Chun (a popular form of Kung Fu). The resulting data confirm the feasibility of our vision. Fine-tuned adaptations of various thresholding and pattern-matching techniques known from the fields of computational intelligence and signal processing should suffice to automate the analysis and recognition of important Wing Chun movements in real time. Moreover, the data also seem to allow for the possibility of automatically distinguishing between certain levels of expertise and quality in executing the movements.**

Keywords: Body-worn Sensors, Experiment, Games of Martial Arts, Kung Fu, Motion Analysis, Movement Recognition, Wearable Computing, Wing Chun

I. Introduction

Video analysis and motion capturing are standard tools in professional sports to monitor and improve athletic performance by recognizing and 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 hobbyist and gaming masses requires a completely different approach. In particular, as we like to increase the immersiveness of the user experience and interaction in video games of martial arts where people's real-world physical actions directly need to directly affect their playing reality.

We envision to employ inexpensive wearable sensors to achieve this – preferably tiny gyroscopes and accelerometers worn by people on their bodies integrated into their clothes and other personal accessories (e.g., watches or jewelery). Such body-mounted sensors provide an inexpensive alternative for motion analysis while letting users move and roam about freely, independent of any additional infrastructure. As decribed in Section III, we conducted an initial experiment capturing Wing Chun movements with wearable gyroscopes and acceleration sensors to test the feasibility of our vision. Section IV discusses and analyzes the experimental results, proving to be very promising indeed. Based thereon, it certainly seems worthwhile to continue in this direction and try to automate at least some parts (if not all) of an expert analysis for many important Wing Chun movements.

Beside in sports and game play, martial arts from the Far East gain ever more popularity and importance in many other areas as well. Tai Chi, for instance, is of special interest because clinical studies show that it helps to reduce the probability of falling, especially for the elderly [1] and patients with chronic conditions [2].

II. 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., [3], [4], [5], [6], [7], [8], [9], [11]. 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 [5] to more complex tasks of everyday life [4] and even workshop assembly [10].

There are much fewer publications, however, about using wearable sensors in martial arts. In [12], 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, [13] introduces some kind of interactive computerized toy ball. Focusing on Kung Fu, [14] 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. Other video-based capture and processing systems for augmented virtual reality gaming and training are presented in [15] and [16]. The latter introduces a wireless virtual reality system and some prototype Tai Chi training application on top of it. Yet, the system features only limited usability and very restricted degrees of freedom for the user. Moreover, it does not evaluate full motion but just stances instead.

III. EXPERIMENTAL SETUP

Our initial Wing Chun experiment featured the Chum Kiu motion sequence as test action (see Section III-C) and two different persons as test subjects (see Section III-D). For every subject, we recorded and video-taped five distinct performances of the motion sequence overall. The sensor data stem from eight wearable boxes (see Section III-A) affixed to the test subjects' rear hip, neck, wrists, knees, and lower legs directly above their feet (see Fig. 1 and Section III-B).

Fig. 1. Test subjects wearing the wired sensor boxes while performing (expert on top, amateur below)

A. Hardware Details

We used the XBus Master System (XM-B) manufactured by XSens (`http://www.xsens.com/`) as the global sensor control. We wired the XBus master unit by physical cable to eight boxed MT9 sensors. Each such MT9 box houses a 3-axis accelerometer, a 3-axis gyroscope, a 2-axis magnetometer, and a temperature sensor. Up to now, however, we did not use the final two thereof. 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 – thus streaming the captured data in real time.

B. Sensor Placement

We discussed suitable locations for placing the sensors with the Wing Chun expert and finally decided on the following setup with one MT9 box each at the:

- right and left wrist,
- 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 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. Hence, the x-axes of the accelerometers on the wrists always pointed towards the hands and the x-axes of the accelerometers on the lower legs always pointed towards the feet.

We also affixed the XBus master unit at the hip, but on the right side of it (see Fig. 1). To strap and keep everything tight in place, we used flexible bands that work very well in such settings according to our experience [7], [8], [10].

C. Chum Kiu Motion Sequence

The Chum Kiu motion sequence contains a multitude of basic Wing Chun movements (forward and backward) including side steps, full-body turns, arm and leg blows, and more involved motion combinations. It is a standardized form of motion training for Wing Chun. Literally, Chum Kiu means "casting / seeking a bridge" to the opponent. While doing so, you should try to adhere to your so-called central line of action. The full Chum Kiu motion sequence takes about two minutes to perform. In our experiment, completion times varied from one-and-a-half to almost three minutes.

D. Test Subjects

Both test subjects participating in the experiment are co-authors of this text. The Wing Chun expert, Matthias Gruber, is a long-time practitioner and enthusiast of the art. Kai Kunze, on the other hand, is a Wing Chun amateur with limited experience of roughly two-and-a-half years of training overall spanning several years on and off. But you must not mistake him for an absolute beginner, of course.

IV. EXPERIMENTAL RESULTS

As described in Section IV-A, the raw z-axis signals of the gyroscopes at the necks seem to suffice for counting and recognizing at least some turns. For the rest of the analyses, we applied 20 different features to the raw signal data, including absolute value, frequency entropy, frequence range power, median, mean, 75%-percentile, standard deviation, variance, and others over the accelerometer and gyroscope data for each axis and for the absolute sum using a 100-sample sliding window.

A. Raw z-Axis Signals of Gyroscopes at Neck

Fig. 2 shows the expert (top) and amateur (below) perform three special turns in one direction, followed by another three in the opposite direction. The graphs on the right visualize the respective raw z-axis signals for one particular performance of the turns by each test subject as recorded by the gyroscopes mounted on their necks. The difference in appearance of these graphs is quite stunning. Whereas the

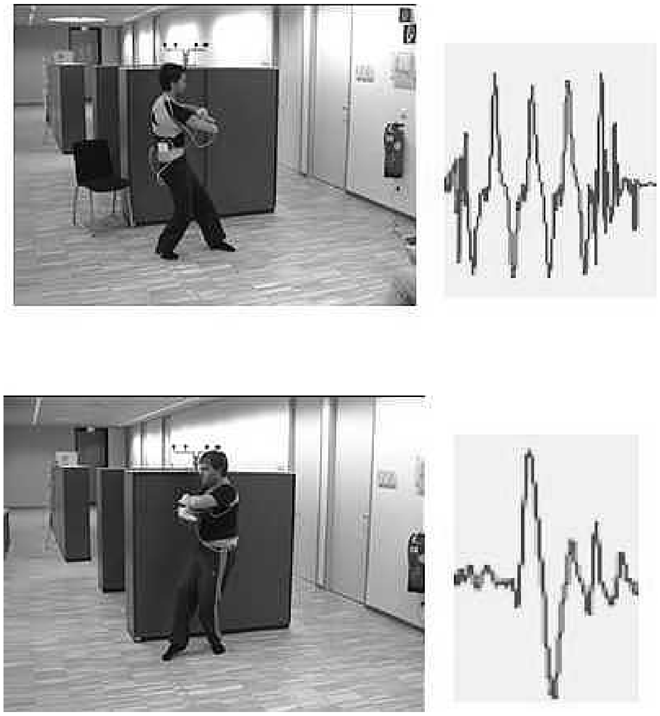

Fig. 2. Sequence of six (2 x 3) special turns, graphs show raw z-axis signals of gyroscopes at neck (expert on top, amateur below)

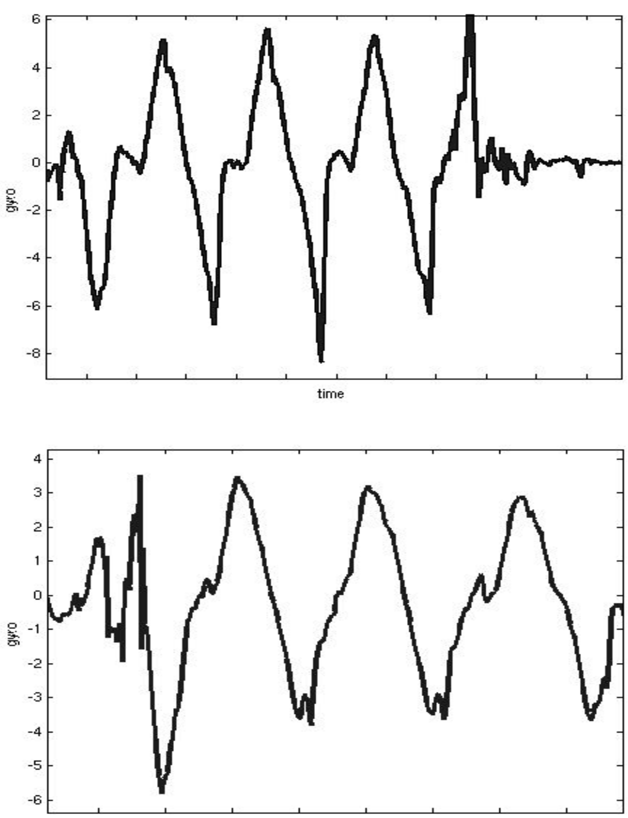

Fig. 3. Raw z-axis signals of gyroscopes at neck when first turning left (on top, expert) vs. first turning right (below, amateur)

expert's signal shows clear and regular peaks and troughs of compellingly steady height, the amateur's signal almost completely lacks these characteristics featuring fewer irregular peaks and troughs of rather diminishing height. Taking the regularity of the expert's peak signals over time, width, and height into account, the distinction between badly, fairly, and really well executed turns should not be too hard. With appropriate thresholding and sliding windows, the real-time counting and recognition of such turns also proves feasible in general. Fig. 3, for instance, presents two graphs showing the raw z-axis signals for sequences of turns starting in different directions (expert on top begins with a left turn, while the amateur below starts with a right turn). Here, the sign of the z-axis signal easily identifies the direction of the turn.

B. Freq. Range Power of Accelerometers at Lower Left Leg

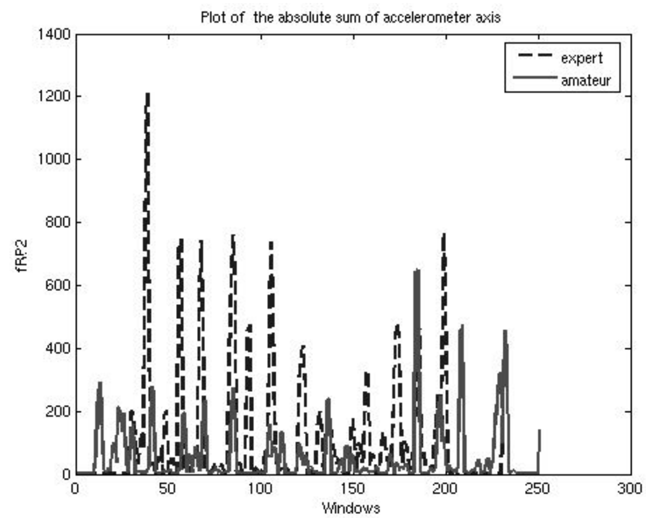

Fig. 4. Frequency range power (FRP) of absolute sum of signals from all three axes over different sampling windows for accelerometers at lower left leg (expert's peaks much higher than the amateur's ones)

An important characteristic for many blows and other movements in martial arts is the speed, or more excatly, the explosiveness of execution. A typical feature known to bear the potential of achieving good results in the context of motion explosiveness runs by the name *frequency range power (FRP)*. It computes the power of the discrete Fast Fourier Transform (FFT) components for a given frequency band. Thus, the frequency range power may serve as some kind of measure for the explosiveness or impulsiveness of movements and their specific execution.

Fig. 4 illustrates that FRP delivers as hoped for in Wing Chun, too. The graph plots the FRP values of the absolute signal sums from all three axes over different sampling windows for the accelerometers worn by the test subjects at their lower left legs. The expert's peak FRP values are clearly much larger than the amateur's according ones for most sampling windows. Here, again, appropriate thresholding and sliding windows should suffice to recognize different kinds of movements and qualities of motion execution.

C. Frequency Range Power of Remaining Accelerometers

The FRP graphs of the remaining acceleration sensors look very similar to that of the accelerometer at the lower left leg (see Fig. 4). In order to avoid almost identical repetitions, we refrain from including the other FRP plots with this text. Please note, however, that the explosiveness of movements and their execution is equally visible for all the other accelerometers as well. Direct comparisons of the FRP plots for corresponding left / right accelerometers from the same performer may actually hint at some preferred or better trained body half for the particular person. This in turn provides valuable information for future exercise and possible improvements.

D. Other Promising but More Complex Features

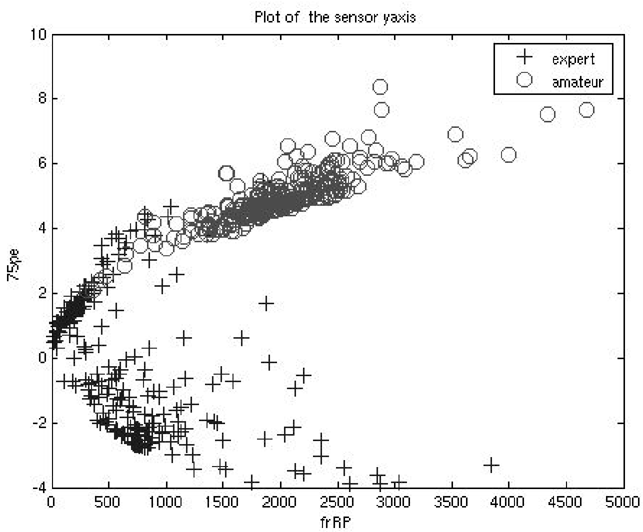

Fig. 5. 75% percentile vs. full FRP of absolute signal from y-axis of accelerometers at neck (expert's values cluster on lower left, amateur's values cluster on upper middle)

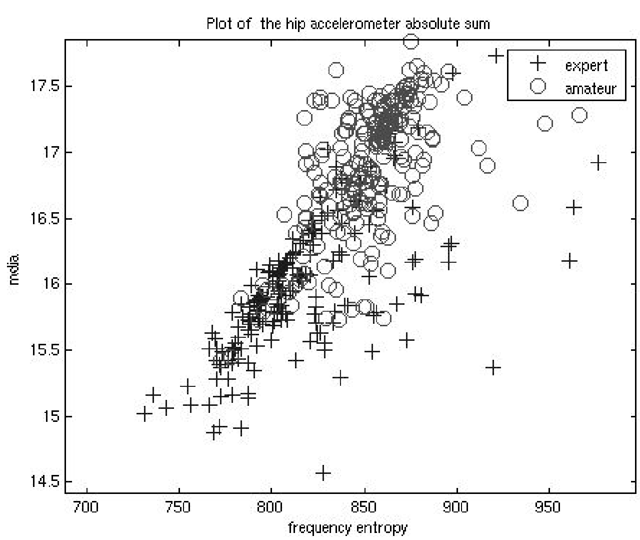

Fig. 6. Median vs. frequency entropy (FRE) of absolute signal sums from all three axes of accelerometers at hip (expert's values cluster around diagonal bar, amateur's values show high divergence instead)

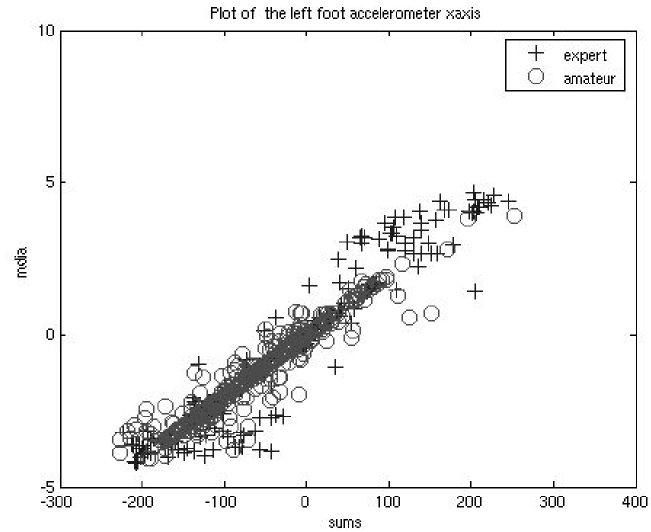

Fig. 7. Median vs. absolute signal sum from x-axis of accelerometers at lower left leg (amateur's values cluster on diagonal bar, experts's values show divergence instead)

The *frequency entropy (FRE)* is defined as $H_{freq} = -\sum p(X_i) * log_2(p(X_i))$ where X_i are the frequency components of the windowed time-domain signal for a given frequency band and $p(X_i)$ the probability of X_i. The frequency entropy is the normalized information entropy of the discrete FFT component magnitudes for the windowed time-domain signal. Thus, it is a measure of the distribution of the frequency components in the given frequency bands.

The three combinations of complex features visualized in Figs. 5 to 7 all exhibit promising cluster structures. We verified the promise by quick, successful classification trials with three powerful machine-learning algorithms, namely C4.5, KNN, and naive Bayes.

V. Conclusion and Future Work

The initial experimental results discussed in Section IV look extremely promising. Our manual analyses of the captured data identify several different features and ways of calculation to apply to the raw sensor signals in order to automate the recognition of important Wing Chun movements. Of course, we still need to adapt and fine-tune the respective general thresholding and pattern-matching techniques to achieve acceptable real-time performance.

This requires us to feed much more input data to machine learning algorithms among other things. Hence, we continue to conduct further experimental sessions with additional Wing Chun motion sequences (e.g., Biu Tse and Siu Nim Tau) and other test subjects of different skill levels (e.g., intermediary). At the same time as aiming towards a statistically representative data set and model inferred from it, we also hope to be able to identify even better novel features for the recognition tasks at hand. The automatic distinction between certain levels of expertise and quality in executing the Wing Chun movements readily deserves our special interest in this respect. For, once possible, it opens up a whole new realm of applications based on fully automated and computerized, interactive Wing Chun training functionality. Immersive games, for instance, could exploit the functionality for special training modes and for adapting the skill levels of computer-guided opponents to match the human players.

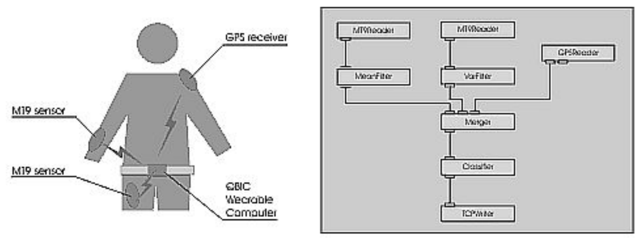

Fig. 8. Software toolbox to ease the usage of wearable sensors for complex context recognition tasks on heterogenous systems (including mobile platforms)

Last but not least, our envisioned real-time motion analysis and movement recognition for Wing Chun needs to be implemented and integrated into suitable gaming applications. To attract interest therein and decrease the required effort to really do so, we developed a freely available software toolbox easing the usage of wearable sensors on heterogenous systems [17]. We invite everybody to try and download the current version from our server at `http://csn.umit.at/download/toolbox/`. Just to wet your appetite a bit, we like to briefly summarize the main advantages and features of our sensor toolbox (see `http://csn.umit.at/research/toolbox/` for more details). The toolbox is GUI-based (see Fig. 8) enabling users to quickly build distributed, multi-modal context recognition systems by simply plugging together reusable, parameterizable components. Thus, the toolbox simplifies the steps from prototypes to final implementations that might have to fulfill real-time constraints on low-power mobile devices. Moreover, it facilitates portability between platforms and fosters easy adaptation and extensibility. The toolbox also provides a set of ready-to-use parameterizable algorithms including different filters, feature computations and classifiers, a runtime environment that supports complex synchronous and asynchronous data flows, encapsulation of hardware-specific aspects including sensors and data types (e.g., `int` vs. `float`), and the ability to outsource parts of the computation to remote devices.

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