# Body Sensor Networks for Baseball Swing Training: Coordination Analysis of Human Movements Using Motion Transcripts

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*Abstract*—**Becoming proficient in a sport requires significant investment in training. Wearable sensor devices can improve training due to the high level of mobility, ubiquity and intelligent feedback offered. In this paper, we present a wearable platform that provides baseball players with corrective feedback based on multidimensional physiological data collected from a body sensor network. We attempt to generate motion transcripts, which simplify interpretation of complex movements. We then use transcripts to measure coordination among limb segments and joints of the body. The starting times of key events are found in the transcripts, and the coordination between these times is analyzed.**

*Keywords*-**Body Sensor Networks; Sports Training; Motion Transcript; Coordination.**

## I. INTRODUCTION

Learning to perform well in sports is difficult and time consuming. Sports often involve physical tasks that require specific choreography in order to be most effective. For example, golf swings, tennis serves, basketball free throws, and martial arts kicks all involve a series of movements that must be properly timed and executed. Acquiring the physical skills necessary to perform such movements well requires an effective performance assessment mechanism. Assessing performance is challenging due to complexity of movements. Even if the learner fully understands what to do, it may be difficult to effectively compare performed actions to the intended action. Videotaping can be effective, but it does not provide fine grain detail of joint movement, and identifying performance mistakes using video may require an expert. Even when coaches are available, they have many students and limited time, and diagnosing problems can be time consuming. An automated system that can assess the overall performance of a learner and pinpoint problem areas in the learners movements would facilitate performance assessment, increasing the effectiveness of unsupervised practice.

Movement coordination refers to the relative timing of motions made by different body segments. Traditional studies on coordination analysis use kinematic variables of human motions to discover inter-joint time differences. Most techniques originate from a method by Grieve [1] who proposed the use of a plot of angular time series of two joints to visualize intersegment coordination. These plots, called angle–angle diagrams, can be used in coordination assessment [2]. Inter-joint coordination can be used in both biomedical and sports training applications. In gait analysis, kinematic-based approaches are used to measure coordination between rear-foot and fore-foot during walking [3]. In sports training, changes in coordination during the practice, e.g. soccer kick [4], can be reported, and is used for skill development. A major problem with these approaches is that they rely on video data to extract the dynamics of motion, or require expensive components to analyze physical models of movements.

The idea behind our coordination analysis approach is to use clustering techniques to extract temporal behavior of the signal during a baseball swing. By enforcing constraints during clustering, we highlight key events important in baseball swing. The resulting clusters enable us to represent each signal in terms of a sequence of clustered data points in time. Using specific sequences of clusters, we identify the movement and extract timing information from certain transitions in the clustering, which correspond to the key events. Coordination is assessed by an expert watching associated videos. The most representative swing from this practice set of swings is chosen as a template. A new swing is then compared to the template, and the quality of movement is quantified based on the degree of variation.

## II. BASEBALL SWING MODEL

Numerous baseball players and coaches have suggested methods for successful batting. The swing model presented in this section is obtained based on studies in [5] and our extensive discussions with coaches and baseball players [1].

A good swing is the result of a sequence of rotational movements including foot, knees, hips, shoulder, and hands movements. Generally, the action of the batter starts in the lower body and moves upwards. Properly performed motions executed at the right time maximize the power of the swing. Major components of a good swing include bat speed, bat swing plane and timing. The components aim to improve the

[1] Shane Shewmake (UT-Dallas head coach) and Randy Black (college baseball player)

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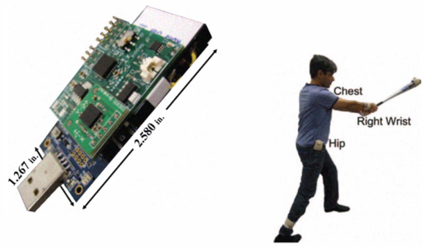



(a) Sensor node (b) Sensor Placement

Figure 1. Sensor Node and Placement on Experimental Subject

chance that the bat connects with the ball, and increase the strength with which the bat hits. Common mistakes include late rotation of lower body, back shoulder dip, and drifting of the front foot. Late movement of the foot and hips impair the swing timing. Dropping the back shoulder affects the bat plane so as the bat does not pass through the strike zone horizontally, decreasing the chance of a successful hit. Drifting refers to improper weight transfer from the back foot to the front foot. One consequence is losing power in the hips, which decreases the bat speed at impact. Therefore, proper weight transfer necessitates coordination between different body segments during the swing.

Our model of the baseball swing emphasizes three major events: 1) Rotation of the lower body (feet, knees, hips) toward the pitcher, 2) rotation of the upper body into the swing, and 3) the swing of the arms and hands toward the pitcher. These key events should be executed in a specific and overlapping sequence. The coordination is extremely important as it ensures that the maximum power from arms, shoulders, and hips is delivered exactly as the bat crosses the plate [5]. Our measure of swing quality is based on this coordination.

The coordination, $\tau_{ij}$, between two body segments $s_i$ and $s_j$ is defined as the time difference between corresponding key events $e_i$ and $e_j$ [6].

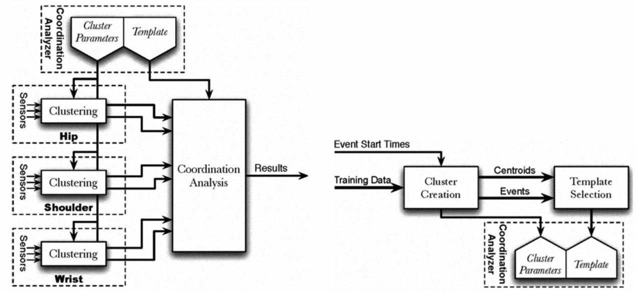
$$\tau_{ij} = t_{e_i} - t_{e_j} \tag{1}$$

The three key events in our swing model are the starting hip rotation, shoulder rotation, and arm extension.

## III. System for Swing Validation

### A. Sensing Platform

We use several wireless sensor nodes, collectively called a body sensor network (BSN), to monitor swing dynamics. The sensor nodes are commercially available TelosB motes from XBow®. We use a custom-designed sensor board, shown in Fig. 1(a). Each sensor node includes a three-axis accelerometer and one two-axis gyroscope. The motes sample their sensors at 50 Hz and use a TDMA scheme to communicate all data to an off-body base station. Three sensor nodes are placed on the subjects, as shown in Fig. 1(b). The base station relays the information to a PC via USB.




(a) Usage of swing analyzer (b) Training for swing analyzer

Figure 2. Baseball swing evaluation model

Two webcams are used to record video of all experimental trials, and MATLAB collects and synchronizes the sensor and video data.

### B. Signal Processing

The data collected from motion sensors is filtered using a five-point moving average filter to ehnance the Signal to Noise Ratio (SNR). Next, statistical features including *mean*, *standard deviation*, *root mean square*, and *first* and *second derivatives* are extracted from a small moving window centered about each point of the signal segment. The signal processing model shown in Fig. 2(a) is then used to provide feedback on coordination measure based on the definition in (1). Each sensor node independently extracts a sequence of symbols, known as a motion transcript, based on the features extracted from sampled data, and according to previously trained cluster parameters. Transcripts aim to highlight the key events using a semi-supervised clustering technique. Event times (e.g. start of hip rotation) are extracted from each transcript using simple string matching. These event times are sent from each node to a base station and compared to a template, which is the event times from a representative proper swing. Players are provided these deviations as feedback to determine swing quality.

The coordination analysis in Fig. 2(a) requires several inputs including a template transcript (i.e. representative proper swing) and clustering parameters. A set of practice swings and event timings for those swings are required to train the model. An expert uses timing criteria to select good swings from a set of practice swings, and then to specify key event times for those swings. This data is used to train the model as shown in Fig. 2(b). The cluster creation and template selection steps are explained below.

*1) Motion Transcript Generation:* The idea of motion transcripts is motivated by the hierarchical representation of human speech. Like words in spoken language that are divided into phonemes, human movements can be represented by coordinated sequences of simple motions and postures, referred to as primitives. Each body segment has its own sequence of motions that is coordinated with and affected by the motions on other limbs. For instance, in a baseball swing, the wrist initially is held motionless next to the head, then swings down, and finally is pulled across the body.

Using motion transcripts, we divide sensor readings into overlapping frames. During training, an expert can use videos of the movements to label certain frames as events of interest (e.g. hip rotation). Other frames may remain unknown or are not of interest to designer; however, they may represent particular motions of individual limbs. Therefore, the process of transcript generation needs to be semi-supervised. Our system uses a semi-supervised clustering [7] based on the well-known $k$-means clustering to generate transcripts.

The exact time of certain key events is known (i.e. $t_{e_i}$), so the frames for a short period of time before the event are labeled $\alpha_1$ and those right after the event are labeled $\alpha_2$. The labels $\alpha_3 \ldots \alpha_k$ for the rest of the frames are unknown; therefore clustering is used to assign these labels. The time of a key event can be extracted from a transcript by locating the transition from $\alpha_1$ to $\alpha_2$.

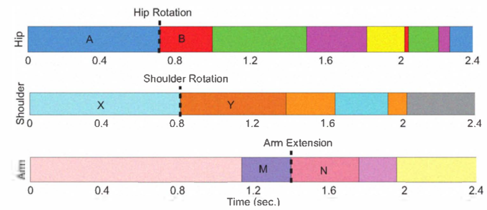
The clustering is based on the $k$-means technique to define primitives. Two important parameters when training the model are the number of clusters, $k$, and cluster centers. A number of different values of $k$, varying between 2 and 9, are tried, and the resulting models are evaluated using the Silhouette measure [8]. The clustering model that has the highest silhouette index is chosen. The second major parameter is the initial clustering. A common technique in the literature for choosing the proper cluster centers is to train the model with different initial centroids and calculate the sum of square error (SSE) for each. In each phase of the algorithm, we randomly assign distributed data points as initial centroids. The configuration that has minimum SSE value is chosen for clustering.

*2) Template Selection:* The goal of template selection is to pick a representative swing from the trials with proper sequence and timing of the key events. Coordination of a new swing will be measured against this template, and the degree of deviation is reported as the quality of the performed movement. The template, $T$, is selected from the set of "coordinated" training swings, $C$. The trial with the lowest summed deviation in coordination between itself and the other trials is selected, as shown in (2).

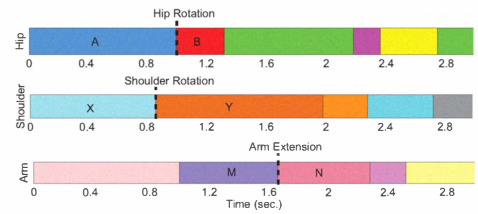
$$T = \underset{T \in C}{\arg\min} \sum_{S \in C} \sum_{i,j} |\tau_{ij}^{(T)} - \tau_{ij}^{(S)}| \tag{2}$$

## IV. Experimental Results

We conducted a set of experiments to determine coordination between the key events of hip rotation, shoulder rotation, and arm extension. Three male subjects with no previous swing training, aged 25–35, were asked to execute 20 baseball swings each with varying timing and sequences of the key events. The video data was used to manually identify timing of key events to train the system and validate




(a) A swing with proper sequence and timing of motions




(b) A bad swing with improper ordering of key events

Figure 3. Transcripts of sample good and bad swings

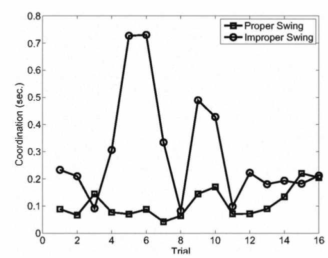
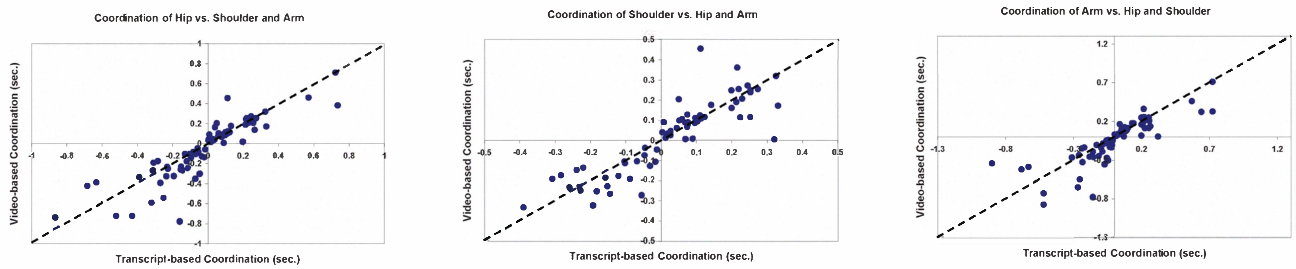



Figure 4. Coordination of good and bad swing trials

its performance. We used 50% of the trials with proper ordering of the events (22 trials out of a total 44 good swing trials) to train our system. The rest of the trials (other 22 proper trials as well as 16 improper trials) were used for validation. Transcripts of all swings were prepared using our previously described technique. Fig. 3 shows transcripts of sample swings in terms of sequence and timing of the events. Each unique motion primitive is assigned a different color for visualization. Each key event is identified by two symbols, illustrating a transition from one primitive to another. "Hip rotation" is detected when the pattern "AB" is observed on the transcript. Similarly, "shoulder rotation" and "arm extension" are detected by "XY" and "MN" respectively.

After training the coordination analysis system using the procedure shown in Fig. 2(b), the intersegment coordination was calculated using (1). By comparing this value with the one obtained for the template, we provide feedback to the user in terms of the amount of deviation from the "perfect" swing. The template matching can be done for every pair of key events. Fig. 4 shows the average amount of deviation in coordination from the template for the first 16 test trials for both groups of proper and improper swings. The values were averaged over all three pairs of events (hip vs. shoulder, hip




(a) (b) (c)

Figure 5. Comparing transcript-based coordination measurments with coordinations extracted from video

vs. arm, and shoulder vs. arm). As it can be observed from the figure, improper swings have been identified as to have significantly larger deviation from the template. Overall, good swings had an average distance of 109 msec from the template while this number was 295 msec for improper swings.

Table I
MEAN AND STD OF COORDIANTION MEASUREMENTS (MSEC)

| | Transcript | | Video | |
|---|---|---|---|---|
| | **Proper** | **Improper** | **Proper** | **Improper** |
| **Mean** | 119 | 295 | 133 | 316 |
| **Std** | 95 | 237 | 89 | 221 |

In order to measure accuracy of our coordination evaluation system, we further compare coordination values calculated from transcripts with those measured from video. Fig. 5 shows this evaluation for the set of 38 test trials. These plots visualize the error of transcript-based coordination assessment. Fig. 5(a) illustrates the plot of coordination measured from transcripts versus that of videos for the node placed on the hip. Fig. 5(b) and Fig. 5(c) compare transcript-based and video-based coordination measurements for the shoulder and arm nodes respectively. Given the video-based analysis as the ground truth, the points closer to the dashed line exhibit less error with respect to motion transcripts. Table I shows mean and standard deviation of measurements made by our transcripts as well as those calculated from video-based analysis.

The accuracy of our coordination analysis based on motion transcripts is demonstrated by measuring the mean absolute error (MAE) between our technique and the coordination analysis based on video. Table II shows the absolute error for both groups of improperly coordinated test movements and proper swings. The overall error over all categories was 101 msec which is 3.4% of the total length of the template (3 sec.).

Table II
MAE FOR COORDINATION BETWEEN EVENT PAIRS (MSEC.)

| | **Hip vs. Shoulder** | **Hip vs. Arm** | **Shoulder vs. Arm** |
|---|---|---|---|
| **Proper** | 52 | 58 | 54 |
| **Improper** | 114 | 152 | 175 |
| **Overall** | 83 | 105 | 114 |

## V. CONCLUSION

In this paper, we introduced a novel approach for generating transcripts of human movements using body sensor networks, and developed a technique for measuring coordination between body segments. We used a semi-supervised clustering technique to construct basic patterns of movements. The motions include motions specified in the training data as well as motions found automatically.

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