Coordination Analysis of Human Movements With Body Sensor Networks: A Signal Processing Model to Evaluate Baseball Swings

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***Abstract*—Becoming proficient in a sport requires significant investment in training. Traditional training approaches such as training with a partner or an expert, and training with the help of videotaping can significantly increase progress. These techniques, however, do not provide fine grain detail about movements of the player, are time consuming, or are limited to specific locations. In contrast, 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 employ a swing model that specifies actions that must be performed properly, in the correct order, and with precise timing between limbs. The system evaluates a baseball swing using motion transcripts. Transcripts simplify interpretation of complex movements and can be used to reduce the size of data that need to be transmitted across the network. Using transcripts, we 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. The swing quality is then assessed by comparing the intersegment coordination of a test swing to that of a template swing.**

***Index Terms*—Body sensor networks, inertial sensors, motion transcripts, signal processing, sports training.**

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 three steps: 1) task definition; 2) practice; and 3) performance assessment. The process is iterative and continues indefinitely, with feedback from performance assessment at each step revising the task definition.

Task definition can be determined by watching a video, reading a book, or listening to a coach. 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 learner's 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. Our study focuses on detecting coordination problems in a baseball swing. 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 rearfoot and forefoot 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 the current methodologies that quantify coordination is that they rely on video data to extract the dynamics of motion, or require expensive components to analyze physical models of movements. In contrast, we propose an effective model that uses machine learning and signal processing techniques to extract coordination information from inexpensive off-the-shelf motion sensors [5].

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 swings. 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. Our swing analyzer is trained on inertial data recorded from a number of practice swings with properly coordinated movements. Coordination is assessed by an expert watching associated videos. The most representative swing from this practice set of swings is chosen

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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.

In this study, we make the following contributions: 1) We present a mobile sports training system using body-worn motion sensors [5] to analyze body movements during a baseball swing. 2) We introduce motion transcripts that are extracted from sensor readings and specify prominent movements of individual body segments. 3) We develop a signal processing model to assess coordination between different body segments using motion transcripts.

II. Related Work

Much effort has been expended on building sport apparatus and training systems that help people improve their sport skills. These devices can be broadly categorized into mechanical and electronic devices. Mechanical training systems (e.g., [6] and [7]) have been traditionally used to provide high-level feedback on quality of movements. While these systems have simple structure and are easy to use, they lack fine grain details of movements a player can perform. Furthermore, most traditional sports training systems have constraints in terms of training location and degree of intelligence they offer. For instance, [8] uses a laser beam attached with the golf club which along with a convex mirror helps the player to track the path of a hitting ball.

Use of sensor-based platform has proved effective in evaluating quality of movements. Majority of the research focuses on recording and analyzing the body movements of the person using different types of sensors such as cameras, RFIDs, and inertial sensors. Authors in [9] use a motion capture system to record and analyze dynamics of human motions when learning tennis strokes. They show that alternative forehand and backhand movements outperform discrete forehand or backhand practices due to the inertia of the trunk rotation movements between subsequent strokes. Authors in [10] present an optical approach for the purpose of capturing high-speed motion of a hitting ball in baseball using multi-exposure images obtained by low-cost still cameras and a stroboscope. They derive algorithms to track the ball and analyze dynamics of the motion by measuring position, velocity, rotation, and spin of the ball. The work in [11] presents a system for accurate detection of a tennis ball using task-level learning from practice approach. The authors program a robot to juggle a tennis ball and use binary-vision to track the movements and measure the performance. The task-level learning improves the performance with every successive practice. A motion capture system is used in [12] to build a virtual baseball training system. The batter swings the bat toward a virtual ball rendered over a screen, and the trajectory of the swing is used to provide qualitative results. Another training system presented in [13] integrates accelerometers and video data to detect human action and provide visual feedback in real-time. Although vision-based training approaches provide sufficient resolution of human movements, they are relatively expensive and are constrained to lab conditions and cannot be used in the field.

Lack of fine grain detail in traditional training systems and lack of mobility in video-based training warrant the need for use of wearable mobile platforms. Advancements in electronic and wireless technologies have enabled design of wearable sensory platforms that can be woven into our daily lives. Body-worn motion sensor systems are primarily used for healthcare monitoring [14]–[16]. Accelerometers and gyroscopes are the most commonly used sensors to detect motor movements [17], [18] in wearable healthcare domain. These sensors can be placed on the human body or sport equipments and provide information on movements. Virtual training systems that use such platforms are portable. They accelerate training by providing students with information regarding mistakes made during practice at anytime and in any location. In [19], authors present an on-body wireless sensor platform for real-time snowboard training. They deploy inertial sensor, bend sensors and force-sensitive resistors along with communication facilities in a wireless network to capture and analyze rider's motion and posture on the snowboard. Authors in [20] develop signal processing algorithms to measure the angular rotations of wrist during golf swings. [21] describes how to use body-worn sensors, accelerometer and gyroscope in particular, to record the actions made by humans in martial arts. The acquired data are then used to find the quality of the moves and level of expertise the person has while making those moves. In [22], authors model the golf swing as a double pendulum system and use inertial sensors placed along the body and golf club to determine how closely the movements of the body follow predetermined motion rules.

Several researchers have investigated coordination between joints and body segments with the use of kinematic variables of human motions. Most techniques are originated from the method presented in [1] that uses a plot of angular time series of two joints in order to visualize intersegment coordination. These plots, so-called angle-angle diagrams, have been used in coordination assessment [2]. An application of this technique in sports skill verification is given in [4] where changes in coordination are examined during the practice of a soccer kick. Quantification of movement coordination, however, has been a challenging problem. Several attempts have been made to quantify timing difference in movement patterns. Authors in [23] describe a chain-encoding technique originally presented in [24]. The vector coding technique involves using a superimposed grid to transform the angle-angle trajectory into digital elements.

Our work is different from aforementioned studies. We use body sensor networks to build a signal processing model for evaluation of baseball swings in terms of coordination between movements of different body joints. To the best of our knowledge, coordination analysis of baseball swings using wearable sensors has not been previously studied by other researchers.

III. Baseball Swing Model

Baseball batting involves hitting a thrown ball with the primary objective of transferring maximum force to propel the ball as far as possible in a desired direction. Successful batting requires proper sequence and timing of movements by different body segments. Numerous baseball players and coaches have suggested methods for successful batting. The swing model presented in this section is obtained based on studies in [25] and our extensive discussions with coaches and baseball players.[1]

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

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 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 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 [25]. Our measure of swing quality is based on this coordination.

The coordination, τ_{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 [26]

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

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

IV. System Overview

This section provides a brief overview of our swing validation system including hardware infrastructure and statistical signal processing techniques. In Section V, we will elaborate on core processing components of our system. In particular, we will show how human movements can be transformed into a sequence of primitives, and how transcripts can be generated to highlight specific key events of a baseball swing.

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 [27] consist of a three-axis accelerometer and a 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. Sensor nodes are secured at the locations that capture movements of our specific key events in a baseball swing. The base station relays the information to a PC via USB. Two webcams are used to record video of all experimental trials, and MATLAB collects and synchronizes the sensor and video data. The video data are used during training for segmentation. We also use video data as a gold standard to validate our signal processing techniques.

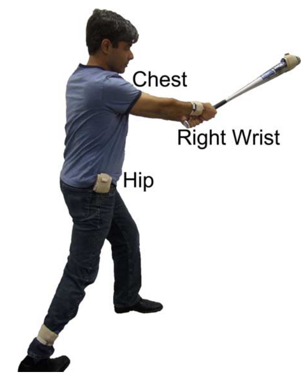

Fig. 1. Experimental subject with three sensor nodes placed on "hip," 'chest," and "wrist" to capture "hip rotation," "shoulder rotation," and "arm extension."

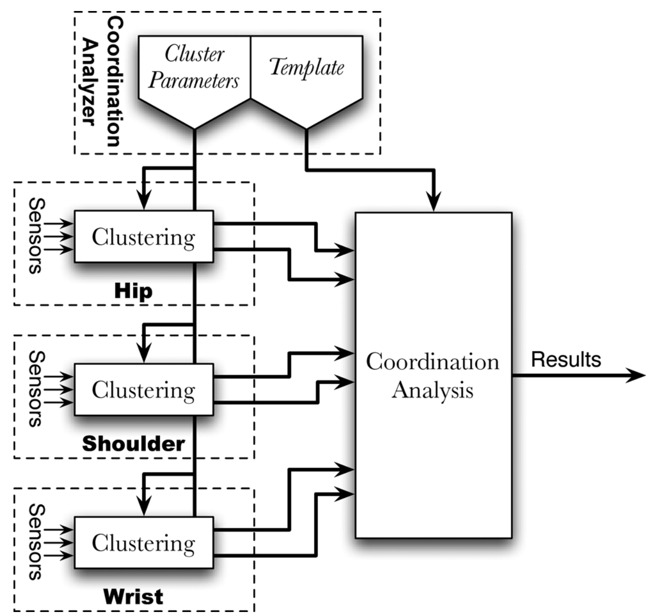

Fig. 2. Using swing analyzer for coordination analysis. Cluster parameters are determined during training, and are used by individual sensor nodes for transcript generation. Template is defined during training, and is used by a base station to analyze timing of different body movements.

B. Swing Analyzer

Our system aims to evaluate a baseball swing in terms of coordination between body segments by processing raw sensor readings acquired from movements of hip, shoulder, and arm. A top-level block diagram of our signal processing model for evaluation of a given movement is shown in Fig. 2. The processing takes the following steps. The data collected from motion sensors are filtered using a moving average filter to enhance the signal-to-noise ratio (SNR). Next, simple 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 is then

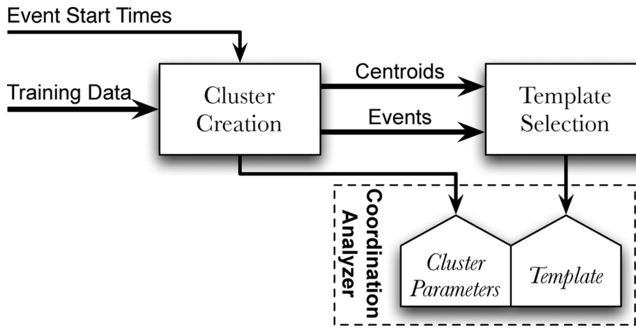

Fig. 3. Training for swing analyzer includes cluster creation, which is used for transcript generation, and creation of a template swing.

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 reference 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 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 are used to train the model, as shown in Fig. 3. The cluster creation and template selection steps are explained in Section V.

V. Motion Transcripts

The movements of interest in our system can be performed well, poorly, or not at all. For example, problems with hip rotation could include: 1) not rotating the hips at all; 2) allowing the swing to pull the hips instead of making the hips push the swing; or 3) starting to rotate the hips too late. We aim to build transcripts of movements that can be used to identify and grade the movements of interest as well as analyze the coordination between joints to provide further feedback. We call this *body choreography modeling*.

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. Further, rotation of the hip will affect the speed and timing of the hand movement. Motion transcripts can significantly reduce complexity of raw data and provide a simple and compact representation of human movements [28], [29].

A transcript of motion is a record in time of simple movements performed by several joints. A simple movement, which we call a primitive, is a segment of motion with persistent physical behavior. The transcript describes the order and timing of movement primitives that creates overall complex movement. For example, a transcript for the foot during walking consists of: 1) lifting the foot; 2) moving the foot forward; 3) placing the foot on the ground; and 4) bearing weight on the foot, with certain periods of time associated with each primitive. The pattern repeats as long as walking continues. At the same time, a transcript for the hip consists of: 1) rotate clockwise and 2) rotate counterclockwise, repeatedly. The primitive sequences for different joints in the body may not be independent. For example, in walking, the hip should rotate clockwise when the left foot moves forward and rotate counterclockwise when the right foot moves forward. When the coordination between joints is incorrect, the movement may be performed poorly, or a different movement may be performed. Transcripts of consistent movements should be consistent, and transcripts of inconsistent movements should highlight the differences between them. Achieving this requires finding the proper number of relevant movement primitives to use when describing complex movements. If no prior knowledge exists about changes in physical behavior of a particular movement, then transcript of that movement can be generated in an unsupervised manner as follows. At every point in time, the movement has certain characteristics. We can assume that adjacent points belong to the same movement primitive if they have similar characteristics. We can determine the characteristics for each data point in the signal by extracting statistical features such as *mean*, *standard deviation*, *root mean square*, and *first* and *second derivatives* from a moving window centered about the current point. In the next step, individual data points can be clustered based on these features. The centroid of each cluster then defines a movement primitive. In our baseball training system, however, some of the events such as "hip rotation," "shoulder rotation," and "arm extension" can be identified from video during training. This information can help the clustering algorithm highlight specific parts of the signal, and therefore, can be used to measure timing of the events during testing.

A. Transcript Generation

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 should be semi-supervised. Our system uses a semi-supervised clustering [30] based on the well-known k-means clustering to generate transcripts. While information about certain motions (e.g., hip rotation) is provided during training, a swing includes unspecified movements of body segments. Important information about the key motions at any given time may be contained in a short interval of sensor readings centered on the time of interest. These short, overlapping intervals (frames)

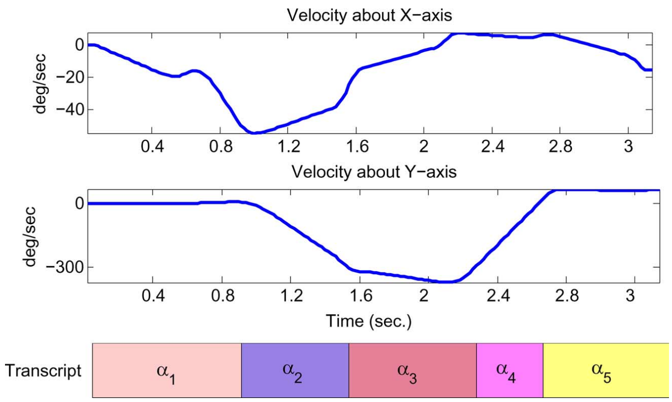

Fig. 4. Raw sensor readings and corresponding transcript generated from a node placed on the "wrist" during a baseball swing. Only gyroscope readings are shown in this figure; however, both accelerometer and gyroscope sensors were used to generate the transcript.

are individually assigned symbols. Furthermore, the unknown events are automatically detected by grouping frames together based on a similarity measure and assigning unique labels to each grouping.

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 α_i and those right after the event are labeled α_{i+1}. The labels $\alpha_1 \ldots \alpha_k$ (with $k \notin \{i, i+1\}$) 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 α_i to α_{i+1}. An example of a transcript generated from sensor node placed on the "wrist" is shown in Fig. 4. In this figure, the two top graphs illustrate angular velocity about X and Y axes. The graph at the bottom shows a transcript generated using k-means clustering. From the node placed on the "wrist," we intend to highlight the time of "arm extension." From our training data, we detect the value of the time (relative to the start of the swing) when a player starts extending his/her arms. This information is used to enforce the clustering algorithm to group sample points prior to and after occurrence of the "arm extension" to separate clusters. In Fig. 4, a transition from α_2 to α_3 illustrates the "arm extension" event.

B. Clustering Algorithm

Statistical classification uses training data to create a model which can be used to assign labels to the frames in new data. If the labels are known for the training data, then a classifier can be built which tries to assign one of the known labels to a new frame based on how closely it matches the data for the training frames. If the frame labels for the training data are unknown, methods known as clustering can group frames together based on similarity and assign unique labels to each grouping. Our system uses a hybrid approach called semi-supervised clustering [30]. The k-means technique is used to define our primitives because it is algorithmically simple and efficient to use after training [31], [32]. Two important parameters when training the model are the number of clusters, k, and cluster centers. Proper choice of k is important because too few clusters will cause the transcript to miss key details and too many clusters will produce irrelevant and misleading clusters. A number of different values of k, varying between 2 and 9, are tried, and the resulting models are evaluated using the Silhouette measure [33]. The *silhouette index* is given by

$$Sil = \frac{1}{N}\sum_{i=1}^{N}\frac{b_i - a_i}{\max\{a_i, b_i\}} \tag{2}$$

where N is the number of data points in the training set, a_i is the average distance between the ith data item and all the items inside same cluster, and b_i is the minimum of the average distances between the ith item and all the items in other clusters than ith data point. The clustering model with 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. The SSE is given by

$$\mathrm{SSE} = \sum_{k=1}^{K}\sum_{i\in C_k}(x_i - \mu_k)^2 \tag{3}$$

where x_i denotes the ith data item, μ_k denotes the centroid vector associated with kth cluster, and K is the total number of clusters. 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.

C. 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 (4)

$$T = \arg\min_{T\in C}\sum_{S\in C}\sum_{i,j}|\tau_{ij}^{(T)} - \tau_{ij}^{(S)}|. \tag{4}$$

D. Template Matching

The process of comparing a test trial against the template to detect start time of a key event is not trivial. An event e_i which is represented by transition from one symbol to another ($e_i = \alpha_i\alpha_{i+1}$) might be repeated several times in a transcript. Therefore, it is required that a template matching function finds the right timing information about the event. Let T be the template generated for sensor nodes s_i with the key event e_i. For a test trial S, template matching finds the instance of e_i that has the minimum time difference among all existing $\alpha_i\alpha_{i+1}$ patterns. The resulting event is given by

$$\hat{e}_i = \arg\min_{e_i}|t_{e_i}^{(T)} - t_{e_i}^{(S)}|. \tag{5}$$

VI. System Prototype

In this section, we illustrate how our swing analyzer can measure quality of baseball swings and provide quantitative feed-

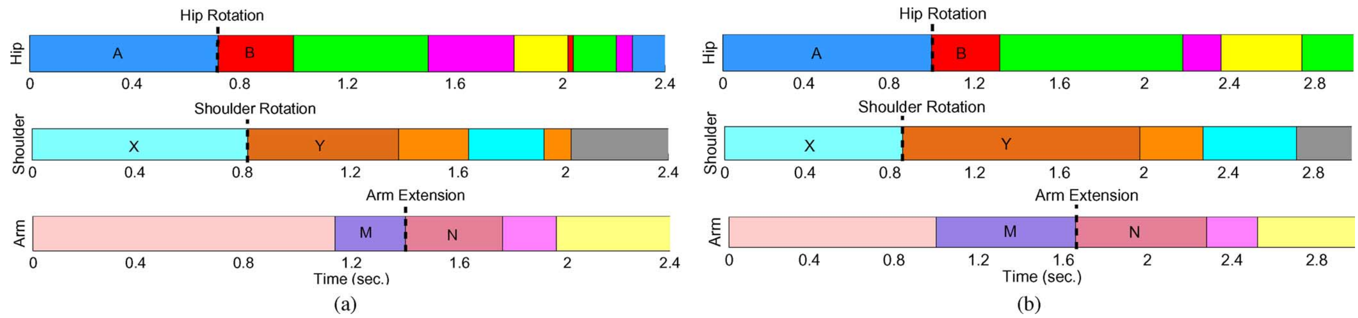

Fig. 5. Transcripts of sample swings with good and bad ordering of key events. (a) A swing with proper sequence and timing of motions. (b) A bad swing with improper ordering of key events.

back on intersegment coordination. We specifically describe different steps for data collection, signal processing and transcript generation, and swing validation.

A. Data Collection

We conducted a set of experiments to determine coordination between the key events of hip rotation, shoulder rotation, and arm extension. For this purpose, three male subjects were asked to wear our body sensor network as shown in Fig. 1. The subjects had no previous swing training, and aged between 25 and 35. They were asked to execute 20 baseball swings each with varying timing and sequences of the key events. The data were collected on a Laptop through a base station, as described in Section IV-A. Video of all trials was captured for training our swing analyzer in subsequent steps.

B. Preprocessing

The raw sensor readings were passed through a five-point moving average filter to reduce the effect of high frequency noise. To capture parts of the signal that correspond to a complete baseball swing, we used the video data which was recorded during data collection. Using video, we found the start and the end of each swing and ignored the rest of the signal in subsequent processing. The video data was further used to manually identify timing of the key events to train the system and validate 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.

C. Transcripts

The next step in our signal processing flow was feature extraction. The five statistical features described in Section IV-B were extracted from a moving window centered about each sample. These features were calculated for all training trials. The features were then used for k-means clustering which aimed to construct primitives of the movements. These features are computationally inexpensive that can be executed on our lightweight sensor nodes and their effectiveness in capturing structural patterns of motion data and detecting the key events is established through our experiments.

Transcripts of all swings were prepared using our previously described technique. Fig. 5 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.

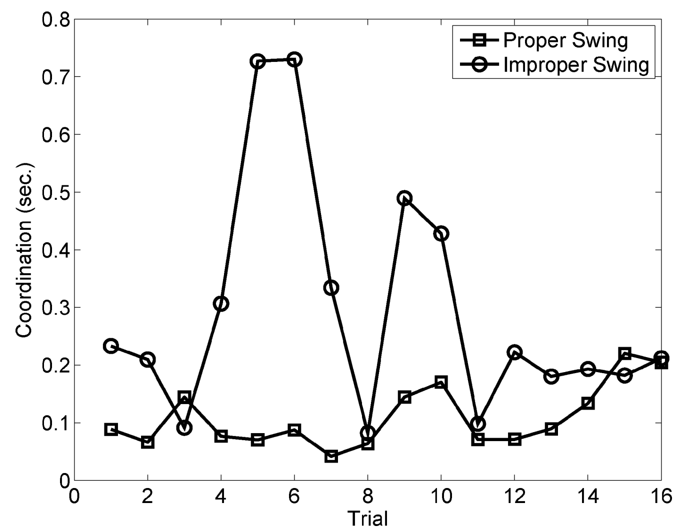

Fig. 6. Coordination of good and bad swing trials.

D. Coordination

After training the coordination analysis system using the procedure shown in Fig. 3, 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. 6 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 versus shoulder, hip versus arm, shoulder versus 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.

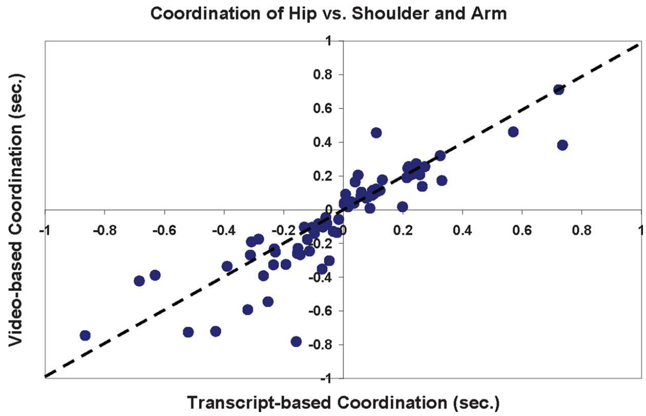

Fig. 7. Comparing transcript-based coordination measurements with coordination extracted from video, for “hip-shoulder” and “hip-arm” coordination.

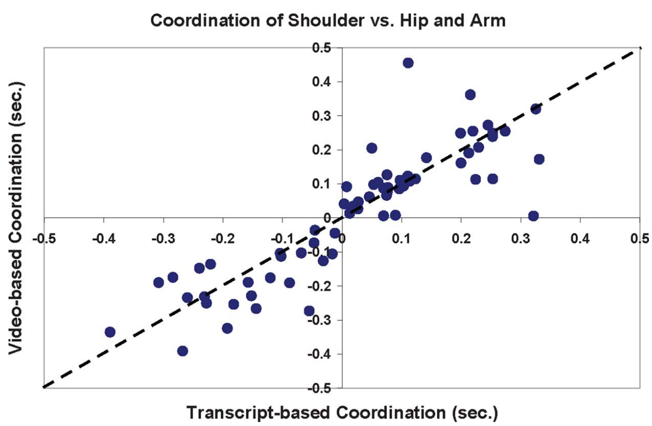

Fig. 8. Comparing transcript-based coordination measurements with coordination extracted from video, for “shoulder-hip” and “shoulder-arm” coordination.

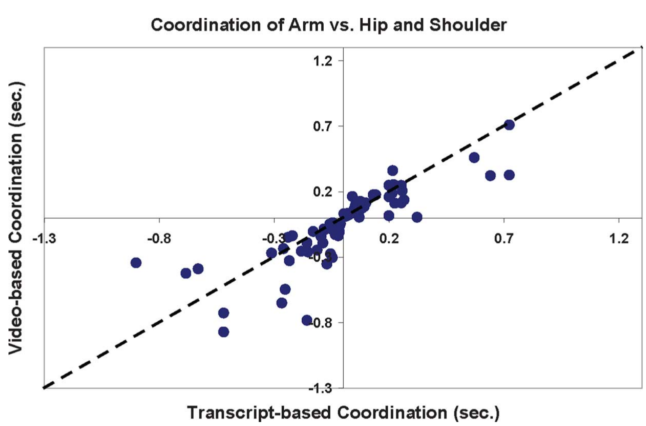

Fig. 9. Comparing transcript-based coordination measurements with coordination extracted from video, for “arm-shoulder” and “arm-hip” coordination.

In order to measure accuracy of our coordination evaluation system, we further compare coordination values calculated from transcripts with those measured from video. Figs. 7–9 show this evaluation for the set of 38 test trials for different pairs of body joints. These plots visualize the error of transcript-based coordination assessment. Fig. 7 illustrates the plot of coordination measured from transcripts versus that of videos for the node placed on the hip. Figs. 8 and 9 compare transcript-based and

TABLE I
MEAN AND STD. OF COORDINATION MEASUREMENTS (MSEC)

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

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

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.).

Algorithm Complexity

The five statistical features described in Section IV-B are calculated from each sampled data. As a result, the feature extraction linearly grows with the number of samples within each action and the number of features, turning the feature extraction into a linear function in the number of features and length of actions.

Once k-means clustering is used to create and define clusters, it can be used to assign an unknown observation to one of the clusters. Transcript generation for a given test trial consists of finding proper label for each data point based on distance between every sample point and previously defined cluster centroids. For a given baseball swing, this process is linear in the length of the trial and the number of clusters. In our system, the length of swings and number of created clusters were 3 sec and 5 clusters on average.

VII. CONCLUSION AND FUTURE WORK

In this paper, we introduced a novel idea on how to train a player in baseball by using portable sensor networks which also would prove to be more economical than a coach. To achieve this we plan prepared the system for generating transcripts of various 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. We further demonstrated the effectiveness of motion transcripts for analysis of baseball swings using inertial data collected from several subjects.

As part of our ongoing research, we are developing our existing techniques for real-time signal processing on the motes. We are also working with a baseball coach to develop criteria for detecting other common mistakes, and to determine the most useful types of feedback for players and coaches. The model of transcripts was chosen because it can label motions that are not directly specified. For instance, an athlete might have a motion that hurts the swing, but is difficult to see in the video. This might be shown in the transcripts, and allow the motion to be diagnosed. As an example, in our data, the transcripts clearly label the hitting zone even though it was not specified as a key event. We intend to more formally investigate these properties in the future.

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References

[1] D. Grieve, "Gait patterns and the speed of walking," *Biomed. Eng.*, vol. 3, pp. 119–122, 1968.

[2] C. Hershler and M. Milner, "Angle-angle diagrams in the assessment of locomotion," *Amer. J. Phys. Med.*, vol. 59, no. 3, p. 109, 1980.

[3] R. Chang, R. Van Emmerik, and J. Hamill, "Quantifying rearfoot-forefoot coordination in human walking," *J. Biomechanics*, vol. 41, no. 14, pp. 3101–3105, 2008.

[4] D. Anderson and B. Sidaway, "Coordination changes associated with practice of a soccer kick," *Res. Quart. Exercise and Sport*, vol. 65, no. 2, pp. 93–99, 1994.

[5] N. Barbour and G. Schmidt, "Inertial sensor technology trends," *IEEE Sensors J.*, vol. 1, no. 4, pp. 332–339, Dec. 2001.

[6] M. Rizzo, "Softball/baseball training machine," U.S. Patent 6,305,366 Bl (45), 2001.

[7] R. Kuster, "Golf swing training device," U.S. Patent App. 10/717,841, Nov. 20, 2003.

[8] R. Nelson, "Laser beam golf swing training device," U.S. Patent 3953034, 1976.

[9] Y. Yamamoto, "An alternative approach to the acquisition of a complex motor skill: Multiple movement training on tennis strokes," *Int. J. Sport and Health Science*, vol. 2, pp. 169–179, 2004.

[10] C. Theobalt, I. Albrecht, J. Haber, M. Magnor, and H.-P. Seidel, "Pitching a baseball: Tracking high-speed motion with multi-exposure images," *ACM Trans. Graph.*, vol. 23, no. 3, pp. 540–547, 2004.

[11] E. Aboaf, C. Atkeson, and D. Reinkensmeyer, "Task-level robot learning," in *Proc. IEEE Int. Conf. Robot. Autom.*, Apr. 1988, vol. 2, pp. 1309–1310.

[12] T. Komura, A. Kuroda, and Y. Shinagawa, "NiceMeetVR: Facing professional baseball pitchers in the virtual batting cage," in *Proc. ACM Symp. Appl. Comput.*, New York, 2002, pp. 1060–1065.

[13] D. Kwon and M. Gross, "Combining body sensors and visual sensors for motion training," in *Proc. 2005 ACM SIGCHI Int. Conf. Adv. Comput. Entertainment Technol.*, New York, 2005, pp. 94–101.

[14] R. Jafari, R. Bajcsy, S. Glaser, B. Gnade, M. Sgroi, and S. Sastry, "Platform design for health-care monitoring applications," in *Joint Workshop on High Confidence Medical Devices, Software, and Systems and Medical Device Plug-and-Play Interoperability, HCMDSS-MDPnP*, Jun. 2007, pp. 88–94.

[15] A. Gaddam, S. C. Mukhopadhyay, and G. S. Gupta, "Necessity of a bed-sensor in a smart digital home to care for elder-people," in *IEEE Sensors*, Oct. 2008, pp. 1340–1343.

[16] I. Pappas, T. Keller, S. Mangold, M. Popovic, V. Dietz, and M. Morari, "A reliable gyroscope-based gait-phase detection sensor embedded in a shoe insole," *IEEE Sensors*, vol. 4, no. 2, pp. 268–274, Apr. 2004.

[17] N. Kern, B. Schiele, and A. Schmidt, "Multi-sensor activity context detection for wearable computing," in *Ambient Intell.*. Berlin/Heidelberg, Germany: Springer, 2003, vol. 2875, Lecture Notes in Computer Science, pp. 220–232.

[18] J. Lester, T. Choudhury, N. Kern, G. Borriello, and B. Hannaford, "A hybrid discriminative/generative approach for modeling human activities," in *Proc. 19th Int. Joint Conf.Artif. Intell., IJCAI'05:* , San Francisco, CA, 2005, pp. 766–772.

[19] D. Spelmezan and J. Borchers, "Real-time snowboard training system," in *Proc. Extended Abstracts on Human Factors in Computing Systems, CHI'08*, New York, 2008, pp. 3327–3332.

[20] H. Ghasemzadeh, V. Loseu, and R. Jafari, "Wearable coach for sport training: A quantitative model to evaluate wrist-rotation in golf," *J. Ambient Intelligence and Smart Environments, Special Issue on Wearable Sensors (JAISE)*, vol. 1, no. 2, pp. 173–184, 2009.

[21] E. A. Heinz, K. S. Kunze, M. Gruber, D. Bannach, and P. Lukowicz, "Using wearable sensors for real-time recognition tasks in games of martial arts – An initial experiment," in *Proc. IEEE Symp. Computat. Intell. Games,* , 2006, pp. 98–102.

[22] D. K. Arvind and A. Bates, "The speckled golfer," in *Proc. ICST 3rd Int. Conf. Body Area Networks, BodyNets'08*, Tempe, AZ, Mar. 2008.

[23] M. Hoy, W. Whiting, and R. Zernicke, "Stride kinematics and knee joint kinetics of child amputee gait," *Archives of Physical Medicine and Rehabilitation*, vol. 63, no. 2, p. 74, 1982.

[24] H. Freeman, "On the encoding of arbitrary geometric configurations," *IRE Trans. Electron. Comput*, vol. 10, no. 2, pp. 260–268, 1961.

[25] C. Welch, S. Banks, F. Cook, and P. Draovitch, "Hitting a baseball: A biomechanical description," *J. Orthopaedic Sports Physical Therapy*, vol. 22, no. 5, p. 193, 1995.

[26] K. Davids, S. Bennett, and K. M. Newell, *Movement System Variability*. Champaign , IL: Human Kinetics, 2006.

[27] H. Ghasemzadeh, N. Jain, M. Sgroi, and R. Jafari, "Communication minimization for in-network processing in body sensor networks: A buffer assignment technique," in *Proc. Design, Autom. Test in Europe Conf. Exhib., DATE'09*, Apr. 2009, pp. 358–363.

[28] H. Ghasemzadeh, E. Guenterberg, S. Ostadabbas, and R. Jafari, "A motion sequence fusion technique based on pca for activity analysis in body sensor networks," in *Proc 31st IEEE Annu. Int. Conf. Eng. Med. Biol. Soc., EMBS'09*, Sep. 2009.

[29] H. Ghasemzadeh, V. Loseu, and R. Jafari, "Structural action recognition in body sensor networks: Distributed classification based on string matching," *IEEE Trans. Informat. Technol. Biomed.*, vol. 14, no. 2, pp. 425–435, Mar. 2010.

[30] K. Wagstaff, C. Cardie, S. Rogers, and S. Schrödl, "Constrained k-means clustering with background knowledge," in *Proc. 18th Int. Conf. Mach. Learning, ICML'01*, San Francisco, CA, 2001, pp. 577–584.

[31] J. Hartigan and M. Wong, "A k-means clustering algorithm," *J. Royal Statist. Soc.*, vol. 28, p. 100, 1979.

[32] T. Kanungo, D. Mount, N. Netanyahu, C. Piatko, R. Silverman, and A. Wu, "An efficient k-means clustering algorithm: Analysis and implementation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 7, pp. 881–892, Jul. 2002.

[33] P. Rousseeuw, "Silhouettes: A graphical aid to the interpretation and validation of cluster analysis," *J. Comput. Appl. Math.*, vol. 20, no. 1, pp. 53–65, 1987.

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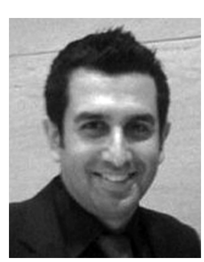

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