POINT OF VIEW

The New Moneyball: How Ballpark Sensors Are Changing Baseball

By **GLENN HEALEY**, ***Fellow IEEE***

Department of Electrical Engineering and Computer Science
University of California, Irvine, CA 92617 USA

Advancements in the capability of sensors, processors, and storage devices have led to an explosion in the amount of data that is captured during sporting events. The Statcast system, for example, uses Doppler radar and stereoscopic video from two arrays of high-resolution optical imagers to acquire seven terabytes of data during each Major League Baseball (MLB) game. One use of these data is to enhance the experience of sports fans. As a case in point, Statcast data are used to generate information and visualizations that are disseminated in real time through telecasts and other media such as an app which displays pitch parameters derived from sensor measurements.

Before advanced sensors invaded major league ballparks, the best-selling and movie-inspiring *Moneyball: The Art of Winning an Unfair Game* [1] put forth compelling evidence that the use of analytics-based models can provide a competitive advantage in baseball. Another use of ballpark sensors is to provide a new source of data that can be mined to improve these models. As a practical low-tech example, consider that the labor-intensive manual review of standard video data led to detailed models for the batted ball tendencies of hitters. These models have enabled the widespread deployment of defensive shifts which represents the most conspicuous change in baseball strategy over the last decade.

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I. BALLPARK SENSORS

By the start of the 2008 season, Sportvision's PITCHf/x system was operational in all 30 MLB ballparks. This system applies computer vision techniques to video obtained from cameras located high in the stands along the first and third base lines and in centerfield to estimate the 3-D path of pitched balls. Pitch descriptors derived from the PITCHf/x measurements are publicly available and are augmented by pitch labels such as "fastball" or "curveball" that are generated by a real-time pattern classification algorithm.

Pitchers have used PITCHf/x data to monitor and hone their repertoire of pitches. The system has also improved on a camera system from QuesTec for providing feedback to umpires and, in so doing, has effected significant changes to the game on the field. Concurrent with an increase in umpire accuracy has been the growth of the strike zone from 435 in^2 in 2009 to 475 in^2 in 2014 as measured in a vertical plane that intersects the front edge of home plate [2]. This larger strike zone contributed to increases in strikeout rates and decreases in walk rates over the first few years of the PITCHf/x era.

Trackman's phased-array Doppler radar has recently replaced PITCHf/x as MLB's primary pitch-tracking technology. The Trackman radar is typically mounted high behind home plate and operates in the X-band at approximately 10.5 GHz. In addition

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to measuring 3-D pitch trajectories, the radar provides a measurement of the magnitude of a pitch's total spin [3]. The Sportvision and Trackman systems also characterize batted balls but access to these data has been more limited.

Statcast, a system designed to track the ball and every player on the field, was functional in all major league stadiums for the 2015 season. The Trackman radar serves as the ball-tracking component of Statcast. This radar, however, is less useful for tracking players since their slower speeds lead to smaller Doppler shifts which cannot be distinguished from clutter returns. Hence, Statcast employs a system from ChyronHego that uses two arrays of optical video sensors and stereo vision techniques to track the location of players. Each array includes three high-resolution cameras with views that are stitched together to span the field. The dual three-camera arrays are configured 15 m apart and are typically located high in the stands along the third base line.

II. MEASURING PLAYER SKILL

Baseball executives face many options as they work to construct a competitive roster while adhering to organizational payroll constraints. The stakes are high. Single decisions can affect a team's long-term health as individual player contracts have reached the level of hundreds of millions of dollars. Although there are substantial differences in the resources available to MLB teams, the *Moneyball* thesis is that the ingenuity of a small market franchise can win out over the financial might of a wealthier opponent. Critical to success in this process is a team's ability to measure and forecast the performance of players.

With the rise of analytics in baseball, teams depend more and more on mathematical models rather than subjective evaluation to guide personnel decisions. Player models are usually based on talent level estimates for each of a set of skills where each estimate is derived from a statistic. Future talent level is forecast by using a function that describes how each skill typically changes with age. For several reasons, statistics derived from sensor measurements are playing an increasingly prominent role in player assessment.

Sensor measurements have enabled the quantification of new skills that can be incorporated into player models. PITCHf/x data, for example, revealed the surprising degree to which catcher mechanics can affect the probability that a pitch will be called a strike [4]. Several teams realized that the underlying catcher skill, termed pitch framing, was undervalued in the marketplace. These teams enjoyed a short-term advantage which has largely disappeared as pitch framing ability has been accurately quantified and factored into catcher valuation.

Sensor measurements also support the representation of traditional skills with greater accuracy. During the 20th century, for instance, estimates of fielding skill were subject to uncertainty due to the lack of data on factors such as how hard a ball was hit or how far a fielder had to range for a ball. Over the last 15 years, advanced fielding metrics have been based on the manual partitioning of batted balls into bins according to their type, e.g., ground ball or fly ball, speed, and direction. The bins typically have widths of 10 mph in speed and a few degrees in angle. This partitioning allows estimation of how frequently a given batted ball is fielded successfully which establishes a framework for defensive evaluation.

Statcast's time-synchronized radar and video subsystems provide the potential to further improve fielding evaluation. The radar component acquires higher resolution measurements of batted ball parameters than are possible with the manual binning methods while the stereoscopic video component records fielder starting positions which are typically not available to current metrics. Statcast's player-tracking technology also allows the components of fielding skill such as reaction time, route efficiency, and speed to be separately quantified. The effectiveness of defensive positioning strategies, which are often derived from analytical models, can also be assessed using Statcast.

III. FROM SENSOR DATA TO INTRINSIC VALUES

As a more detailed illustration of how sensor measurements can improve the accuracy of player models, we consider the representation of batted-ball skill. This skill is of particular interest since about 70% of batter/pitcher matchups result in a batted ball. Traditional statistics that represent batted-ball skill depend on observed outcomes such as whether a batted ball resulted in a hit or an out. These statistics are corrupted by sources of variation that are beyond a player's control. A player's batting average, for example, depends on variables such as the quality of the opponent defense and the ambient weather conditions [5]. These variables add uncertainty to talent level estimates and forecasts that are derived from these statistics.

The Sportvision and Trackman systems provide measurements of a batted ball's initial speed s and direction as specified by two angles. The vertical launch angle v is defined so that $-90°$ is straight down and $+90°$ is straight up. The horizontal spray angle h specifies a batted ball's initial direction in the plane of the playing field where $-45°$ is the direction toward third base and $+45°$ is the direction toward first base. A nonparametric machine learning algorithm within a Bayesian framework [6] has been used to generate a mapping from the (s, v, h) contact parameters to a batted ball's intrinsic value which is invariant to variables such as fielder quality, the weather, the ballpark, and random luck. These variables cause traditional outcome-based statistics for batted-ball skill to have a low degree of repeatability.

Intrinsic value is defined as a batted ball's expected weighted on base average (wOBA) [7]. The wOBA model quantifies run expectancy with values normalized so that an out has a wOBA

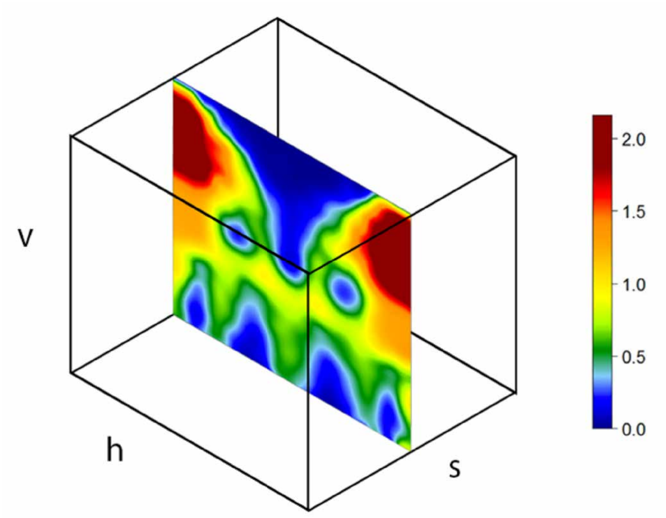

Fig. 1. ***wOBA cube.***

value of zero and a home run has a wOBA value of about two. The mapping from the (s, v, h) measurements to intrinsic value depicted in Fig. 1 is known as the wOBA cube. Fig. 2 displays in more detail the slice through the cube for a fixed initial speed s of 93 mph. A baseball fan might recognize the four cold zones at the bottom of the figure ($v < 0$) which correspond to ground balls that are hit in the direction of an infielder and the three cold zones near the middle of the figure ($v \in [15°, 20°]$) which correspond to fly balls that are hit in the direction of an outfielder. For this initial speed of 93 mph, the most valuable batted balls are those hit with a large launch angle ($v \in [25°, 40°]$) near the foul lines ($|h| \in [35°, 45°]$) which often result in home runs.

The wOBA cube assigns an intrinsic value to individual batted balls according to their initial speed and direction. The average of a player's intrinsic values over a period of time, therefore, defines a statistic that represents batted-ball skill which is unaffected by confounding variables such as the opponent defense, the weather conditions, and the ballpark dimensions. A similar statistic [8] has been defined to represent the intrinsic value of pitches based on their measured speed and trajectory. Reliability estimates based on Cronbach's alpha have shown that statistics derived from sensor measurements have a significantly higher repeatability than traditional statistics that are derived from outcomes [6], [8]. This leads to less uncertainty in the talent level estimates obtained from these statistics.

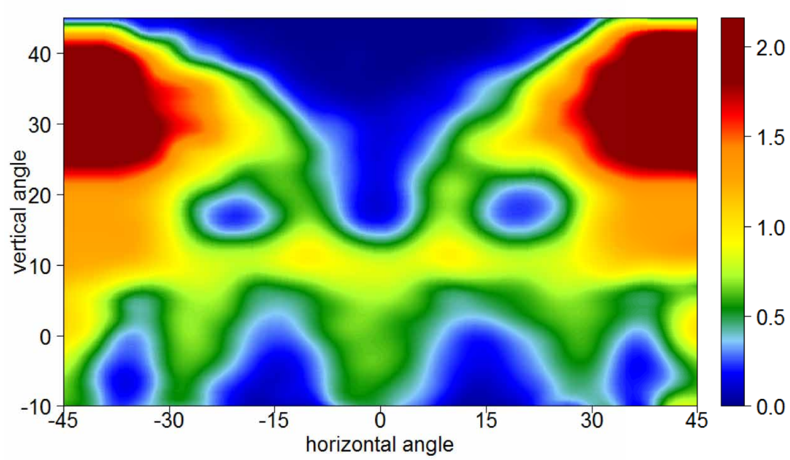

Fig. 2. ***wOBA cube slice for speed s of 93 mph with angles in degrees.***

IV. SIMILARITY GROUPS FOR FORECASTING

A player's talent level for a skill is defined as the expected value of the statistic that represents the skill. One estimate of talent level is simply the observed value of this statistic over a period of time. Several forecasting studies [7], [9], however, have shown that more accurate talent level estimates are obtained by regressing the observed value of a player statistic toward the population mean. An important step in this process is the identification of a group of similar players to define this population.

Sensor measurements provide a way to generate similarity groups based on descriptors that are intrinsic to player skill. A pitch, for example, can be represented by its speed and movement [10] as measured by a pitch-tracking system and a pitcher can be represented by his distribution of pitches in speed-movement space. To illustrate, Figs. 3 and 4 are pitch distributions for a pair of left-handed pitchers in 2016 where the speed s is in miles per hour, the horizontal and vertical movement parameters (x, z) are in inches, and different colors represent different pitch types. A metric [11] based on a whitened earth mover's distance has been developed to compare these kinds of distributions. This approach enables the derivation of similarity groups from sensor measurements which can be used to define populations for computing talent level estimates.

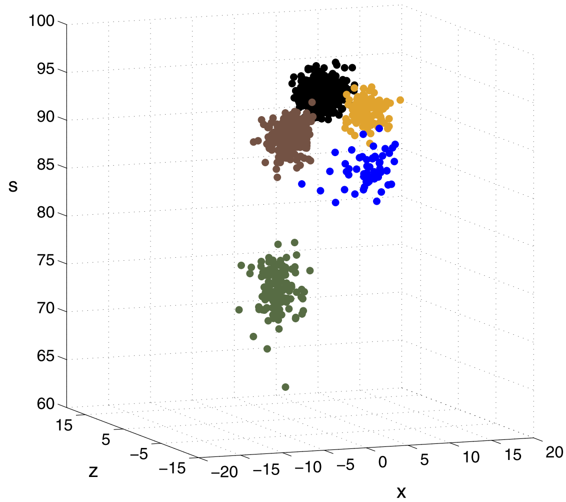

Fig. 3. ***Jon Lester pitches in 2016.***

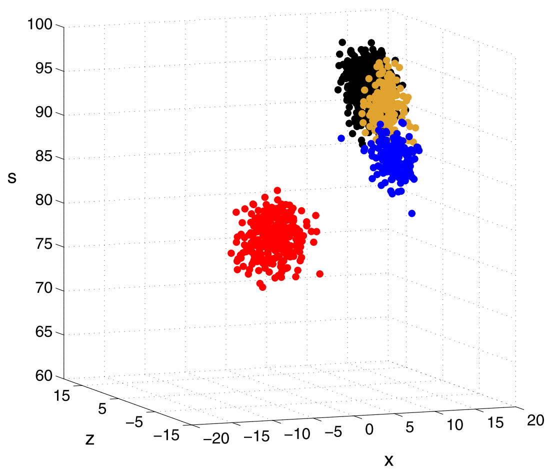

Fig. 4. ***Chris Sale pitches in 2016.***

V. WHAT'S NEXT

Major League Baseball is a multibillion dollar industry where the difference between winning and losing is often small. As a result, teams have endeavored to exploit the data acquired by ballpark sensors to gain an edge. Efforts that began with the manual analysis of standard video have evolved into projects that apply machine learning techniques to descriptors extracted by computer vision algorithms from multisensor inputs. MLB's newest system, Statcast, promises to continue transforming our ability to measure player skill. A few MLB teams have taken the next step and installed a system from KinaTrax that uses video acquired at 300 frames per second from between eight and 16 cameras in the stands to track the 3-D location of 26 joints on a pitcher's body during pitch delivery. This biomechanical data can be used to monitor and refine pitching mechanics with the goals of improving performance and reducing injury risk. Similar systems will likely become available to evaluate batter mechanics. Although there has been great progress, baseball's sensor revolution is still in its early stages. As teams continue their relentless pursuit of knowledge, engineers and computer scientists will continue to support the revolution in a wide array of technical areas. ■

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ABOUT THE AUTHOR

Glenn Healey (Fellow, IEEE) received the B.S.E. degree in computer engineering from the University of Michigan, Ann Arbor, MI, USA and the M.S. degree in computer science, the M.S. degree in mathematics, and the Ph.D. degree in computer science from Stanford University, Stanford, CA, USA.

He is a Professor of Electrical Engineering and Computer Science at the University of California Irvine (UC Irvine), Irvine, CA, USA. Before joining UC Irvine, he worked at IBM Research. He is Director of the Computer Vision Laboratory at UC Irvine where his work focuses on using physical models to develop algorithms that extract information from large sets of data.

Dr. Healey has been elected a Fellow of the International Society for Optics and Photonics (SPIE) and is a member of the Society for American Baseball Research (SABR). He has served on the editorial boards of the IEEE Transactions on Pattern Analysis and Machine Intelligence, the IEEE Transactions on Image Processing, and *Journal of the Optical Society of America A*.