Jump Detection Using Fuzzy Logic

Claire L. Roberts-Thomson[1], Anatole M. Lokshin
AlpineReplay, Inc.
Huntington Beach, USA
Email[1]: claire@alpinereplay.com

Vitaly A. Kuzkin
Saint Petersburg State Polytechnical University,
Institute for Problems of Mechanical Engineering,
Russian Academy of Sciences
Saint Petersburg, Russia

***Abstract*—Jump detection and measurement is of particular interest in a wide range of sports, including snowboarding, skiing, skateboarding, wakeboarding, motorcycling, biking, gymnastics, and the high jump, among others. However, determining jump duration and height is often difficult and requires expert knowledge or visual analysis either in real-time or using video. Recent advances in low-cost MEMS inertial sensors enable a data-driven approach to jump detection and measurement. Today, inertial and GPS sensors attached to an athlete or to his or her equipment, e.g. snowboard, skateboard, or skis, can collect data during sporting activities. In these real life applications, effects such as vibration, sensor noise and bias, and various athletic maneuvers make jump detection difficult even using multiple sensors. This paper presents a fuzzy logic-based algorithm for jump detection in sport using accelerometer data. Fuzzy logic facilitates conversion of human intuition and vague linguistic descriptions of jumps to algorithmic form. The fuzzy algorithm described here successfully detected 92% of snowboarding jumps identified visually (rejecting 8% of jumps identified visually), with only 8% of detected jumps being false positives. The fuzzy algorithm presented here has successfully been applied to automate jump detection in ski and snowboarding on a large scale, and as the basis of the AlpineReplay ski and snowboarding smartphone app, has identified 6370971 jumps since August 2011.**

I. Introduction

Jumps are the most spectacular aspect of many sports including water and alpine skiing, snowboarding, skateboarding, wakeboarding, motorcycling, biking, gymnastics, and the high jump, among others. The total number, duration, and height of jumps are of particular interest. In the past, jump duration has been determined by observing an athlete in real time or by carefully inspecting a video recording. These techniques are extremely time-consuming and are inappropriate for wide-scale use by non-professionals. Much effort has consequently been made to automate jump detection and characterization, e.g. [1]–[5].

Advances in electronic sensors and computers make it possible to develop small portable devices that can be attached to an athlete or his or her equipment to detect jumps. Such devices may contain various sensors, among which accelerometers have the most straightforward application to jump detection.

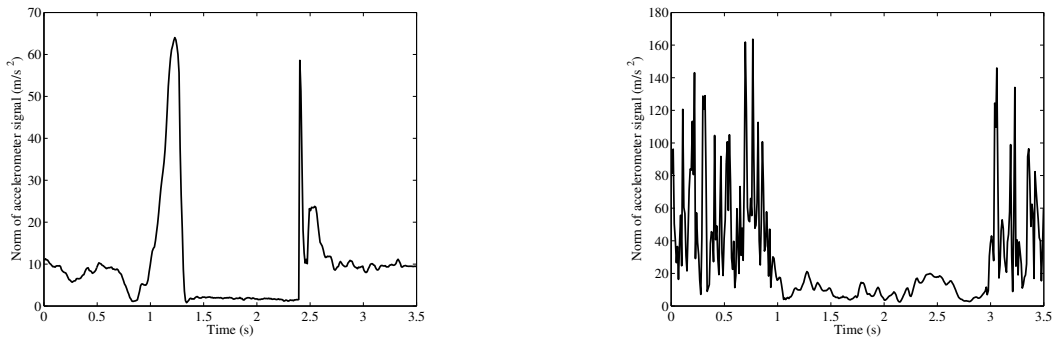
The simplest model of a jump is of free-fall conditions while the athlete is in the air. It is well known that the acceleration of the center of mass of a falling body is 9.81 m/s^2 in the case of negligible air resistance. In this model, the accelerometer signal should theoretically equal zero during the jump. This simple model underpins patents [6], [7] for jump detection. This principle, however, is sufficient for jump detection only in controlled experiments. For example, when tossing a smartphone in the air, the duration of time it is in the air can be simply detected by finding points where the acceleration signal is lower than some threshold value (see Fig.1a). Note that even in this simple case the threshold approach will detect two jump-like events rather than one, because the accelerometer signal before the main event is also very small.

Detecting jumps performed by real athletes is challenging for several reasons. Firstly, real data are usually noisy. Secondly, accelerometer readings during a jump are not necessary zero due to vibration of equipment and/or rotation of the athlete (see Fig.1b). Consequently the free-fall model for jumps described above is insufficient to detect jumps in many sports. Additional criteria to aid jump detection can be formulated by combining physical principles with knowledge of accelerometer data collected from athletes under real conditions. The common property of such criteria, however, is that they are qualitative/intuitive rather than quantitative/rigorous. In this situation, developing a computer algorithm using rigorous rather than vague statements is challenging.

The approach chosen to convert an intuitive reasoning process to a computer algorithm is fuzzy logic, originally proposed by Zadeh [8]. Fuzzy logic describes objects by their degree of belonging to a set. Every object is assigned a membership function (MF) for each fuzzy set that takes a value from 0 to 1 inclusive, in contrast to binary logic where an object either does or does not belong to a set. Fuzzy logic formalizes vague or imprecise descriptions of data, including linguistic descriptions [9]. Fuzzy rules and algorithms enable a human-like decision-making process through combining linguistic variables in an intuitive way.

Fuzzy logic has successfully been applied to a range of pattern recognition problems, including fault detection in induction motors [10], power quality disturbances [11], event detection in wireless sensor networks [12], semi-automatic interpretation of seismic data [13], fault diagnosis [14], fall detection [15], and alarm event detection [16]. In relation to sport, fuzzy logic has been applied to shot detection in football videos [17], estimation of kicking range [18], execution of strength training exercises [19], and to analyze cricket batting technique [20].

In this paper we use fuzzy logic to develop a robust algorithm for jump detection in sport from accelerometer and GPS data. The paper is organized as follows. The main physical principles of jumps, and jump detection logic, are described in Section 2. These ideas form the basis of an algorithm for jump detection using fuzzy logic, presented in Section 3. In Section



(a) (b)

Fig. 1. Norm of accelerometer data for (a) a smartphone tossed in the air, and (b) a real snowboarding jump.

4 the algorithm is applied to snowboarding data. Conclusions and discussion of the results are presented in Section 5.

II. Physics of jumps and jump detection logic

Jumps can be divided into three stages: take off, trajectory through the air, and landing. These stages are clearly distinguishable in controlled experiments such as in Fig.1a. During both take off and landing, acceleration is high; during the jump, acceleration is small. Furthermore, acceleration is sharply peaked during the landing shock. These general characteristics also hold for jumps under real conditions, such as in Fig.1b.

In any sport, an athlete performs a variety of physical maneuvers, some of which have acceleration patterns similar to jumps. A successful jump detection algorithm should screen out these maneuvers, which will differ by sport. For example, Fig.2 presents acceleration data collected during walking, with the accelerometer placed in a hip pocket. Normal walking generates acceleration peaks similar to jump landing shocks, preceded by small acceleration values; this signal is similar to a series of jumps. A successful jump detection algorithm must have few false positives from other athletic maneuvers such as walking.

It is easy for a human with some experience in visually examining acceleration data to intuitively identify jumps. Criteria used in such a reasoning process are easily described in linguistic terms, and generally result from comparing the acceleration signal during a jump with the signal during other athletic maneuvers.

The approach chosen for the algorithm presented in this paper is fuzzy logic, since it handles vague statements and linguistic variables well. Alternative approaches to detecting and classifying jumps include more traditional methods such as binary decision diagrams (BDDs). BDDs have certain advantages, particularly in understanding logical equivalence and formula validity and satisfiablity, and reduction of redundancy [21]. While BDDs are a familiar representation for algorithms, they do not facilitate converting linguistic descriptions to algorithmic form. For example, consider the following characterizations of two similar types of jumps:

- average duration, well-defined shock, small acceleration while athlete is in the air

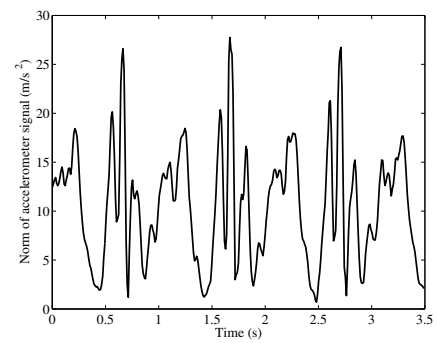


Fig. 2. Norm of acceleration data collected during normal walking by a 3-axis accelerometer placed in the hip pocket. The signal is similar to a series of jumps.

- average duration, similar magnitude of acceleration during take off and landing, high acceleration in 5s surrounding jump

A BDD classifying these two jump types requires a relatively complex tree that obscures the underlying linguistic description of each type of jump, and is sensitive to the parameters and thresholds chosen. On the other hand, fuzzy logic emphasizes the linguistic nature of this description, so it is straightforward to conceptualize jump classification. In addition, fuzzy logic handles partial matching of a combination of jump features with ease, resulting in more accurate jump classification. The fuzzy logic-based algorithm is thus effective for many athletic styles and conditions. Part of the BDD corresponding to the algorithm presented in Section 3 is shown in Fig.3. The diagram is complex, but corresponds to 4-5 fuzzy rules.

III. An algorithm for jump detection using fuzzy logic

A fuzzy logic system may be described as follows. Crisp input enters the fuzzy decision-making process through fuzzification. Various fuzzy rules are applied to determine membership of fuzzy sets before defuzzification produces a crisp output [22]. The jump detection algorithm presented here follows this framework; the algorithm is summarized and identified with the corresponding components of a fuzzy logic system in Table I.

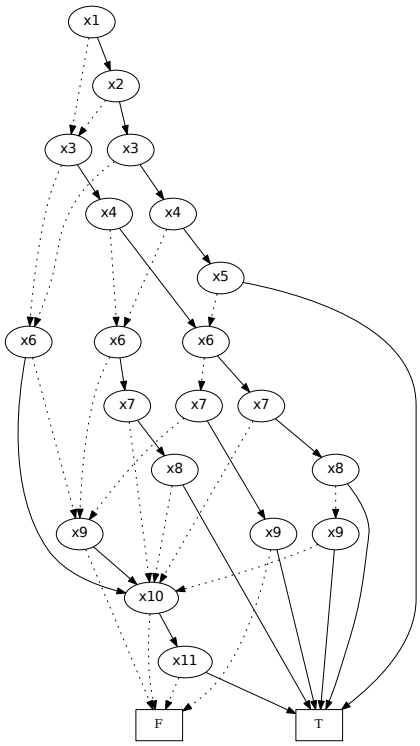


Fig. 3. Part of the fuzzy algorithm in Table I represented in binary decision diagram (BDD) form.

TABLE I. SUMMARY OF FUZZY ALGORITHM FOR JUMP DETECTION AND CORRESPONDING COMPONENTS OF A STANDARD FUZZY LOGIC SYSTEM

1.	Input sensor data (accelerometer, GPS, ...) a. Clean input data b. Identify data segments of interest e.g. those with high velocity and negative change in altitude	[Crisp input]
2.	TakeOff, InAir, Shock MFs	[Fuzzification]
3.	Potential jump event: TakeOff then InAir then Shock	
4.	Jump MF: a. Jump quality i. Jump duration (reasonable / short / medium / long) ii. Data sampling rate sufficiently high iii. Comparison of acceleration during jump with surrounding data b. Jump type i. Various requirements of: high acceleration during take off and landing, low and smooth acceleration during jump, sharp landing shock, jump duration	[Apply fuzzy rules to determine fuzzy set MF]
5.	Accept or reject jump based on region in jump duration-Jump MF plane	[Defuzzification to crisp (binary) value]

Crisp input data from an accelerometer are first cleaned (step 1a), and may also be cross-referenced with other sensors, such as GPS, to find data segments of interest (step 1b). In skiing and snowboarding, athletes usually jump at relatively high speed while descending a mountain. The search space can thus be narrowed to segments of data where an athlete is skiing or snowboarding down ski trails. For the snowboarding example presented in Section 4, data segments with high velocity and negative change of altitude that correspond to the athlete descending the mountain on ski trails were identified and analyzed.

Each accelerometer data segment of interest is then fuzzified (step 2). Fuzzy sets TakeOff, InAir, and Shock are introduced that correspond to the three jump stages of an athlete taking off, his or her trajectory through the air, and landing.

During take off, an athlete accelerates. In sports such as skateboarding, gymnastics, and the high jump, athletes use their legs to accelerate into the jump. In sports such as skiing, snowboarding, and skateboarding, athletes often jump from various kinds of ramps, which also impart acceleration. Points that belong to the set TakeOff must therefore have high acceleration.

Free fall is the simplest physical model of an athlete in the air during a jump. In this case, the norm of the accelerometer signal during the jump is theoretically zero. In practice, effects such as calibration errors, sensor bias, centrifugal acceleration, and vibration result in a non-zero accelerometer signal during a jump (see Fig.1b). However, the accelerometer signal during a jump is usually small, unless an athlete is rotating with high angular velocity. Points thus belong to the set InAir if their acceleration is small.

During landing an athlete and/or his or her equipment hits the ground accompanied by a high spike in acceleration. Note that the value of acceleration during landing depends significantly on the placement of the sensors. For example, a shock measured by sensors mounted on a helmet is partially absorbed by the athlete's legs, body, and neck. It is thus significantly smaller than a shock measured by sensors mounted on equipment such as skis, skateboard, or snowboard. Regardless of placement, points belonging to the Shock set should have high acceleration. The rate of change of acceleration during landing should also be high. This is a further distinguishing characteristic of landing shocks.

The fuzzy rules for the sets TakeOff, InAir, and Shock (step 2) can be summarized as follows:

IF acceleration is large
THEN point belongs to TakeOff (1)

IF acceleration is small THEN point belongs to InAir (2)

IF acceleration is large AND acceleration is sharply peaked
THEN point belongs to Shock (3)

In order to detect a jump, a segment of data (a "potential jump") must be found where data points belong to TakeOff, InAir, and Shock in that order (step 3). A decision must then be made whether the potential jump is a real jump or a false positive. Potential jumps are further classified using the fuzzy set Jump (step 4) before a binary decision is made for each potential jump whether it is a real jump or a false positive.

The MFs used in this algorithm are the γ-function

$$\gamma(x) = \begin{cases} 0 & x \leq a \\ \frac{a-x}{a-b} & a < x < b \\ 1 & x \geq b \end{cases} \tag{4}$$

where $a \leq b$, the L-function

$$L(x) = \begin{cases} 1 & x \leq a \\ \frac{b-x}{b-a} & a < x < b \\ 0 & x \geq b \end{cases} \tag{5}$$

where $a \leq b$, and the triangular MF

$$\triangle(x) = \begin{cases} 0 & x \leq a \\ \frac{a-x}{a-b} & a < x < b \\ \frac{c-x}{c-b} & b \leq x < c \\ 0 & x \geq c \end{cases} \tag{6}$$

where $a \leq b \leq c$ [22]. The threshold values a and b (and c when applicable) for the TakeOff, InAir, and Shock MFs are chosen relative to the mean and standard deviation of the cleaned accelerometer signal. Thresholds for intermediate MFs required for the Jump MF are both relative and absolute, adding flexibility in handling different athletes and conditions as well as accounting for hard physical limits.

The fuzzy set Jump reflects the quality of potential jumps and is used to distinguish true jumps from false positives. The fuzzy rules for this set differ by sport. In general, the Jump MF depends on the TakeOff, InAir, and Shock MFs as well as MFs characterizing other features of potential jumps. Several different types of jumps may be present for any given sport. The Jump MF handles different types of jumps by combining the results of intermediate MFs representing these jump types. The Mamdani scheme is used to combine fuzzy rules; the T-norm (AND, fuzzy set intersection) used is the minimum, and the S-norm (OR, fuzzy set union) used is the maximum [22], [23]. The Jump MF also includes rules to distinguish walking and other physical maneuvers from the jumps that are of interest, which should vary by sport.

The final result of the Jump MF (step 4) is an OR operation over MFs representing qualitatively different jump types. For the snowboarding example presented in Section 4, examples of different jump types are short jumps of good quality, and long jumps with small landing shock, among others. This step adds flexibility in assessing different types of jump as conditions on a specific jump feature can differ.

Finally, potential jumps are accepted or rejected through a binary decision represented as a two-dimensional acceptance region in the jump duration-Jump MF plane (step 5). Defuzzification to a binary value using this method allows looser or stricter conditions to be applied to jumps of different duration. Specifically, the Jump MF threshold for jumps of short duration is higher than that for jumps of long duration. This adds flexibility to the algorithm, and accounts for the uncertainty associated with very short jumps, which could be confused with a noisy accelerometer signal.

This fuzzy algorithm is used for jump detection in the AlpineReplay ski and snowboarding smartphone app [24]. From August 2011 through June 2014, 6370971 jumps have been identified in 570899 ski sessions recorded through the app, with a total airtime of 3665435 s. Typical accelerometer and GPS frequencies used with the smartphone app are 30 Hz and 1 Hz respectively. These frequencies are considerably lower than the frequencies used in the example presented in Section 4 (100 Hz and 5 Hz respectively), demonstrating the flexibility and robustness of the algorithm.

TABLE II. RESULTS OF PROPOSED FUZZY LOGIC-BASED ALGORITHM FOR JUMP DETECTION

Trail	Trail duration (s)	Number of			
		Jumps (by hand)	Shocks	Potential jumps	Accepted jumps
1	139.2	0	93	3	0
2	254.4	1	199	10	1
3	184.6	2	193	13	2
4	283.2	2	152	10	2
5	234.6	2	169	11	2
6	232.6	2	163	7	2
7	121.0	0	52	2	1
8	141.8	0	48	3	0
9	334.8	1	139	11	2
10	423.2	1	118	7	1
11	364.4	0	105	7	0
12	330.8	2	116	4	0
13	342.8	2	128	10	2
14	343.0	3	129	8	3
15	490.0	2	78	8	2
16	128.8	0	26	3	0
17	441.4	1	40	4	1
18	463.8	1	156	13	1
19	1298.4	0	3	1	0
20	76.4	0	4	1	0
21	262.4	0	18	1	0
22	1368.4	2	82	6	2
All	8260	24	2211	143	24

IV. EXAMPLE: DETECTION OF SNOWBOARDING JUMPS

The jump detection algorithm presented in Section 3 was applied to data collected by a snowboarder. Data were recorded over the course of 5 hours using a device called Trace mounted on the athlete's snowboard using adhesive. The Trace contains several sensors including a GPS and a 3-axis accelerometer. For this experiment, the sampling rate of the accelerometer was 100 Hz and the sampling rate of the GPS was 5 Hz.

The GPS altitude data were first examined to find segments where the athlete was snowboarding down a ski trail. 22 ski trails were identified with a total of 138 minutes of data, which were first examined visually to find the real number of jumps for each trail. Each trail segment was then analyzed with the algorithm presented in Section 3. For each trail, Table II shows the duration, the number of jumps found through visual examination, and the number of shocks, potential jumps, and accepted jumps detected algorithmically.

24 jumps were found by visual examination over the 22 ski trails. The proposed algorithm identified 2211 shocks, 143 potential jumps, and 24 accepted jumps over the 22 ski trails. All 24 jumps found by visual examination were among the potential jump events detected. The algorithm accepted 22 of the 24 real jumps (91.6%), while 2 were rejected (8.3%). In addition, 2 accepted jumps were false positives (8.3% of all accepted jumps).

Most of the extra potential jump events identified were very short (around 0.1 s), however some were longer (0.3-0.5 s). The false positives were among the longer potential

jumps, as the requirements for other jump features are relaxed when jump duration is long. When creating a jump detection algorithm, there is a trade-off between specificity, which allows a particular athlete's style to be completely accounted for in finding all jumps performed, and generality, which imparts robustness in identifying jumps performed by athletes with a wide range of styles and abilities under varying conditions. The data presented in this example illustrates these issues: there were real jumps that were not accepted, and there were false positives.

Adding input data sources to the jump detection algorithm is of particular interest, as it will provide more information for classifying jumps. The fuzzy algorithm allows such modification without needing to change its existing architecture as the Jump MF can simply be extended to include additional types of jump with specific features. Adding gyroscope data is of particular interest, as this will enable detection of jumps with tricks requiring high rotation. These jumps with high centrifugal acceleration resulting from high angular velocity do not fit the model utilized here. 3-axis gyroscope data are also available from the Trace used in this experiment, and further work is being done to correctly identify and classify jumps with tricks using gyroscope data [25].

V. Conclusion

Fuzzy logic and advances in sensor technology together show promise in automating jump detection in many sports. When applied to accelerometer and GPS data gathered during snowboarding, the fuzzy logic algorithm presented in this paper successfully detected 92% of jumps performed by the athlete, with only 8% of jumps detected being false positives. This algorithm has been applied to data gathered through the AlpineReplay ski and snowboarding smartphone app since August 2011, detecting more than 6 million jumps since that time. This paper demonstrates that the strengths of fuzzy logic in applying intuitive, imprecise methods to uncertain temporal data without need for hard thresholds can successfully be applied to automate jump detection in sport. Many concepts disclosed are covered in pending patent applications [25], [26].

Acknowledgment

The authors would like to thank Prof. Vladik Kreinovich for his encouragement in presenting these results, and Will Mayo for collecting experimental data.

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