An Intelligent Sensor-Driven Skydive Tracking System

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Abstract—This work presents a novel state-of-the-art, streamlined skydive tracking system. Key components and contributions of the system include methods for efficient data consolidation from multiple sensors and immediate intuitive feedback. These attributes afford rapid training, near-real-time tracking and status notification, and post-jump accident investigation and flight debriefing for skydivers. The system also incorporates a simulator which can be used prior to jumps. Furthermore, the proposed methods were extensively evaluated both quantitatively and qualitatively. For post flight analysis, a 2016 injury was analyzed within fifteen minutes after receiving flight data, and detailed 3D flight path, data and graphics were generated. It isolated the cause of the accident, showed the best camera angles for the jump and simultaneously displayed the flight data while also evaluating jumpers, spotters and pilots. This performance is considerably expedited as compared to current methods. For training and real-time feedback, hundreds of real jumps and training with the system were evaluated. With the tracking and feedback system, rookie jumpers overall doubled their landing accuracy between the first and second week of jumps. Indeed, the technology presented here benefits the training, evaluation and continual safety of civilian and military skydivers and smokejumpers.

Keywords—skydiving, jumper training, sensor-driven tracking, data-fusion, error-correction.

I. Introduction

Skydiving is a highly skilled and coordinated task in which accidents can have drastic consequences. To prevent accidents, provide simulated training and debriefing, this work presents a method for a sensor-driven process for near-real-time diver tracking. Even the most highly trained individuals can benefit from tracking simulated failure training. Quantitative and qualitative evaluations were performed on real jumps (over four hundred total jumps), the results of which are encouraging towards the use of this system for all skydivers from training to post-jump feedback. For real-time data acquisition, a holistic approach to jump analysis is utilized, whereby data from global positioning system (GPS) units, inertial measurement units, apriori topological terrain data, flight path, and pilot and spotter information are all consolidated to rapidly inform qualitative feedback to the jumper. This low-cost approach is robust to poor sensor readings by leveraging multiple types of inexpensive, lightweight sensors and a filter-based classifier to isolate and extrapolate only reliable sensor information from hundreds of thousands of relevant data points. The data is then transformed it into intuitive, 3D visual feedback during or almost immediately following the jump.

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II. Background

A. Dive Tracking, Accident Investigation

Precise maneuvering is paramount for safety during skydiving freefall. This includes control in translational directions, including forward/backward, up/down, right/left, which is especially important to ensure that the diver keeps an appropriate distance from other divers [1]. In fact, poor maneuvering has been strongly associated with fatal accidents, and even slight changes in body posture can often lead to aerial instability. Accidents in skydiving oftentimes manifest as the diver crashing into the ground or with other divers, and are commonly due sudden spin [1]. In order to minimize flight accidents and casualties, an autonomous system capable of performing skydive tracking both in near-real-time and in simulation to prevent and investigate incidents is proposed.

One of the causes of loss of stability in skydiving maneuvers is human error, which is defined as any degradation to system performance caused by human action or failure to act [2]. Most studies investigating the role of human error in aviation mishaps and fatalities indicate that human error has caused more accidents than equipment or aircraft failures. Several studies found that human error, indeed, contributes to more than 50% of aviation mishaps and fatalities. Therefore, tracking and simulations present a robust way to both investigate dive performance and train humans prior to potentially fatal mishaps. Simulations can highlight the role that inaccurate behaviors play in such accidents and thus reinforce prevention of such errors [2].

B. Error Correction

Continuous and precise positioning in skydiving is requisite for near-real-time and useful feedback, both during and post jump. Two types of sensors are used to provide the position of a mobile skydiving subject: absolute sensors and dead-reckoning sensors [3,4]. GPS sensors are an example of absolute sensors. Although it can reach precision on the order of centimeters, it lacks credibility in some cases due to multipath or mask effects. This often results in unwanted mixture with other sensors and data streams. In contrast, dead-reckoning sensors, for example gyroscopes and accelerometers (also known as inertial sensors), have the advantage of giving continuous positioning information. The information given in this case has the advantage of being independent from the external environment [3,5,6,7].

Inertial sensors may be classified into two groups: inertial measurement units (IMU) and the inertial navigation system (INS). The IMU delivers raw data that is corrected from scale factors and biases using gyroscopes and accelerometers. The INS is an IMU which output is sent to navigation algorithms to provide position, velocity and attitude of an object [3,5,6,7].

Several methods have been used to consolidate good data and reject outliers from multiple sensors. The Kalman filter has been employed to study GPS/INS data fusion [8,9]. Experimental results have shown that extended degradation or loss of GPS signal can lead to positioning errors quickly drifting with time. This indicates that GPS/INS association is less than satisfactory. To resolve this, additional sensors have been suggested [3]. Augmenting with additional sensors can result in more precise positioning information. The Kalman filter is especially suitable for the integration of multiple sensors. This can be done without reconstructing the filter [4].

Another way to reject errors is through the RANSAC based outlier rejection method [10,11]. This method allows for the random selection of subsets of feature correspondences. In visual odometry and other computer vision tasks, RANSAC estimates egomotion based on random subsets. The number of used subsets is given by

$$\mathrm{n} = \frac{\log{(1-p)}}{\log{(1-(1-\epsilon)^s)}} \tag{1}$$

Here, s represents the minimum number of data points needed in the estimation, p represents the probability that at least one sample contains inliers only and ϵ defines the assumed percentage of outliers in the data set [11].

Upon convergence of the Kalman filter, inliers can be classified via a threshold of Euclidean reprojection error. The final estimate is given using a final estimation step with all inliers of the best sample. The proposed method added on to the RANSAC based outlier rejection scheme generates a robust estimation and outlier rejection method [11].

III. Methods

A. Overall Workflow

The Kalman filter is amenable for multisensory consolidation [3,4,5]. Validity domains of each sensor in the filter are defined in order to reject data errors when detected. This ensures the reliability of the data fusion [3,8,9]. In layman's terms, the Kalman filter is an estimator that employs a prediction step and an update step.

To use Kalman Filters for non-linear problems, linearization around the current state is often performed using a first order Taylor-approximation. This generates the Extended Kalman Filter. The update step is often performed to reduce the approximation error caused by Taylor approximation and consider assumed Gaussian noise.

B. Data Processing

Two Kalman filter models can be considered [3,12]. First recall the standard Kalman filter state model (2). The state model chosen is a Wiener process acceleration model. It is a basic model that gives a good compromise between complexity and performance. In such a model, state transition matrix F and noise w are given by:

$$\mathrm{F} = \begin{bmatrix} I_3 & TI_3 & \frac{T^2}{2}I_3 \\ 0_3 & I_3 & TI_3 \\ 0_3 & 0_3 & I_3 \end{bmatrix} \text{ and } \mathrm{w(k)} = \begin{bmatrix} \frac{T^3}{6}B \\ \frac{T^2}{2}B \\ TB \end{bmatrix} \gamma(k) \tag{2}$$

With $\gamma(k) \in \mathrm{R}$ a zero mean white Gaussian noise of assumed known variance [3],

$$\mathrm{B} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, I_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, 0_3 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

In addition to the standard state model are measurement models. Absolute sensor data is considered, as well as observations from IMUs. These data are obtained by transforming data given by accelerometers from the body frame to the reference frame using gyroscopes [11].

C. User Interface and Graphical Feedback

The proposed interface provides near-real-time and immediate flight path data from jumps based on sensor readings, with relevant data readily available, e.g. above ground level (AGL) and time. Figure 1 and Fig. 2 show 2D and 3D flight data and graphics of a real jump respectively. These figures and analyses were generated within minutes after data is collected from sensors. In addition to immediate feedback from jumps, the software affords a simulation environment in which novices or trainees can simulate failure recovery from broken steering lines and chute malfunctions before real jumps to prevent real injuries.

(a) (b)

Fig. 1 Example of 2D flight data (a) landing in narrow clearing (b) close up of final maneuver, turn at 380 ft. AGL

Figure 1(a) illustrates the 2D feedback from a real jump in which a smokejumper avoided trees in a clearing of only 100 ft, as illustrated by the yellow line. The interface also provides pertinent data, including the fact that the jumper exited the aircraft at 9:07:14 with winds of 4 mph.

Figure 1(b) provides more detail to the landing of the same jump. The close up view shows that to avoid the trees in the narrow landing space, the jumper turned at 380 ft. AGL and landed at 9:08:43. This maneuver within the last 400 ft. above ground level are crucial to safe maneuvers in such a tight space. The flight data captured from the system allow for identification of critical junctures in the flight trajectory, such as the braking and turns used in this example, that lead to crashes vs safe landings.

Figure 2 illustrates the 3D rendering of the final approach and provides even greater detail. In this view, the user can observe obstacles avoided and garner a better spatial awareness of the flight.

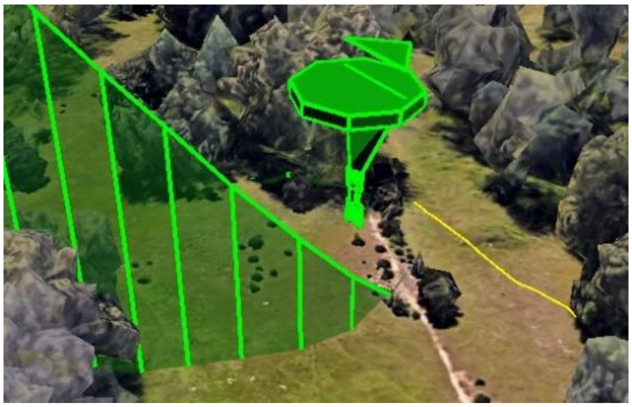

Fig. 2 Example of 3D flight data

The 3D view from the system in this case was in relatively flat terrain, yet the system is capable of rendering and displaying jumps with steeper slopes.

In addition to the jumper flight path, the developed system also makes available the aircraft flight path, providing yet another powerful analytical capability for use in near-real-time tracking, post flight analysis, and simulation/training purposes. Figure 3 illustrates an example of an aircraft flight path from another jump. During this jump, the plane circled at approximately 1,500 ft. AGL to release streamers for determining wind speed. The aircraft, shown in yellow, then increased to 2,000 ft. AGL where the smokejumper exited.

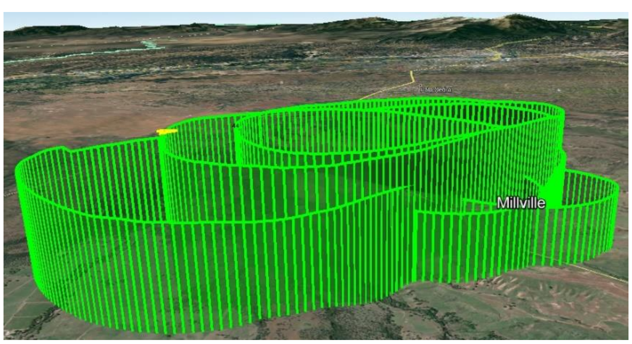

Fig. 3 Example of aircraft flight path – information is immediately displayed via the tracking system

IV. Experimental Procedure

A. Accident Investigation - Post Flight Data

The system is useful as an accident investigation tool. For evaluation, the recorded flight data of a 2016 jump which resulted in injury was used as an input for the tracking software. The system analyzed the accident within 15 minutes after receiving the flight data and displayed in an intuitive graphical format. Note that in prior smokejumpers accident reports it took up to eight months and the amount of consolidated data included much less information and can cost thousands of dollars to generate.

B. Training - Real-time Feedback, Flight Status

Over 400 smokejumper skydives were tracked with the Skydiving Tracker within a span of 6 months, 200 of these were included in a Jump History. As an evaluation, the debriefing and progress of rookie jumpers at smokejumper bases was conducted via the described system.

Key bases responsible for approximately 82 percent of fires jumped in the United State of America by smokejumpers tested the tracking system. The bases used the technology to both debrief and track rookie jumpers over a two week training, and the outcome of landing accuracy, i.e. distance to spot, was measured and considered along with wind speed.

V. Results

A. Debriefing Feedback

Figure 4 shows the flight data used and informs how well jumpers, pilots and spotters worked as a team. In total, four jumpers (1,2,3,4) were tracked. The green and red designate jumpers from the two separate aircraft. The jumpers exited in two passes of the aircraft and into 13 mph winds, the two passes are shown by the red and green lines – these were moved and scaled to fit within the image, but are available to scale in the real output. The yellow “x” denotes the landing target, and the landing locations are marked with large green and red numbers. This provides several forms of useful feedback.

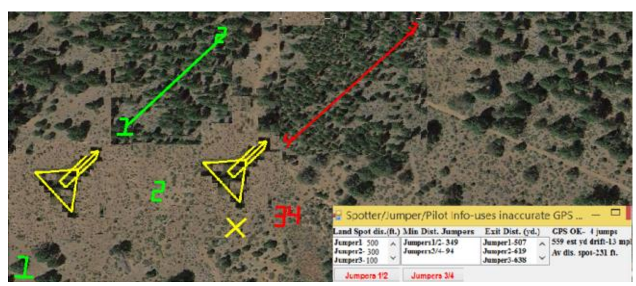

Fig. 4 Example debrief for spotters, jumpers and pilots

Firstly, the green flight path deviated 400 ft. from an ideal flight path (green line drawn). Moreover, jumper 1 landed 500 ft. away from target and crashed into a tree. Meanwhile, jumper 2 landed 300 ft. from target. Finally, in contrast, for the second pass of jumpers, both jumpers 3 and 4 landed within 100 ft. of the target. These tools assist in training to pinpoint useful flight paths for pilots and spotters, and further to ensure that jumpers land safely and on target.

B. Training - Real-time Feedback, Flight Status

A total of 11 planeloads and 75 jumps were tracked with the system. Table I shows the data collected from this experiment.

TABLE I

WIND SPEED vs. DISTANCE TO SPOT

Wind Speed / Distance To Spot	0-5 mph	6-10 mph	11-15 mph
0-55 ft.	6 jumps		
56-110 ft.	24 jumps	4 jumps	6 jumps
111-220 ft.	7 jumps	15 jumps	
221-330 ft.		13 jumps	

*first week *second week *veteran jumper

Recall that the data in Table I were collected from key bases responsible for approximately 82 percent of fires jumped in the United State of America. The bases used the tracker technology to both debrief and track rookie jumpers over a two week training, and the outcome of landing accuracy, i.e. distance to spot, was measured and compared with various wind speeds in May and June of 2016.

Table I shows that while the rookie jumpers landed an average of over 200 feet from spot in their 1st week, by their second week they were landing within roughly 100 feet from spot – a dramatic improvement. The training, debriefing and precise information provided as feedback can attribute to this increased performance. Note that the landing distance to spot is one of the key measures of their success and safety, since the closer a jumper lands to the spot (target), the less likely they are to land in dangerous areas or to crash into trees. Unsurprisingly, the well-trained veteran jumpers performed well, landing at within 70 feet of spot in 11 mph winds and landing within 52 feet with lower winds.

VI. Concluding Remarks

In this work, a method for error-correction and sensor consolidation for skydiver tracking is presented. The system is compatible with low-cost tracking hardware and affords rapid training, real-time tracking, intuitive feedback and status notification. The system also makes use of pre-jump data for debriefing purposes. Furthermore, post-jump analyses are provided for accident investigation. Over four-hundred jumps were performed to evaluate the proposed method with encouraging results. Real data from military and smokejumpers demonstrate a marked improvement in jump accuracy for novice training purposes. For post flight testing, a 2016 accident was analyzed within fifteen minutes after receiving the flight data, including flight path and detailed 3D visualization. This compares well with the real accident investigation, which spanned months until completion.

Acknowledgment

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