Disdrometer Calibration Using an Adaptive Signal Processing Algorithm

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Abstract - **Disdrometers are considered exotic instruments and provide valuable information. As such, their price tag is also high. Impact disdrometers are instruments that produce an electrical impulse output related to the mass of a rain drop colliding at terminal velocity with a sensor. The produced electrical impulse signal amplitude and energy are related to the drop diameters. This relation is in general non-linear and depends heavily on the type of transducer used. Mechanical structure imperfections and electrical tolerances dictate the need for the individual calibration of each instrument in an attempt to create calibration curves that convert impulse amplitudes to equivalent drop diameters. Conventional calibration techniques using drop towers have been a tedious process to say the least. A proposed alternative calibration technique utilizing an adaptive signal processing algorithm eliminates the need of a single drop calibration. An accumulation rain gauge provides a reference signal to the disdrometer that is used for adaptive training and optimization of a model based calibration function.**

In this paper we describe a prototype low-cost disdrometer implementation at the University of Central Florida. A prototype impact sensor was built using an array of piezoelectric elements encapsulated in water resistant material. For the data acquisition and processing we use the soundboard of a general purpose computer. The signal processing algorithms and Matlab implementation will be described. Data have been collected and processed and results will be presented. Future plans on developing a low cost disdrometer will also be discussed. The availability of affordable disdrometers will benefit NASA's upcoming GPM program, as well as many other meteorological agencies.

I. INTRODUCTION

Impact disdrometers were originally developed to measure rainfall rates [1] but have been widely used to estimate drop size distributions. They are instruments that convert a drop impulse at terminal velocity to an electrical output. Processing, counting and measuring the individual raindrop impacts, drop size distributions as well as a rain fall rates and individual drop diameters can by calculated. Mechanical structure imperfections dictate the need for calibration of such equipment in an attempt to create optimal calibration curves that accurately convert impulse amplitudes to equivalent drop diameters [2]. Conventional calibration techniques using drop towers and single, known diameter, drops allowed for only an empirical calibration.

Previously proposed alternative calibration methods utilize adaptive algorithms in an effort eliminate the need of single drop calibration. An accumulation rain instrument such as a tipping bucket provides a measure of comparison with the disdrometer signal for training and optimization of the adaptive coefficients of the algorithm. Accurate, reliable calibration and processing of the disdrometer can significantly contribute to a better understanding of rain fall characteristics, a vital knowledge for cloud physics and radar meteorology

II. RAINFALL MEASUREMENT INSTRUMENTATION

A. Disdrometer

Disdrometers measure, and count individual raindrops. Drop diameters can be estimated by converting the electric impulse produced by the collision of a single raindrop at terminal velocity to an equivalent diameter. Fig. 1 shows the prototype rainfall sensor constructed from seven piezoelectric ceramic (PZT) discs. This arrangement is embedded in a polymer material. For a raindrop impact the polymer transmits strain to the composite producing a voltage. This transducer is very rugged and low cost.

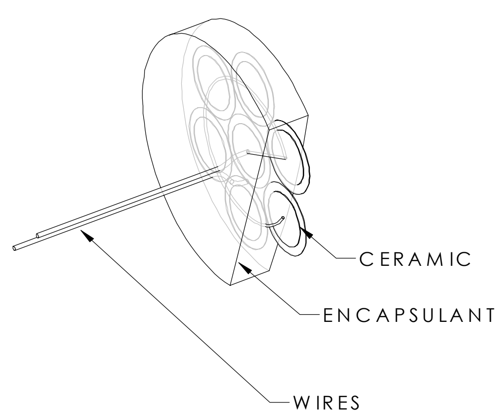

Fig. 1. Section-view of Raindrop Sensor

B. *Tipping Bucket*

Tipping buckets are widely used for measuring rainfall rates. With a resolution of 0.01 in., rainfall rates are computed by dividing the accumulated rain by the time between tips. The tip of the bucket triggers a momentary switch which is used to activate the recording of each tip.

III. ADAPTIVE CALIBRATION ALGORITHM

Disdrometer calibration has been an area of debate and concern for the research scientist. Mechanical structure imperfections dictate the need for calibration of such equipment in an attempt to create optimal calibration curves that convert impulse amplitudes to equivalent drop diameters. Conventional calibration techniques have been the least a tedious process, where the use of drop towers and single, known diameter, drops allowed for only an empirical calibration.

The proposed alternative calibration technique utilizing an adaptive signal processing algorithm eliminates the need of a single drop calibration. This new approach uses a tipping bucket to provide a reference signal to the disdrometer which is used for adaptive training and optimization of a model based calibration error surface function with a set of adaptive coefficients. The response of the impact sensor is modeled rather arbitrarily as shown in (1), where $x_m(n)$ is the amplitude of the *m*th impulse produced by a drop of volume $v_m(n)$ during the *n*th time frame as taken from the disdrometer.

$$\hat{v}_m(n) = \sum_{k=0}^{L-2} \alpha_k x_m^{k\beta}(n) \tag{1}$$

Selecting L to be equal to 3 resulting in coefficients α_0, α_1, β, each individual drop impulse will have an estimate volume of:

$$\hat{v}_m(n) = \alpha_0 + \alpha_1\, x_m^{\beta}(n) \tag{2}$$

Accumulating all drops within a time frame M_n *s*elected to be the elapsed time between three successive gauge tips; corresponding to 0.03 in. of rain, the accumulated disdrometer raindrop volume can be calculated using (3).

$$\hat{V}(n) = \sum_{m=1}^{M_n} \hat{v}_m(n) \tag{3}$$

The error surface shown in (4) can now be selected and is defined to be the sum of the square of the differences between the tipping bucket accumulated volume V_0, and the calculated in (3) disdrometer volume of $\hat{V}(n-k)$ [7].

$$E(n) = \sum_{k=0}^{N-1} \left[V_0 - \hat{V}(n-k) \right]^2 \tag{4}$$

In (4) V_0 and $\hat{V}(n-k)$ are the volumes accumulated and calculated over an equal surface area, which in this case is the surface area of the disdrometer A_s [2].

The algorithm responsible for the error surface minimization of (4) resulting in the adaptive optimization of the coefficients of (1) is based on the simplex search method and implementation of [3], a direct search method that does not use numerical or analytical gradients and is based on the original Nelder-Mead algorithm.

The coefficient optimization produces also the calibration curve described by (1). For a given set of coefficient values, drop diameters are calculated, generating sensor calibration curves that can map any impulse amplitude to a drop diameter.

IV. DATA ACQUISITION AND MATLAB SIGNAL PROCESSING IMPLEMENTATION

Fig. 2 illustrates a complete block diagram of the digital signal processing section combined with the adaptive calibration algorithm section as implemented and processed in MatLab.

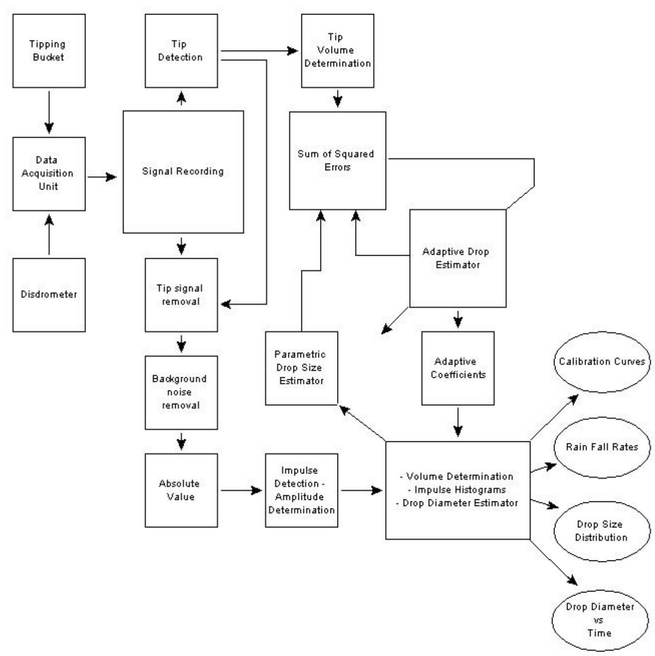

Fig. 2. Adaptive DSP processing and calibration algorithm block diagram

The interface data acquisition unit triggered by the tipping bucket switch creates a 3 kHz square wave which is added to the disdrometer signal.

Together the combined signals are the input to the recording module which is the soundboard of a computer. Recorded as a wave file at sampling frequency of 11.025 kHz, 16 bit, mono the file is read into the MatLab memory using appropriate commands. Filter and amplitude detection applications can separate each individual tip, preserving its time occurrence, from the actual disdrometer signal.

With the use of a threshold, background noise is removed, while further signal manipulation customized to the disdrometer impulse characteristics can result in a 'clean' signal for impulse, amplitude detection and energy determination. Each impulse's energy and time occurrence, falling within a selected period of three tips, is grouped together to calculate their corresponding volume and along with the default volume accumulated for three tips, provide the input to the error surface minimization algorithm.

The algorithm in this process adaptively optimizes the coefficients for a minimum error. Initial coefficient values provide a starting point for the algorithm's iterations ensuring faster results. Individual drop volumes are recalculated taking into account the new adapted coefficients. Calibration curves, rainfall rates, drop size distributions and drop diameter vs. time are relationships that can be extracted and presented at the end of each calibration – optimization cycle for a selected time period.

Using the new coefficients for each optimization period actual single drop diameters using (5) can be calculated, in which each impact was recorder in a form of an impulse, assuming a spherical shape [2].

$$D_m(n) = \left(\frac{6\, v_m(n)}{\pi}\right)^{\frac{1}{3}} \tag{5}$$

$v_m(n)$ is being calculated using (2) and the calibration coefficients.

Rainfall rates $R(t)$ for each optimization time period of Δt can also be calculated by summing the drop volumes given by (2) during the entire interval, accumulated over the sensor area of A_s. Equation 6 shows just that.

$$R(t) = \frac{1}{A_s \Delta t} \sum_{m}^{\Delta t} \sum_{k=0}^{L-2} \alpha_k x_m^{k\beta} \tag{6}$$

Drop Size Distribution (DSD) is defined as a volume density distribution of water droplets, or the number of drops in a volume of air as a function of drop size [1]. Drop size distributions can be extracted from drop diameter versus time (D/t) data, generating DSD histograms and dividing by the drop terminal velocity v_D [2].

$$N(D) = \frac{n_k}{T\ A_s\ v_{Dk}\ \Delta D} \qquad \left[m^{-3} mm^{-1}\right] \tag{7}$$

where n_k is the number of drops taken from the histogram, T is the time interval, ΔD is the selected drop diameter interval and v_{Dk} its corresponding terminal velocity. Equation (8) is a good approximation for terminal velocity used in (7) [4],

$$v_D \approx A e^{bZ} \left\{1 - e^{-(D/a)^n}\right\} \tag{8}$$

where $A = 958\ cm\ s^{-1}, b = 0.0854\ km^{-1}$, z is the elevation at the ground, D is the drop diameter, $a = 1.77\ mm$, .and $n = 1.147\ mm$.

V. EXPERIMENTAL RESULTS

During a rainfall event on October 4, 2004 passing over University of Central Florida (UCF), data from the UCF data acquisition site were collected and processed using the previously described adaptive calibration algorithm.

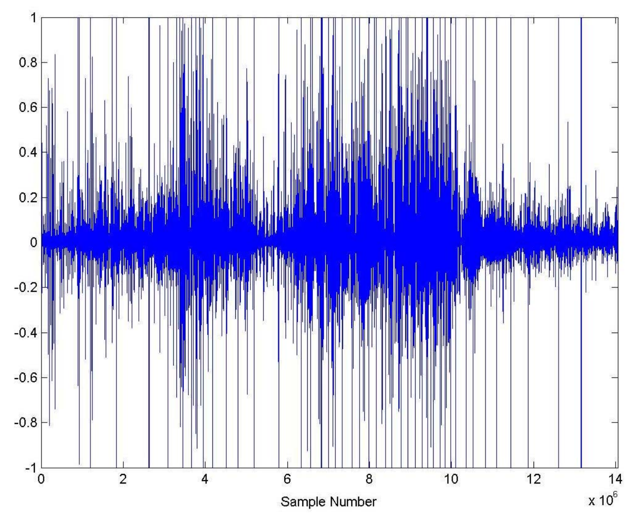

Fig. 3. Input signal

Fig. 3, shows the raw data as collected and loaded into MatLab, before any processing, to illustrate the shape and characteristics of the recorded signal, and the level of complexity the algorithm has to be able to overcome performing for perfect results.

The entire signal is about 21 minutes long and it is composed of disdrometer impulses with maximum length of 3.5 ms and 42 tips. A portion of the processed signal can be seen in Fig. 4.

An 8th order band pass filter centered on the 3 kHz tipping signal frequency, isolates the individual tip recordings as inserted into the original disdrometer signal and allows for individual tip period optimization based on the time stamp of the beginning and end of each tip.

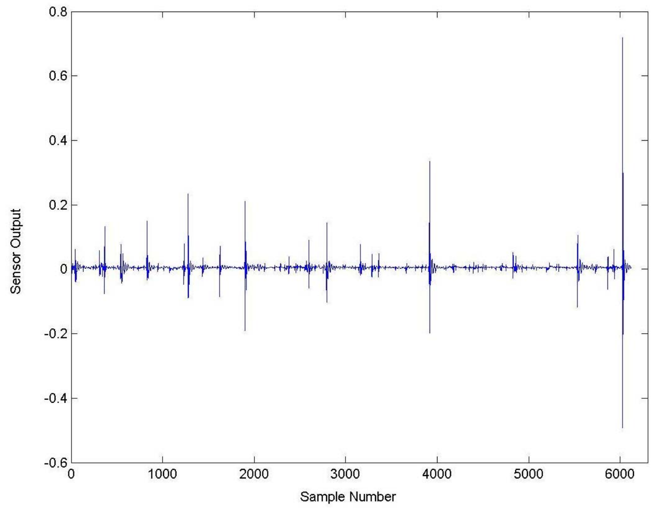

Fig. 4. Sample disdrometer output

During this period, the accumulation time is also defined for the disdrometer, in which drops will be grouped together for the disdrometer volume estimation. After each tip period is defined the tip signal is removed from the original signal and a threshold based on background and other environmental noise is applied.

After the signal is processed, the adaptive algorithm can be applied using (1) through (4). The coefficients are optimized after minimizing (4) and calibration curves for a selected time period of three tips can be calculated using (5). Each one of the drop diameters calculated within the same optimization period use the same coefficients. Fig. 5 shows typical calibration curves for different optimization periods.

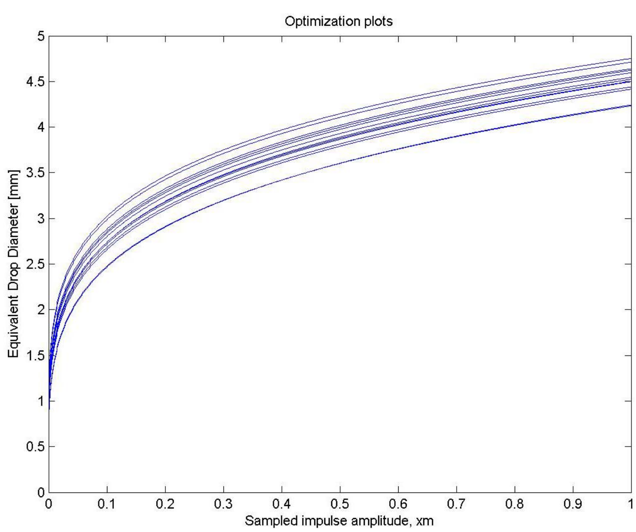

Fig. 5. Calibration curves

It is important to note by observing Fig. 5 that there is a small difference between optimization curves for different optimization periods. Theses differences could be related to non-uniform sensor sensitivity, multiple collisions on the sensor surface and lack of full rain drop spectrum within the optimization period. This is a concern demanding further investigation.

Each diameter size is accompanied with its corresponding time stamp in the original recording, allowing for a drop diameter versus time (D/t) plot to be created.

This type of output data is displayed in Fig. 6, for one of the time periods, by plotting a small dot at the corresponding drop diameter (vertical axis) and the time (horizontal axis) coordinate, where each dot represents a measured raindrop [2].

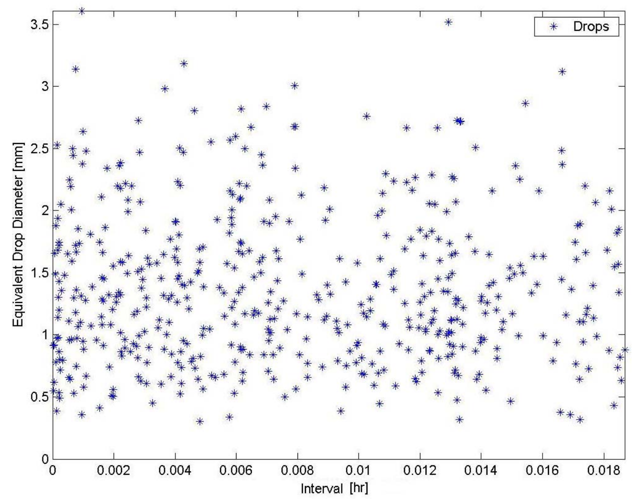

Fig. 6. D/t plot

Rainfall rates can also be computed by dividing the accumulated rain by the time between tips taken directly from the tipping bucket tip signal recordings. The correlation between tipping bucket rain rates and rain rates calculated using (6) shown in Fig. 7, is non-other than the optimized coefficient values estimated to give a minimum error.

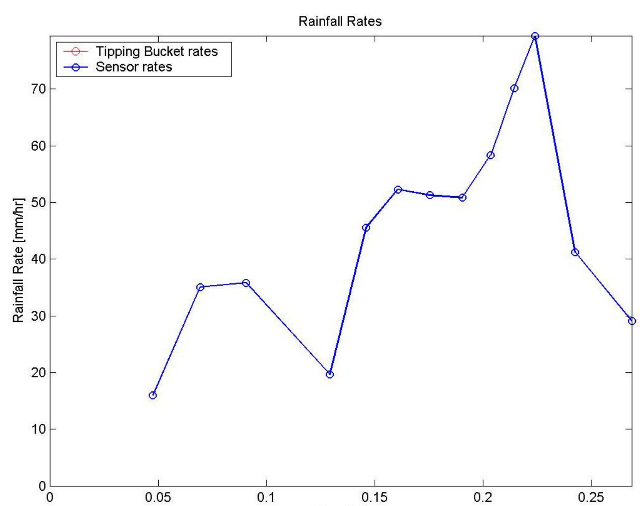

Fig. 7. Rainfall rates

Fig.7 shows clearly that there is no difference between the two rainfall rates indicating that the optimization algorithm and processing techniques used can perform effectively overcoming the small differences observed in the optimization curves and produce acceptable results. Any difference between the two rainfall rates would have only occurred in the event of algorithm ineffectiveness to optimize the coefficients for any of the optimization time periods

In order to create drop size distributions plots data, from drop diameter versus time (D/t) plots shown in Fig. 6, have to be extracted and DSD be calculated using (7) and (8). Fig. 8 shows a sample D/t plot and how data is extracted.

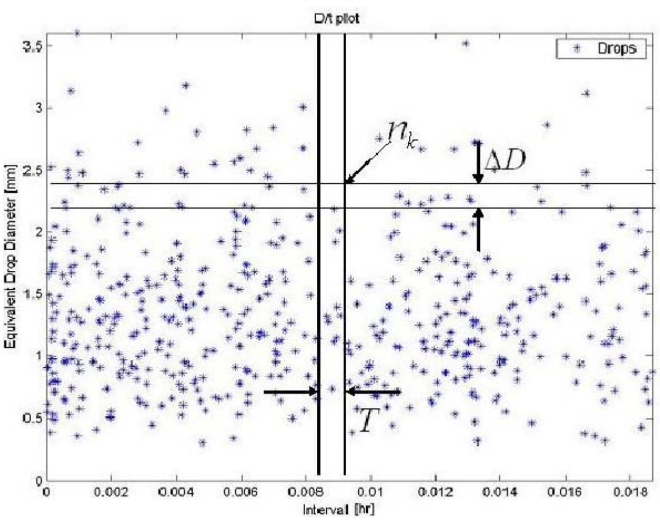

Fig. 8 D/t data extraction method for DSD

Fig. 9, shows the DSD of the entire rain event using (7) and data extracted with the method shown in Fig 8.

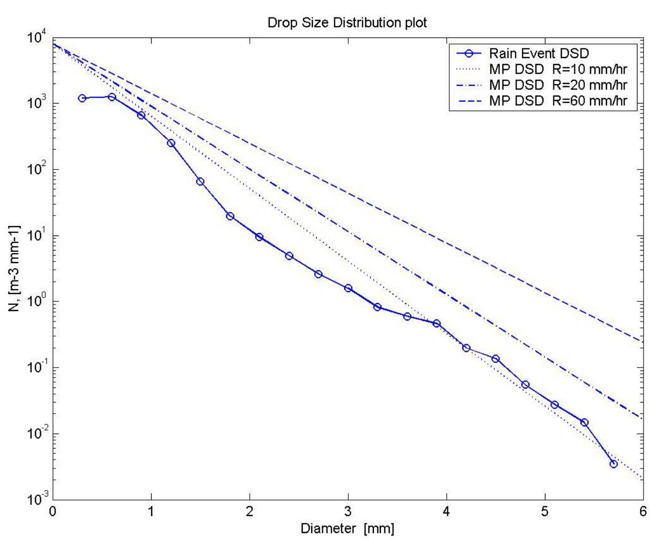

Fig. 9. Drop size distribution

The empirical Marshall – Palmer DSD (MP DSD) derived from [1], which is a special case of the exponential distribution characterized by its explicit definition of fitting parameters, for rain rates of 10, 20 and 60 mm/hour is also shown for comparison.

VI. SUMMARY - CONCLUSIONS

Using the adaptive digital signal processing approach, the proposed calibration algorithm of [2] has been improved and implemented, providing results showing that low cost impact disdrometers can be designed. Utilizing a tipping bucket rain gauge as a reference signal, the impulse amplitudes from the disdrometer sensor are transformed by an adaptive drop size estimating algorithm and summed together within a reference time frame defined by each tip [2]. The simplex search method of the applied algorithm optimizes the coefficients by minimizing the error between disdrometer and tipping bucket volume, producing new set of coefficients which are thereafter used to convert the disdrometer impulse amplitude to drop diameter utilizing the calibration curves.

Significant improvements in data acquisition, signal processing structure, and adaptation algorithm as well as a complete MatLab code with newly introduced techniques for disdrometer signal processing have being implemented. These new improvements and techniques have been evaluated using data form the UCF's data acquisition site and the results indicate that the adaptive algorithm can be the basis for developing low cost disdrometers. The availability of affordable disdrometers can benefit NASA's upcoming GPM program, as well as many other meteorological agencies

Acknowledgments

Special thanks to Sparton Engineering in Deleon Springs, Florida for their contribution in designing and fabricating the disdrometer sensor.

This work was supported by a grant from NASA/TRMM Goddard Space Flight Center.

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Fig. 10. Prototype disdrometer

Fig. 11. Data Acquisition Site