Cross-correlation for Dynamic Predictive Sampling Signals in Biomedical Signal Acquisition

Brandon Gresham
Klipsch School of Electrical and Computer Engineering
New Mexico State University
Las Cruces, New Mexico, USA
bgresham@nmsu.edu

Wei Tang
Klipsch School of Electrical and Computer Engineering
New Mexico State University
Las Cruces, New Mexico, USA
wtang@nmsu.edu

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***Abstract*—This paper presents a novel method to calculate the cross-correlation of signals using dynamic predictive sampling. The primary application is to save computing overhead for wearable devices that monitor biomedical signals. Compared to the conventional Nyquist-rate data acquisition systems, dynamic predictive sampling saves data throughput by only recording the digital value of the turning points in the analog waveform. However, it generates a non-uniform sampled sequence with both amplitude and timestamp data. To calculate the cross-correlation of the recorded waveform, we propose an area-based method that utilizes the Jaccard Index instead of using interpolations. Based on our simulation result, compared to the conventional cross-correlation that uses interpolation for nonuniformly sampled signals, the proposed Jaccard Index method saves computing resources for dynamic predicted sampling sequences and provides better linearity.**

***Index Terms*—nonuniform sampling, dynamic predictive sampling, cross-correlation**

I. Introduction

Wearable biosensors are expecting low-power sensing and computing systems to save power and extend battery life, especially for devices that perform long-term monitoring. Examples could be found for long-term electrocardiogram (ECG) sensors and wearable Electromyography (EMG) sensors. However, the conventional Nyquist-rate sampling method may generate much unnecessary data that overload the signal processing devices [1], which increases the system power. Level-crossing sampling may introduce insertion and deletion errors, which introduce drifts in the reconstructed waveform [2]. Recently, a dynamic predictive sampling method has been proposed [3], [4], which is based on predicting the digital value in slopes. Since it only records the digital value of the unsuccessful predictions, which are the turning points in the analog signal, the dynamic predictive sampling system can greatly reduce the output data amount. However, its output data contains both amplitude and timestamp information of the turning points, which is difficult to process using conventional digital signal processing (DSP) algorithms.

As an example, cross-correlation measures the similarity between two signals or a signal with a template, which is an important signal-processing task for biomedical applications. Examples of applying cross-correlation in biomedical data processing can be found in ECG [5], EMG [6], [7], and electroencephalogram (EEG) [8], [9] applications. Although cross-correlation algorithms are well-studied for uniform sampled signals, it is difficult to be applied to dynamic predictive sampling signals. This is because those algorithms are mostly based on the assumption that the data is uniformly sampled by a fixed-rate clock. In order to apply conventional DSP algorithms, interpolation methods were often applied [10], which generate much unnecessary data that undermines the advantage of using dynamic predictive sampling and increases system power. Therefore, efficient algorithms are expected for processing nonuniform sampling data from dynamic predictive sampled signals.

In order to solve the aforementioned problem and avoid using interpolation for nonuniform sampling signals, we propose a simple method to calculate cross-correlation using the area method. The proposed method borrows the idea of the Jaccad index [11] in calculating the overlap between two areas. The method first calculates the average of the two signals, and then aligns the two signals in the time domain. This can be achieved since in some applications such as ECG, the R-peak can be identified using mature algorithms [12]. After that, the overlap and non-overlap areas of the two signals are calculated using only the amplitude and timestamp of the nonuniformly sampled signals. The cross-correlation is then calculated by comparing the ratio between the overlapping area and the non-overlapping area. The proposed method does not use interpolation, which can save much data storage space and computing overhead. The remainder of the paper is structured as follows: Section II describes the proposed system. Section III presents the simulation results of the proposed method and compares it with the conventional method. Section V concludes the paper.

II. System Design

The proposed system computes the cross-correlation between two input signals from dynamic predictive sampling systems. In this section, we first briefly describe the dynamic predictive sampling method and the structure of the nonuniform sampling signals, then we present the proposed algorithm for computing cross-correlation for such nonuniform sampling signals.

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A. Dynamic Predictive Sampling

Dynamic Predictive Sampling selects the turning point in an analog waveform and performs quantization only on these selected points. This is done by using the quantized digital values of the first two sampling points to predict the next sampling points in the digital domain. The predicted digital value of the next sampling points is added and subtracted by a predefined Delta value to form an upper threshold and a lower threshold. The two thresholds are then converted into analog values and compared with the actual analog value of the next sampling. If the sampling value is between the two thresholds, the prediction is successful and no quantization is performed for the sampling value. The predicted digital value is used for the next prediction until an analog sampling value is out of the window between the two thresholds. In such a case, a full quantization is performed, and the timing between the failed predictions is recorded as a timestamp. Those selected sampling points are turning points in the analog waveform. The output of the dynamic predictive sampling contains both the amplitude of the turning points and the timestamp between the turning points.

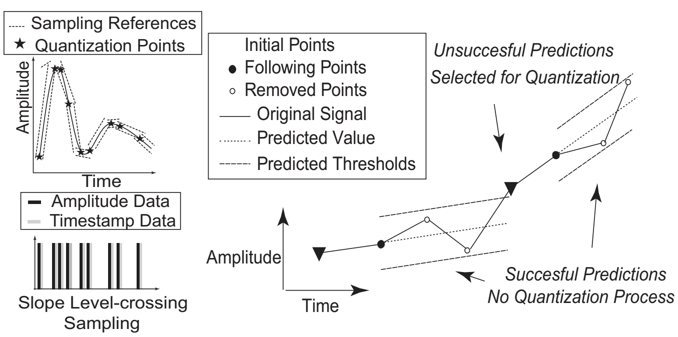

Fig. 1. Predictive Sampling (Left) Sampling point selection and output data format (Right) Selecting sampling points using prediction and thresholds [3].

Fig. 1 presents the operation of a Dynamic Predictive Sampling System. The first two samplings of the input analog signal are converted into digital values using a successive approximation register (SAR) analog-to-digital converter (ADC). Then in the digital domain, the digital values are used to compute the prediction of the new sampling data. After that, the predicted digital values are added and subtracted by a pre-defined Delta value to obtain the digital values of an upper and a lower threshold. Thereafter, a digital-to-analog converter (DAC) converts the threshold digital values into analog values. The analog threshold values are then compared with the new analog samplings to decide if the prediction is successful. Unsuccessful prediction indicates a turning point in the analog waveform, which resets a timer that records the timing between the unsuccessful predicted sampling points. In other words, the output of the dynamic predictive sampling contains a 10-bit digital amplitude value of a turning point and a 10-bit digital timing data that measures the timestamp between the turning points. A circuit diagram with a fabricated chip photo of the Dynamic Predictive sampling ADC was reported in our prior work as shown in Fig. 2 [4].

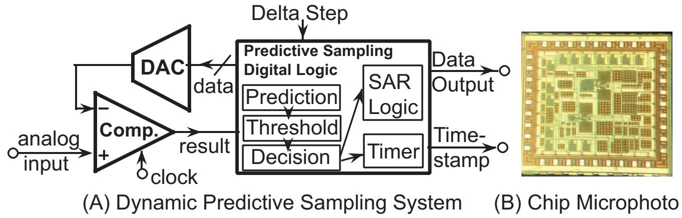

Fig. 2. (a) Block diagram of the Dynamic Predictive Sampling ADC. (b) Chip microphoto. [4]

B. Cross-correlation of nonuniform sampling data

Cross-correlation analysis measures the similarity between two waveforms. For example, in biomedical applications, cross-correlation can be applied to check if a waveform is similar to a template waveform, which could be a stored normal or abnormal signal. The cross-correlation coefficient is calculated by the convolution of the two waveforms with one waveform fixed and the other waveform shifted by a time variable τ called displacement or lag. The maximum value of the cross-correlation is achieved when the two signals are synchronized by the time variable. The maximum value of the cross-correlation is the correlation coefficient which indicates the similarity of the two signals.

The possible value of the correlation coefficient C is between $+1$ and -1. Here $+1$ means the two signals are the same; -1 means the two signals are reversed of each other; and 0 means the two signals are not related to each other. If the two waveforms are acquired by a fixed-rate sampling process, the correlation is calculated by shifting the waveform by one clock cycle each time, which results in a high computing and data storage overhead especially when the sampling rate is high. Fortunately, in certain applications, the synchronization process could be skipped. For example, in ECG monitoring, since the R peak can be reliably detected, the correlation coefficient can be directly calculated after aligning the location of the R peak. However, the large data amount still requires a high computing overhead for calculating the correlation coefficient, which limits its implementation on battery-powered wearable devices.

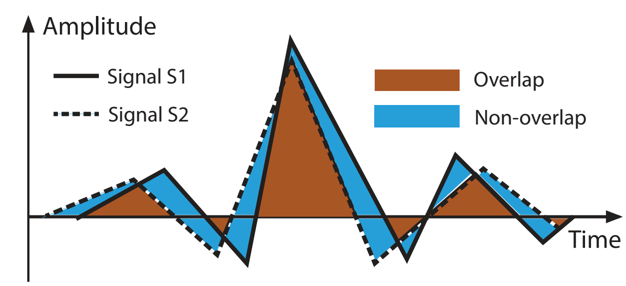

Fig. 3. Overlap and Non-overlap of the two signals using dynamic predictive sampling $S1$ and $S2$ for calculating the Jaccard Index.

The output of the dynamic predictive sampling system contains a two-dimensional vector $S_i(A, t)$, where A denotes

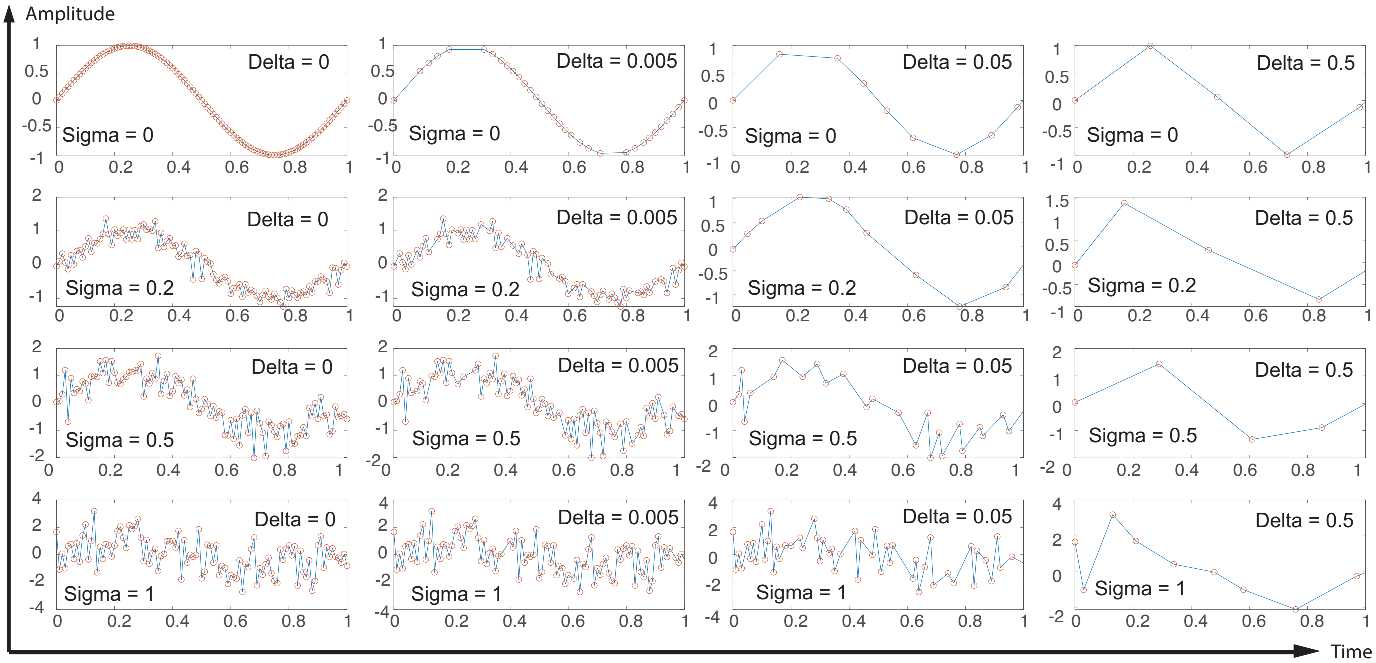

Fig. 4. Signals for evaluating the proposed cross-correlation method. From top to down: Sine wave with different noise Sigma levels; From left to right: dynamic predictive sampling with different Delta levels: a higher Delta level results in fewer sampling points and higher distortion.

the amplitude data of the turning point and t represents the timing between the turning points. Such nonuniform sampling data can be applied for calculating cross-correlation using a conventional cross-correlation algorithm by interpolation. Such interpolation converts the two-dimensional data $S_i(A,t)$ back to one-dimensional data $S_i(A)$ which assumes that the timing between each sampling is the same as the minimum value t. To avoid the high computing and storage overhead of interpolation, we propose a novel method that can compute the cross-correlation coefficient between different two-dimensional vectors $S1_i(A,t)$ and $S2_i(A,t)$. The algorithm borrows the concept of the Jaccard Index which calculates the overlap using the area method. The proposed method contains four steps: averaging, calculating overlap, calculating non-overlap, and calculating the Jaccard Index.

The first step removes the DC component of the signal by subtracting the average value from the signal, which can be achieved by (1) and (2).

$$S1_i'(A,t) = S1_i(A,t) - \overline{S1_i(A,t)} \quad (1)$$

$$S2_i'(A,t) = S2_i(A,t) - \overline{S2_i(A,t)} \quad (2)$$

Where $S1_i'(A,t)$ and $S2_i'(A,t)$ denote two signals that are being compared using the Jaccard Index. $\overline{S1_i(A,t)}$ and $\overline{S2_i(A,t)}$ denote the average of $S1_i(A,t)$ and $S2_i(A,t)$ respectively. $S1_i'(A,t)$ and $S2_i'(A,t)$ are the waveforms with an average value of 0. The area of overlap between two signals $S1_i'(A,t)$ and $S2_i'(A,t)$ is obtained, which is the area that both signal $S1_i'(A,t)$ and $S2_i'(A,t)$ have in common in both positive and negative regions, as shown in Fig. 3. Using linear reconstruction on both signals, the overlap area can be geometrically approximated using the area of trapezoids. Taking a summation of all areas of overlap between signal $S1_i'(A,t)$ and $S2_i'(A,t)$, the overlap area is obtained by (3):

$$Overlap\ Area = |S1| \bigcap |S2| \quad (3)$$

The non-overlap area can also be obtained geometrically by finding the area between $S1_i'(A,t)$ and $S2_i'(A,t)$. Then the total area is given by the sum of the overlap and non-overlap area. The total area can be calculated by (4):

$$Total\ Area = |S1| \bigcup |S2| \quad (4)$$

Finally, the Jaccard Index can be obtained by (5):

$$Jaccard\ Index = \frac{|S1| \bigcap |S2|}{|S1| \bigcup |S2|} \quad (5)$$

The Jaccard Index represents the similarity of the two waveforms from the dynamic predictive sampling results and can be calculated without interpolation. Since dynamic predictive sampling can reduce more than 90% of the data amount when the signal is sparse, this method can save storage and computing overhead.

III. Experimental Results

To validate the proposed Jaccard Index method for evaluating the cross-correlation of signals obtained by dynamic predictive sampling, we choose sinusoidal waves with different noise levels (Sigma) and acquired by different Delta steps. As shown in Fig. II-B, the first column represents sine waves with different noise levels sampled with Delta = 0, which means they are sampled by a fixed-rate clock. In the next three columns, the signals are sampled with a higher Delta value, which means the number of sampling points is reduced. A higher Delta value represents a higher compression factor with the cost of a higher distortion of the signal. The cross-correlation coefficient is calculated between the first row (Sigma=0) and one of the other rows with different Sigma values. Both the conventional cross-correlation coefficient method and the proposed Jaccard Index method are applied in these calculations and the results are compared between the two methods. When calculating the conventional cross-correlation coefficient in dynamic predictive sampled signals, the result is calculated using interpolation.

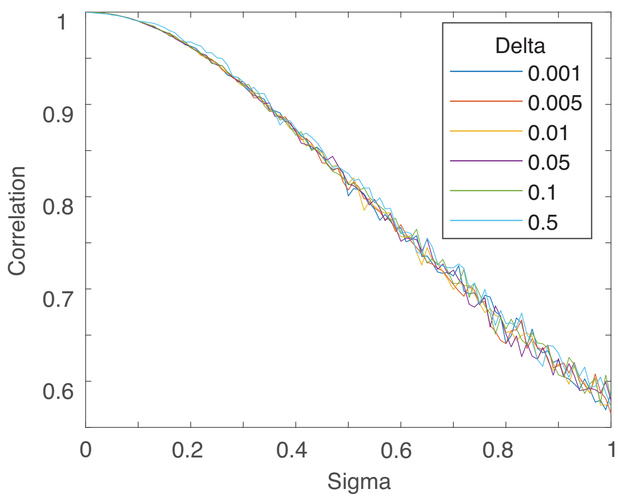

Fig. 5. Conventional cross-correlation coefficient between an ideal sine wave and noisy sine waves acquired by dynamic predictive sampling.

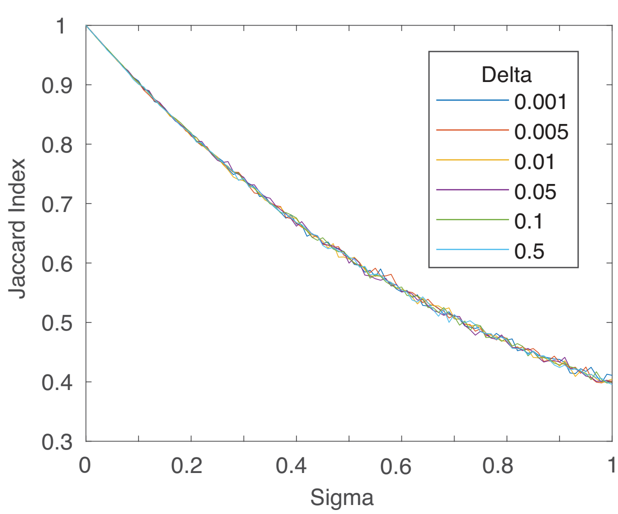

Fig. 6. Jaccard Index between an ideal sine wave and noisy sine waves acquired by dynamic predictive sampling.

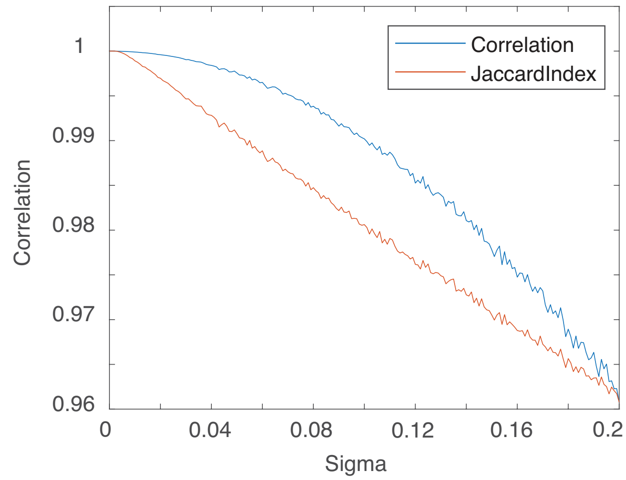

Fig. 7. Comparing conventional cross-correlation Coefficient and Jaccard Index, Jaccard Index has better linearity.

Fig. 5 shows that when the noise level increases, the correlation between the noisy sine wave and the ideal sinewave decreases as expected. Even if both the ideal sine wave and the noisy sine wave are obtained using dynamic predictive sampling methods with different Delta values. This means that while a high Delta value reduces the data amount, it does not affect the calculation of the conventional cross-correlation coefficient. However, since interpolation is applied in this method, the storage and computing overhead is much higher than using the proposed Jaccard Index method. As shown in Fig. 6, the same simulation was performed using the proposed Jaccard Index method. The results show that the Jaccard Index can also be used to evaluate the cross-correlation between the ideal sine wave and the noisy sine wave, while the different Delta values in dynamic predictive sampling also do not affect the result. Moreover, as shown in Fig. III, the proposed Jaccard Index method achieves higher linearity than the conventional cross-correlation coefficient in terms of the Sigma levels.

IV. Conclusion

This paper proposed a novel method to evaluate the cross-correlation between two signals acquired using dynamic predictive sampling. The method is to apply the Jaccard Index method to calculate the areas in the non-uniform sampled signals. So that the cross-correlation calculation does not need to perform interpolation as in calculating the conventional cross-correlation coefficient method. The simulation results show that the proposed Jaccard Index method achieves a similar result as the conventional cross-correlation method with better linearity. Since dynamic predictive sampling can achieve a high compression factor, the proposed method has the potential to greatly reduce the data storage and computing overhead for wearable bio-signal acquisition and related signal processing systems.

REFERENCES

[1] M. Saeed, Q. Wang, O. Mx00E4;rtens, B. Larras, A. Frappx00E9;, B. Cardiff, and D. John, "Evaluation of Level-Crossing ADCs for Event-Driven ECG Classification," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 15, no. 6, pp. 1129–1139, 2021.

[2] W. Tang, A. Osman, D. Kim, B. Goldstein, C. Huang, B. Martini, V. A. Pieribone, and E. Culurciello, "Continuous Time Level Crossing Sampling ADC for Bio-Potential Recording Systems," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 60, no. 6, pp. 1407–1418, 2013.

[3] M. Renteria-Pinon, X. Tang, and W. Tang, "Real-Time In-Sensor Slope Level-Crossing Sampling for Key Sampling Points Selection for Wearable and IoT Devices," *IEEE Sensors Journal*, vol. 23, no. 6, pp. 6233–6242, 2023.

[4] X. Tang, M. Renteria-Pinon, and W. Tang, "Dynamic Predictive Sampling Analog to Digital Converter for Sparse Signal Sensing," *IEEE Transactions on Circuits and Systems II: Express Briefs*, pp. 1–1, 2023.

[5] F. J. Chin, Q. Fang, T. Zhang, and I. Cosic, "A fast Critical Arrhythmic ECG waveform identification method using cross-correlation and multiple template matching," in *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*, pp. 1922–1925, 2010.

[6] R. Bose, K. Samanta, and S. Chatterjee, "Cross-correlation based feature extraction from EMG signals for classification of neuro-muscular diseases," in *2016 International Conference on Intelligent Control Power and Instrumentation (ICICPI)*, pp. 241–245, 2016.

[7] M. B. Jensen, K. S. Frahm, J. Biurrun Manresa, and O. K. Andersen, "Novel cross correlation technique allows crosstalk resistant reflex detection from surface EMG," in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 3531–3534, 2012.

[8] S. Siuly and Y. Li, "Improving the Separability of Motor Imagery EEG Signals Using a Cross Correlation-Based Least Square Support Vector Machine for Brain–Computer Interface," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 20, no. 4, pp. 526–538, 2012.

[9] B. R. Hermanto, T. R. Mengko, A. Indrayanto, and A. S. Prihatmanto, "Brain signal reference concept using cross correlation based for brain computer interface," in *2013 3rd International Conference on Instrumentation, Communications, Information Technology and Biomedical Engineering (ICICI-BME)*, pp. 388–391, 2013.

[10] J. Wagner, "NXCORR: Cross-correlation for non-uniform sampling." https://www.mathworks.com/matlabcentral/fileexchange/55920-nxcorr-cross-correlation-for-non-uniform-sampling, 2023. Retrieved April 23, 2023.

[11] A. W. Setiawan, "Image segmentation metrics in skin lesion: Accuracy, sensitivity, specificity, dice coefficient, jaccard index, and matthews correlation coefficient," in *2020 International Conference on Computer Engineering, Network, and Intelligent Multimedia (CENIM)*, pp. 97–102, 2020.

[12] Y.-R. Tsai, Z.-Y. Chang, and C.-W. Huang, "Time-domain multi-level r-peak detection algorithm for ecg signal processing," in *2019 IEEE Eurasia Conference on Biomedical Engineering, Healthcare and Sustainability (ECBIOS)*, pp. 35–38, 2019.