Non-uniform Sampling Pattern Recognition Based on Atomic Decomposition

Tugdual Le Pelleter*, Taha Beyrouthy*, Robin Rolland†, Agnès Bonvilain*, Laurent Fesquet*†
*TIMA Laboratory
46, avenue Félix Viallet, 38031 GRENOBLE Cedex, France
Email: {tugdual.le-pelleter, taha.beyrouthy, agnes.bonvilain, laurent.fesquet}@imag.fr
†CIME Nanotech
3 parvis Louis Néel, BP 257, 38016 GRENOBLE Cedex, France
Email: robin.rolland-girod@grenoble-inp.fr

***Abstract*—Non-uniform sampling is an interesting scheme that can outperforms the uniform sampling with low activity signals. With such signals, it generates fewer samples, which means less data to process and lower power consumption. In addition, it is well-known that asynchronous logic is a low power technology. This paper deals with the coupling between a non-uniform sampling scheme and a pattern recognition algorithm implemented with an event-driven logic. This non-uniform analog-to-digital conversion and the specific processing have been implemented on an Altera FPGA platform. This paper reports the first results of this low-activity pattern recognition system and its ability to recognize specific patterns with very few samples. The objectives of this work target the future ultra-low power integrated systems.**

I. Introduction

The advances in microelectronics and wireless communication has facilitated the development of tiny sensor platforms, smart sensors that can be integrated in mobile devices. Currently, mobile communication devices have sophisticated internal hardware architectures and embed a wide range of internal sensors including three-axial accelerometers. Accelerometers are widely used in the context of health monitoring with the detection of motions, actions and activity.

The pattern recognition processing can be very challenging to be achieved on mobile devices because they have limited processing, memory and computing ressources. Figo et al. [1] evaluated preprocessing techniques for recognizing basic daily physical activities (jumping, running and walking) with accelerometric data performed on a mobile device. The battery autonomy that supplies the mobile device is an inherent limitation that depends on the computational costs, storage requirements and precision. Energy scavenging techniques such as thermoelectric effect, vibrations or body movements may also complement the battery power [2].

In activity monitoring, important amount of energy can be saved since activities occur sporadically. Efforts are made to avoid useless processing. For example, Jafari and Lotfian [3] propose a low-power architecture dedicated to the Dynamic Time Warping (DTW) for physical movement monitoring. The idea is to activate the processing unit that performs the pattern recognition only when necessary. The architecture consists of a granular decision making module (GDMM) that detects *a priori* relevant information in the signal.

Traditional activity recognition methods use uniform sampling scheme, however the non-uniform sampling defined by level crossing is a better candidate for signals with infrequent activity. In this approach, levels are disposed along the amplitude range of the signal and a sample is only captured when the input signal crosses one of the defined levels (cf. Fig.1.). Relation can be made with the field of symbolic dynamics where the data space is partitioned and associated to a symbol. Such method leads to data compression and is a way to save energy, because irrelevant samples are pruned off. The data partitioning is an active area of research. Some partitioning methods are the data mean, midpoint, median, equal-size intervals over the data range, or regions of the range with equal probability [4].

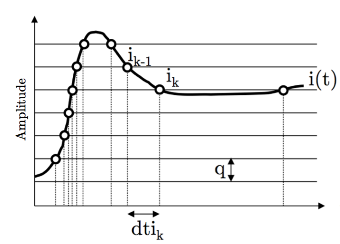

Fig. 1. Level crossing sampling with regularly spaced levels along the amplitude range of the signal

In this work, we propose a pattern recognition algorithm dedicated to mobile applications.

This paper is divided into three parts. We begin with discussion of the current state of pattern recognition methods for mobile devices. Secondly, we present our low-power pattern recognition method. In the third part, we present the hardware implementation. Finally, a discussion and a conclusion outline the method strength and weakness.

II. Related works

Benbasat and Paradiso [5] suggest to use the peaks structures in the accelerometer signal as a way to simplify the human gestures signature detection in inertial gesture recognition framework. The recognition is performed with simple parameters : peaks magnitude, duration and number. This method, called *atomic gestures* decomposes complex human gesture into a set of peaks. For example, a straight-line motion generated by an arm movement will create a two-peaked trace. The inertial measures are obtained with two two-axis MEMS accelerometers and leading to a six degree-of-freedom inertial measurements. The concept of motion decomposition into atoms is used by Fan et al. [6] for the detection of translational and rotational motions using a tri-axial accelerometer. An interesting characteristic pointed out by the authors is that for translational motions the translation starts by a tangential acceleration followed by a tangential deceleration. As a consequence, the acceleration signature consists of two peaks with opposite signs. The specific pattern allows to perform the motion decomposition on the human gestures in order to generate the sequences of motion directions defining the translational motions (clockwise circular, counter clockwise circular and hop right). One of the advantage of the detection method based on atomic decomposition is its insensibility to time distortion. Indeed, the gestures vary between individuals and for the same individual.

A gesture can be performed at several speeds, leading to similar shaped patterns but with different duration. The pattern matching performed using the euclidean metric leads to poor results for highly time distorted patterns since it does not take into account the distortion due to its linear alignment. A more adapted method is the dynamic time warping (DTW) distance introduced by Sakoe and Chiba [7] in the context of speech recognition. It is widely used in speech recognition, for online signature verification and for fall detection in the elderly. This technique aims to find an optimal alignment between two given sequences. The non linear complexity in $O(N \cdot M)$ strongly restricts its implementation on mobile devices. Global constraints such as *Sakoe-Chiba band* [7] or adapted constraints [8] are used to linearize the computational cost. Jafari and Lotfian [3] implemented a low-power architecture of pattern recognition for mobile applications based on the DTW.

Many algorithms have been proposed for pattern recognition framework. The most popular method is the hidden Markov model (HMM). It can achieves high recognition rate in motion and gestures recognition. For example, Joselli and Clua [9] propose a detection method of patterns performed in the air for games processed on a mobile phone. The method is energy intensive so the implementation on mobile devices where battery cannot be easily recharged is restricted. In this work, we use a finite state machine (FSM) model used for its simplicity in hardware implementation. For more details about gesture recognition algorithms, we refer the reader to [10].

III. Tools & Methods

The proposed method is designed to perform pattern recognition in activity signals. To take into account their sporadic characteristic, a non classical sampling scheme called level crossing sampling (LC) is used. With the LC sampling, a sample is only captured when the continuous time input signal crosses one of the defined levels (cf. Fig. 1.). Contrary to the uniform sampling, the samples are not uniformly spaced along the time axis, because they depend on the signal variations. The time elapsed between samples i_k and i_{k-1} is defined by $dt_{i_k} = t_{i_n} - t_{i_{n-1}}$. For the hardware implementation of the LC sampling, a local timer of period T_c is dedicated to record dt_{i_k}. Contrary to the Nyquist sampling, the amplitude of the sample is known and the time elapsed between two samples is quantized. The Signal to Noise Ratio (SNR) depends on the timer period T_c and not on the number of quantization levels [11]. An empirical framework is proposed in this paper, to choose the minimum number of necessary levels with their respective amplitude to properly perform the pattern recognition.

A. Atomic decomposition

The manipulated data are time series. A time series $T = t_1, ..., t_m$ is an ordered set of m real-valued variables. The patterns of interest are considered as the local subsections of the time series, called subsequences. A subsequence C of length m is a sampling of length $n \leq m$ of contiguous positions from p, that is, $C = t_p, ..., t_{p+n-1}$ for $1 \leq p \leq m-n+1$.

In the proposed framework, the pattern recognition can be considered as a two-class classification problem, let {p,n} the two classes. A known process generates two different patterns to detect, that belongs to the positive class p. The subsequences generated by unknown processes are considered as noise and associated to the negative class n. The two different type of patterns of interest belonging to class p are depicted in Fig. 2. There are four types of variations to detect

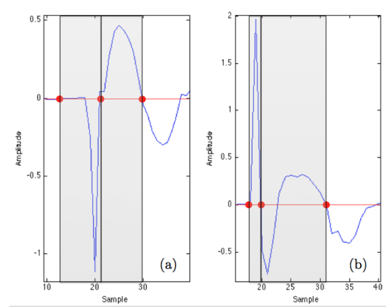

Fig. 2. The patterns consists of at least 2 peaks with opposite sign : (a) Negative peak P_1^- followed by positive peak P_2^+ (b) Positive peak P_1^+ followed by negative peak P_2^-

We suggest to detect these pair of opposite polarity peaks with two levels (positive and negative). Their respective amplitude is determined with the ROC curve.

B. Data labelization

The data labelization (cf. Fig. 3), consists of 3 steps : (1) The time series T is non-uniformly sampled with regularly spaced levels along the amplitude range. (2) The signal is then divided into two parts : positive T^+ and negative T^-. (3) Every peak bounded by contiguous zeros crossings, called epoch, are labeled. When the peaks belong to the positive (resp. negative) class, it is labeled 1 (resp. 0).

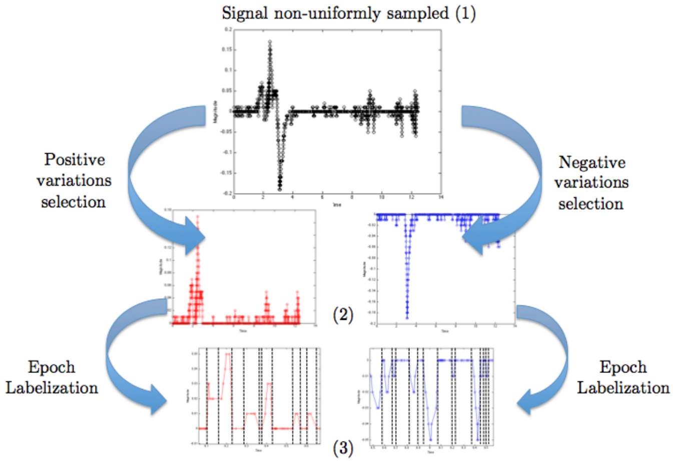

Fig. 3. Data labelization framework

C. ROC curve

The ROC curve is a technique mainly used for selecting a classifier in pattern recognition and is well-known in the medical decision community. Considering a two-class classification problem, each pattern of interest or instances are mapped to one element of the set $\{p, n\}$ of positive and negative class labels. There are four possible outcomes.

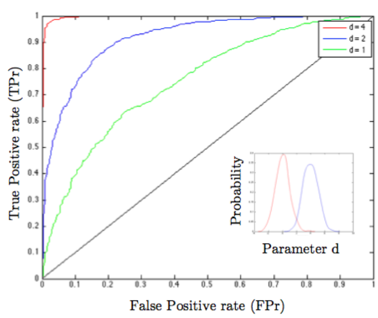

Fig. 4. The ROC graph plotted for two Gaussian data

If the instance is labeled positive and it is classified as positive, it is counted as a true positive tp. If it is classified as negative, it is counted as a false negative fp. If the pattern is negative and is classified as negative, it is counted as a true negative tn. If it is classified as positive, it is counted as a false positive fp. The number of positive (resp. negative) instances is noted P (resp. N). The true positive rate tpr (resp. false positive rate fpr) is defined by tp/P (resp. fp/N), where P (resp. N) is the number of positive (resp. negative) instances. The receiver operating characteristic (ROC) curve is a graph where the true positive rate tpr is plotted on the Y axis and the false positive rate fpr is plotted on the X axis. A ROC curve depicts relative tradeoffs between benefits (true positive) and costs (false positives). The Fig. 4. illustrates the ROC curve for two data sets with Gaussian distribution. Each set belongs to one class, positive p and negative n. As the distance d between the two distributions increases, the decision error decreases. When there is no overlapping between the two data sets, there is no error in classification, which is represented by the point (0,1) in the ROC curve. The ROC point (0,0) means that there is no false positive nor true positive and the point (1,1) represents a maximum rate of true positive and false negative. The classification performance can be calculated with the Area Under the Curve (AUC). We refer the reader to [12] for more information about the ROC curve.

In the time series T^+ (resp. T^-), two ROC curves are plotted to determine the optimal level for detecting peaks P_1^+ and P_2^+ (resp. P_1^+ and P_2^+). In the ROC space, the optimal level is considered as the one which generated the more distant point from the diagonal.

D. Algorithm

The pattern recognition algorithm is modeled by a finite state machine (FSM). The Fig. 5. shows the two types of signatures non-uniformly sampled with four levels. To validate a pattern, two peaks with opposite sign must occur in a pattern window δ. Two levels of minimum amplitude (positive and negative), defined as silence levels, are necessary to detect the pattern beginning.

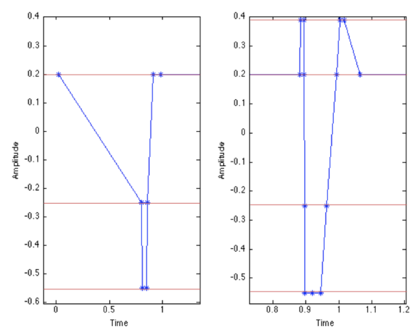

Fig. 5. The patterns depicted in Fig. 2 non-uniformly sampled with 4 levels

The algorithm is designed to detect a global pattern that contains a set of 4 patterns. Consequently, another window Δ is defined in which 4 patterns must be detected. This redundancy is used to decrease the false positive rate fpr without reducing the true positive rate tpr.

IV. Simulation & Results

The data manipulated in this paper consists of experiments with 5 different scenarii. They were sampled at 100 Hz, which is the minimum frequency for detecting the patterns of interest. Our procedure works directly with raw data and thus does not need to extract features and pre-processing. The pattern recognition algorithm was tested with MATLAB. The level crossing sampling scheme allows to drastically reduce the number of sample to process. The results in Tab. I. prove that the non-uniform sampling is adapted to sporadic signals. Indeed, the highest ratio between the number of samples for non-uniform sampling and uniform sampling is less than 1 %. The performance results are summarized in Tab.II. It globally shows good performances with a very low number of false positive detections. The method proves that well positioning the levels along the amplitude axis allows to prune off non-relevant samples that leads to useless processing.

Record	N_{US} (100 Hz)	N_{NUS}	N_{NUS}/N_{US} [%]
1	8 344 216	39 240	0.47
2	8 640 070	17 000	0.20
3	8 661 893	33 198	0.38
4	8 314 179	12 697	0.15
5	8 060 294	63 394	0.79

TABLE I
RATION BETWEEN THE NUMBER OF SAMPLE FOR NON-UNIFORM SAMPLING N_{NUS} AND UNIFORM SAMPLING N_{US} AT 100 HZ

Record	False detection	True detection	Detection rate [%]
1	0	31/37	84
2	0	26/36	72
3	0	12/30	40
4	0	25/25	100
5	1	33/39	85

TABLE II
THE PATTERN RECOGNITION ALGORITHM DETECTION RATE

V. HARDWARE IMPLEMENTATION

The non-uniform sampling scheme based on level crossing can be implemented with the Asynchronous Analog-to-Digital Converter (A-ADC). The A-ADC, depicted in Fig. 6., consists of four parts [13]. The difference quantifier compares the continuous input signal $i(t)$ and the reference V_{ref}. If the continuous input signal $i(t)$ increases, Up = 1 and Down = 0.

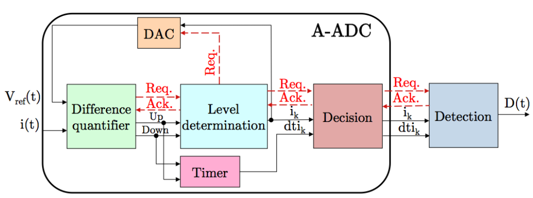

Fig. 6. Block diagram of the A-ADC with the detection block connected to its outputs

In the other case, when $i(t)$ decreases, Up = 0 and Down = 1. The signals Up and Down feed the level determination block that allows to select the appropriate reference signal recorded in memory. Then it is converted to continuous value with a DAC to make the comparison possible with $i(t)$. The timer aims to determine the time elapsed since the previous sample. When the A-ADC is fed with a new sample k, its time dt_{i_k} and amplitude i_k is determined by the decision block. The A-ADC being asynchronous, it establishes a communication with its neighbors blocks in order to exchange data with ack and req signals. The A-ADC and the detection algorithm were implemented on an Altera DE1 Board with Cyclone II EP2C20F484. The input signal was generated with a GBF Tektronix AFG3021 that generates an arbitrary signal from a MATLAB file. $V_{ref}(t)$, obtained at the DAC output, is the input signal $i(t)$ approximated with four level determined with the proposed method (cf. Fig. 7). $wr(t)$ is the write-read signal command of the digital-to-analog converter. It can be considered as the A-ADC activity signal.

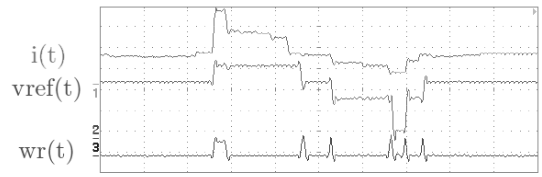

Fig. 7. The approximation of the input signal $i(t)$ with four levels

VI. CONCLUSION

In this paper, we presented a threshold-based partitioning scheme to perform pattern recognition with a level crossing sampling scheme method without pre-processing. The non-uniform sampling is well-adapted to sporadic signals and allows to only capture samples with relevant information. The results show that less than 1 % of data necessary to perform the pattern recognition and to preserve a good detection rate of about 76 %, similar to that of the uniform sampling scheme. Moreover, the proposed method allows to determine the most adequate levels, thanks to the ROC curve.

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