TABLE VII. EXPORTING DATA TO FILE PER 1000 SECOND VIA LOCAL DATABASE.

Smartphone	Local Database (per 1000 sec)	
	Method UI Thread	*Method AsyncTask*
Galaxy Tab 10	17 packets	18
Galaxy Tab 2 7.0	20	21
Galaxy S2	15	17
HTC	39	25

B. The Acquisition framerate of the embedded sensors

All Here, the Data Acquisition uses the sensor's frequency. The purpose is to check the performance of Smartphone data reception and compare different devices at this frequency in order to determine its impact. The aim of this experiment is to determine the slope during a limited moment, which permits us to check the frequency of a sampled value of Data acquisition. We should ensure that the movement of each device (the shaking) is fast enough to observe the sampled data, and by the movement, it will have a frequency that is higher than the frequency of sampled value of the sensor; for that reason we will observe the crenels.

For this operation, we had to shake each Smartphone in several directions, five times up and down, five times forward and backward and five times left and right. The objective was to analyze the signals of the Smartphone obtained by the applied movement, then to check the performance of its frequency by acquiring data to test the quantity of received data. These experiments are performed using the method *UI Thread* via Wi-Fi, because we had good results for the first experiment. Figure 6 presents the sampled values for the 3-axis accelerometer (ax, ay and az), over a 15 seconds period where the device was shaken in three dimensions (X-axe, Y-axe and Z-axe).

In order to bring out the significant changes in the sensor's data, corresponding to the shaking moments, we take only a sample of the signals to analyze the frequency of data acquisition during milliseconds (Figure 6).

To estimate the frequency of these sampled values during a time of acquired Data. Mean (µ) and Sd (σ) are calculated on these sampled values to analyze statistically the significant changes. Table VIII, IX and X show the results of these statistics for all type of Smartphones.

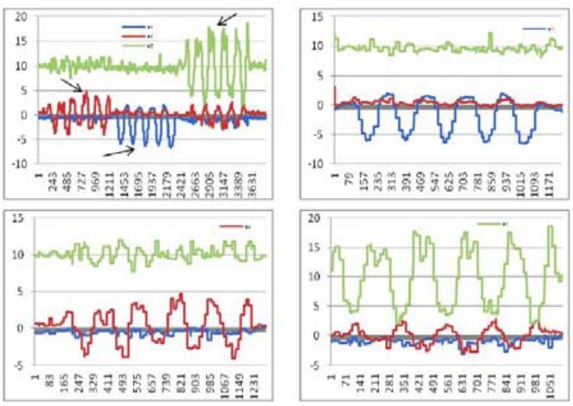

Fig. 5. Sensor data of 3-axis accelerometer.

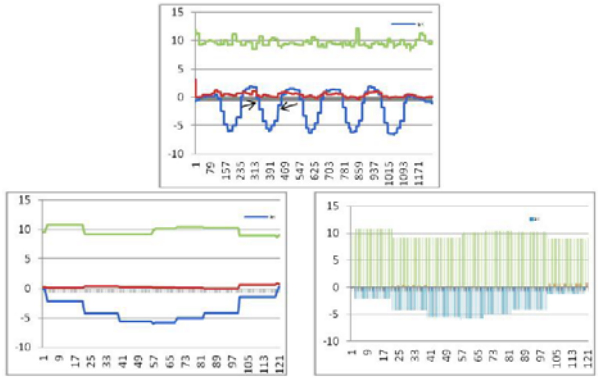

Fig. 6. Sampled values for Tablet 10.

TABLE VIII. CALCULATED Σ, M AND ESTIMATED FREQUENCY FOR RANDOM SAMPLED VALUES (AX).

Ax(x)	0,14	2,109	4,278	5,562	6,017	5,764	4,193	1,352	0,499
F(x)	2	19	18	17	1	11	14	18	19

Sampled Values(ax)	Mean µ	Standard Deviation σ	Frequency (F)	Time
336-456	-3,7819	1,671	12	0.08s

TABLE IX. CALCULATED Σ, M AND ESTIMATED FREQUENCY FOR RANDOM SAMPLED VALUES (AY).

Ay(x)	-5,899	5,057	-2,49	-1,417	-0,766	-0,421	1,034	2,873	4,559
F(x)	6	5	2	2	10	3	3	5	3

Sampled Values(ax)	Mean µ	Standard Deviation σ	Frequency (F)	Time
32-81	1,134	4,673	3,6	0.27s

TABLE X. CALCULATED Σ, M AND ESTIMATED FREQUENCY FOR RANDOM SAMPLED VALUES (AZ).

Az(x)	9,485	9,935	9,61	8,336	6,612	5,728	5,358	4,875	4,768
F(x)	2	5	4	- 2	6	1	6	4	2

Sampled Values(ax)	Mean µ	Standard Deviation σ	Frequency (F)	Time
199-289	6,3199	1,8548	3,826	0.26s

We conclude, it is not relevant to acquire and store the data at more than 12Hz for Galaxy Tablet 10, and the estimated frequency for HTC and Galaxy S2 is about 4Hz. We consider that this difference in the frequency is not related to the current version of Android for each Smartphone but to its processor. The best results are achieved by Galaxy Tablet 10 then HTC and lastly Galaxy S2 (see Table XI).

We found that the used method is sufficient to observe the frequency (ex. The crenels) and the frequency depends on the puissance of the smartphone.

Smartphone	Galaxy Tab 10	Galaxy S2	HTC
Estimated Frequency	12 Hz	3.6 Hz	3.8 Hz
Time	0.08s	0.27s	0.26s

V. CONCLUSION

main objective of this study is to propose a method to identify the performance of various Smartphone's embedded sensors, like Galaxy Tablet10, Galaxy Tablet7, Galaxy S2 and HTC for our experiments. The technical tools of Android platform have two classes UI Thread and AsyncTask, which are exploited to achieve our purpose. Two experiments have been conducted and we have ensured a sufficient time: The first one is to develop a method to store the acquired data with a frequency 200Hz. The second one is to identify the acquisition frame-rate of the embedded sensors (accelerometers and gyrometers). We found that the closer for the frequency is the better for the performance.

Three communication modes are elaborated for acquiring data via Wi-Fi, via USB and via local database. The local database mode is not considered in this study, for the frequency of acquired data because it consumes more time to deal with the memory of the device and Database engine at the same time. By a high speed of data, the received data was not written. For the pre-defined frequency of 200 Hz via Wi-Fi, both classes AsyncTask and UI Thread are efficient to send and store all acquired data completely. For the second experiment *Acquisition framerate of the embedded sensors*, is performed to check the performance of Smartphone data reception and compare different devices at this frequency, in order to determine its impact during a period of time.

To ensure that the performance of the sensor is determined by the processors, not by the Android system, we will take into account another Smartphone (Galaxy S5) to compare and confirm the additional results. In additional, by the knowledge of the Smartphone's context hardware, this allows us to estimate and identify a hybrid solution for data acquiring by their embedded sensors. For our future works, we will evaluate the performance of the Smartphone's sensors for failure detection (sensors faults , false alarms, transport accident case, etc.) to be able to distinguish between the sensors that correctly measure the structural data, and sensors that may fail to correctly measure the structural ones in real-time.

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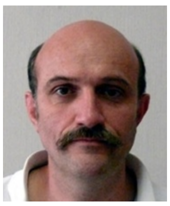

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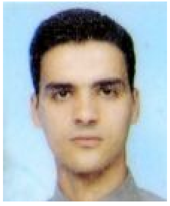

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