Smartphone-based Mobile Gunshot Detection

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***Abstract*—The ability to detect gunshots can provide someone with invaluable information in various circumstances. For the military and public servants, detecting gunshots can help save lives and potentially target offenders. People participating in shooting sports as beginners or professionals can also benefit from the use of sensors for improving their reaction and self control during training. Most current methods for gunshot detection require expensive devices that are purpose built or developed and often only examine one or two features of the gunshots such as the sound, recoil, or visible flash. Using the current sensors built into smartphones, 15 samples utilizing 10 different sensors are used examine how gunshot detection can be performed through the use of simple sensors. This extension of human activity recognition resulted in gunshot classification accuracy ranging from 0.0% – 99.7% with an average of 86.6%. Understanding how simple sensors respond to gunshots can provide simple and easy accessibility to new detection methods and ample opportunities to improve this potential field for various personal and smart city applications such as crime detection, policing, gunshot violence monitoring and control in the community.**

***Keywords*—Data fusion, mobile computing, gunshot detection, sensors**

I. Introduction

Monitoring, detecting, and assessing gunshots have tremendous potential for many emerging social and smart service systems applications. Gunshot detection could help law enforcement officials to timely localize a crime spot and its stretch, severity, and impact on human lives to take appropriate actions such as requesting backup, emergency personnel on the scene or rerouting traffic and passers-by to mitigate further causalities or loss of human lives. Gun-based violence and crime rates are prolific in the United States downtowns and other urban cities across the world [10]. Detecting and mitigating those unwanted and horrific crimes are always warranted for maintaining safety and security of the residential and business premises and the prosperity, livelihood, and safe lifestyle of the citizens. The city council and the government invest millions of dollars and manpower, vote for new policy and legislation in senate and encourage community policing to reduce and control the violence and crime as involved with this heinous activity. In cases of home violence, automatic gunshot detection helps to identify the shooter and helps investigators immensely in their post crime scene analysis. Gunshot detections applications also help strengthening better policing practices and the role and involvement of the shooters and its catchers. Furthermore, this also plays a critical role in providing better feedback to military and other gun professionals during their training and deployment regiment. Motivated by the above societal needs, we take an early attempt to study the feasibility of gunshot detection using off-the-shelf everyday device such as a smartphone.

Typical human activity recognition (HAR) in a smart home or beyond focuses on distinguishing common activities people do on a daily basis. This includes walking, running, driving a car, watching a movie, riding a bike and many others. As mobile computing allows devices to contain more and more sensors within them, it provides researchers with many options in improving HAR. While custom designed devices provide specific sensors and software needed for the tasks they are designed around, many smartphones provide similar capabilities. Examining how these sensors can be used to extend HAR with mobile devices for detecting gunshots is the focus of this study.

The accuracy of HAR with mobile devices has improved recently with the use of multi sensor data fusion. This allows different sources of data to be collected and fused in order to better increase the accuracy of the classifier employed to determine activities being performed by the user. Following a similar approach, we examine if the sensors within a phone are able to detect different aspects of gunshots while still retaining the accuracy of traditional HAR classifiers. Typical gunshot detection methods [11], [12], [13], [16], [17], [19], [21] focus only on a few aspects of a gunshot such as sound or recoil but more often they ignore the context of the user within the setting of shooting. For this study we examine how sensors respond to shooting and other typical HAR activities. The activities examined are walking, running, standing, policing brass/ cleaning and two types of shooting. Gunshot related activities are slow and fast shooting, and policing brass where the user collects all the spent cases fired. Data is collected with the use of a Samsung Galaxy S5 smartphone and AndroSensor application [1]. Shooting is done with a FN 5.7 pistol with SS197SR ammo. SS197SR has the following specifications; bullet weight 2.6g, velocity 1,950 fps, muzzle energy 340 Ft lbs., max chamber pressure 50,000 psi, sound level 160 dB [20].

Using 10 sensors within the S5 phone, the application of mobile HAR is examined to include shooting and the behaviors of users. The context of the user and their behavior around the time of the shots could be useful for the detection of a gunshot in relation to a crime or for hobby applications as well. Employing a multi sensor approach utilizing current mobile

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phone could increase the accuracy of gunshot detection while decreasing cost.

II. Related Work

The purpose of this study is to examine how multiple sensors within smartphones can be adapted to gunshot detection in a mobile environment. Gunshot detection has been examined through the use of sensors which are able to capture various features of the act of shooting. This includes the sound of the gunshot itself [12], [13], [14], [16], [17], [21], pressure of the bullet as it passes through the air [13], pressure of the expanding gasses [4], [5], and recoil generated by the shot [11], [17]. For the most part these have been examined separately, but within the past 5 years new devices have been developed. The ShotMaxx timer developed by Double Alpha-Academy [17] also works with their mobile application [18] and provides mobile data fusion with sound and accelerometers for gunshot detection. This however took them two years to develop and requires the purchase of their device instead of utilizing sensors already contained within a smartphone.

Recently the use of multiple sensors has been extended to include gunshot detection and counter sniper sensing. This has included the use of both acoustic sensors, Firefly, and thermal sensors, Serenity, [16] for the military. Simple studies utilizing sensors within smart phones illustrate the versatility and potential opportunities for research. Some of these include being able to detect door events of buildings with HVAC with a phone's barometer [22], determine social context via Bluetooth [3], along with accelerometers and other sensors for HAR [6], [9], [23]. Recently developed shot trackers for shooting provide a more mobile friendly product with an accuracy of 1 millisecond or 1,800 shots a second [14] but still only relies on acoustics.

Traditional gunshot detection has employed the use of acoustic sensors that can provide some combination of gunshot detection, classification, direction, or location. Sensors have been employed within cities as a smart network [19] and by the military [16], [21]. With advances in technology, the focus has also shifted to increase the effectiveness and efficiency of gunshot detection through the use of better algorithms [6] and portability.

III. Methodology

With the purpose of this study being a proof of concept, the proposed system focuses on examining mobile sensors for extending HAR into gunshot detection with a Nave Bayes classifier. This follows common architectures for activity recognition systems starting with data collection, preprocessing, sensor evaluation, classification and activity recognition.

Data Collection: Data collection was accomplished with the using a Samsung Galaxy S5 smartphone and the mobile app AndroSensor [1]. As examined in [12], [13] the length of acoustic and pressure features of the gunshots and bullet itself last between about 0.5 and 25 milliseconds. In order to account for these events, collection rate is set to the max rate of 200 Hz. As shown in table I 10 sensors accessed with AndroSensor collect at different rates and is not adjustable for individual sensors. The delays between sensor data changes are examined to estimate each sensors actual update rate in seconds.

Preprocessing: Preprocessing removes data generated from manually starting and stopping the AndroSensor application. Labeling the data is also performed during this step. For the activities involving gunshots, it was chosen to label the 25 samples before and after a gunshot occurred, to include about 50 rows or 0.25 seconds of data. If multiple gunshot samples are overlapping they are labeled as fast shooting and if 50 samples contain only 1 gunshot it is labeled as slow shooting. The other activities are walking, running, standing, shooting (slow/fast) and policing brass.

Sensor Evaluation: Before classification training and testing, samples with just gunshots were used to examine sensor effectiveness at recognizing gunshots. This is done with the use of the Weka information gain attribute evaluation with ranker. The same samples are then evaluated manually to see how the sensor data behaved and was ranked as well. The 3 best performing sensors from both manual and the Weka information gain attribute evaluation are then used for the HAR classifier.

Classifier: The use of different classifiers for HAR has been examined in many different studies. While it was shown that support vector machines performs better than other classifiers [6], [8] the use of a simple Nave Bayes classifier has been shown to have acceptable accuracy for HAR [9], [12]. This was implemented with 10 fold cross validation in Weka where it is first trained and tested with separate datasets. The main focus is to determine how the classifier is able to perform with higher data collection rates, multiple sensors and at distinguishing gunshots.

IV. Data Collection

Data collection was completed with the phone and firearm mentioned by one person in order to ensure consistent and safe collection of data. All samples were collected at the same location to ensure consistency since some data such as pressure varies depending on location and the environment. Other studies have examined the impact of the variability of users with data collected from phones during HAR [8], [9]. Consistency was accomplished by placing the phone in the same pocket and orientation for collection.

Multiple samples of walking, standing, running, policing brass, shooting slowly, and shooting fast were collected. Samples containing each separate activity were collected to be used primarily as training data for consistency, with larger samples containing combinations of activities for testing.

Sensor Shooting Data. The samples collected for testing the sensors ability to recognize gunshots was done under two conditions and shooting styles. The first condition is with the

[1]The microphones of android devices are designed to capture normal speech and dismiss any other sound. No phone or tablet can be used to substitute professional equipment for this usage. Do not rely on this reading if your hearing is at stake [1].

TABLE I: Sensor Descriptions and Update Rates

Sensor	Update Rate	Type	Description
Accelerometer	0.015	Hardware	Measures the acceleration force in m/s^2 that is applied to a device on all three physical axes (x, y, and z), including the force of gravity
Gravity	0.2	Hardware or Software	Measures the force of gravity in m/s^2 that is applied to a device on all three physical axes (x, y, z)
Gyroscope	0.15	Hardware	Measures a device's rate of rotation in rad/s around each of the three physical axes (x, y, and z)
Light	0.175	Hardware	Measures the ambient light level (illumination) in lx
Linear Accel.	0.2	Hardware or Software	Measures the acceleration force in m/s^2 that is applied to a device on all three physical axes (x, y, and z), excluding the force of gravity
Magnetic Field	0.2	Hardware	Measures the ambient geomagnetic field for all three physical axes (x, y, z) in T
Orientation	0.5	Software	Measures degrees of rotation that a device makes around all three physical axes (x, y, z)
Pressure	0.18	Hardware	Measures the ambient air pressure in hPa or mbar
Proximity	0.46	Hardware	Measures the proximity of an object in cm relative to the view screen of a device
Sound[1]	0.32	Hardware	Measures the intensity of sound that the phone's microphone receives

phone lying on a table and the handgun held 12" above the face of the phone. The second condition is with the phone in the pocket of the user while standing to replicate typical user behavior. The first shooting style is slow shooting where a user takes the time to place well aimed shots, which also can help collect any acoustic reflection or echo's that are typical of gunshots [12]. The second style of shooting is where someone would be shooting as fast as they can. To account for the variation of different users abilities, bursts of 1, 2, 3, 4 shots with slight pauses between each were repeated twice. The 20 shots for fast shooting contains about 12 seconds of data and slow contain 40 seconds for both conditions for a total of 4 samples.

These four shooting samples were preprocessed and combined with ambient samples of the phone just sitting on the table and with the phone in the users pocket to test the sensors ability to detect any changes within the data caused by the gunshots. The best performing sensors from Weka and manual evaluation are then used with the classifier for HAR and gunshot detection.

Classifier Training Data. While it is typically the case to have balanced datasets for training and testing, unbalanced datasets can have better accuracy [6] since not every activity is performed for the same amount of time by a typical user. For the non shooting training data, samples of each activity were collected in the same manner as the gunshot samples. This was done to produce distinct samples of each activity that could be easily labeled and combined. Training data includes the standing shooting samples used for the sensor evaluation since they were collected in conditions similar to that seen at a gun range. Total dataset size for training data contains around 30,000 rows of data.

Classifier Testing Data. The samples used for testing do not contain any reused data and incorporates natural transitions from one distinct activity to another instead of the separate training samples. The total amount of data for shooting is also reduced since realworld data could result in very small and short windows of shooting. Longer samples containing multiple activities were collected and then labeled in order to represent the unpredictability of user behavior. Some activities such as walking were done multiple times throughout the sample while others such as policing brass were done once. Table II illustrates the differences between the distribution of training and testing datasets. Total dataset size for testing data contains around 17,000 rows of data.

TABLE II: Training and Testing Dataset Composition

Activity/ Dataset	Walking	Running	Standing	Cleaning Brass	Slow Shots	Fast Shots
Training	22%	12%	11%	22%	25%	8%
Testing	46%	9%	13%	30%	1%	1%

TABLE III: Comparison of Manually Ranked Sensor Accuracy and Weka Ranker Scores for Gunshots

Sensor	Manual Table		Weka Table		Manual Standing		Weka Standing	
	Rank	%	Rank	Score	Rank	%	Rank	Score
Accel.	2	100	4	1.375	2	100	5	1.369
Gravity	6	? - 95	5	1.368	7	0	1	1.424
Linear Accel.	1	100	8	0.320	1	100	8	0.293
Gyro.	3	100	9	0.237	3	? -100	7	0.348
Light	8	? -35	7	0.941	9	0	9	0.134
Mag. Field	9	0	2	1.449	8	0	2	1.424
Orient.	7	? -100	3	1.395	6	0	3	1.419
Proxi.	10	0	10	0	10	0	10	0
Press.	5	0-100	6	1.256	5	0	6	0.939
Sound	4	40-100	1	1.468	4	40-100	4	1.414

Additional Preprocessing. Since samples were collected with all 10 sensors running, training and testing datasets are reduced to the sensors chosen for evaluation. This provides every combination of the three Weka and also the three manually chosen sensors so accuracy and effects of multiple sensors can be examined.

V. Results and Discussion

Some key observations should be noted as they relate to how the behaviors of users and sensor data can impact and improve the ability to detect gunshots. This includes proper shooting techniques taught by the NRA, police, and military training where gun and body control improves accuracy. This reduction in noise appears as the user takes time to aim before placing a shot. Linear accelerometer movement before a shot can be seen in Figure 3 leading up to the detection of typical gunshot features such as the sound or recoil. The difference between standing and aiming could be nonexistent since there is no actual gunshot. It is only when a shot is fired that the activity of standing can switch to shooting. Since the sampling rate is so high and classification was performed without filtering or smoothing the data, these samples are much noisier then typical HAR. Studies have shown that online HAR systems are capable of using collection rates for similar sensors at 50Hz [8] and 36Hz [23]. With a 200Hz sampling rate it was noticed that some sensors did behave similarly to accelerometers where every movement was recorded and showed up within the data in different ways.

Sensor Evaluation: Sensor evaluation was completed by manually examining the gunshot samples by hand in order to see how each sensor reacted to slow and fast shooting during the table and standing samples. The sensors were then ranked according to how many gunshots could be detected within the sample. Questionable gunshots are labeled as a potential range since the difference between noisy data and gunshots might not be clear. The same samples were then used for the Weka information gain attribute evaluator. Table III lists the scores used to rank each sensor, and since some sensors contained X, Y, and Z axis, the highest axis rank was chosen for that specific sensor.

The manually examined samples chosen for classification are acceleration, linear acceleration, and sound. The only difference between linear acceleration and accelerometer data is the removal of gravity, a common preprocessing step. The phones ability to record identifiable data associated with gunshots could indicate potential for a phone to be used in place of devices mentioned previously. The sensors chosen from the Weka ranker include gravity, magnetic field, and orientation. Some trends noticed in both rankings were that update rate and number of axis impacted effectiveness. Limited range for certain detection methods were also noticed, such as light from the muzzle flash and barometer from the blast pressure. Gunshots directly over the phone were detectable but not when the distance increased to the pocket. For the two sets of sensors, the training and testing samples are created as 14 separate samples that are used with the Nave Bayes classifier with 10 fold cross validation.

Classification accuracy is examined by looking at how the sensors perform in regards to the F score for each activity being classified as seen in Table IV and V, and overall accuracy as seen in Figure 1. Gunshot F scores for both manually and ranker sensors tend to be the highest, with Weka outperforming manual sensors by 3.3%. Walking and running had the lowest F scores for Weka sensors while running and standing had the lowest for manual. There is a 0.5% and 1.8% improvement in gunshot accuracy as ranker sensors are combined, while other activities improve by 6.6-26.7%. For the manually chosen sensors there was a greater improvement in F scores, 94.4% and 40.8% for gunshots and 21.1-75.6% for other activities.

As seen with the F scores associated with each activity, classification accuracy for the most part improves as sensors are combined. There is a 6.5% improvement in overall classification for the ranker sensors once combined, but 34.3% improvement when the manually selected sensors are combined. Despite being considered the 4th, 5th, and 8th ranked sensors by Weka, the combined classifier was able to outperform the top 3 sensors by 0.4%. One limitation to the sound sensor could be that it had the slowest update rate, and did not contain X Y and Z axis data like every other sensor examined.

One extra dataset was created in order to examine how accuracy is improved when data from all 10 sensors is used,

TABLE IV: Classification F Scores for Weka Ranker Sensors

Sensor	Fast	Slow	Clean	Run	Stand	Walk
Gravity	97.5%	99.3%	58.7%	54.6%	62.0%	51.7%
Magnetic	98.3%	99.2%	57.2%	41.8%	74.6%	50.0%
Orientation	98.5%	99.7%	65.2%	56.5%	81.1%	53.2%
G + M	98.4%	99.6%	65.5%	67.2%	81.6%	54.8%
G + O	98.0%	99.5%	63.3%	56.6%	72.7%	52.4%
M + O	99.3%	99.7%	63.8%	68.5%	83.5%	56.6%
G + M + O	98.9%	99.7%	66.7%	68.2%	83.0%	54.1%

TABLE V: Classification F Scores for Manually Chosen Sensors

Sensor	Fast	Slow	Clean	Run	Stand	Walk
Sound	0.0%	57.5%	41.8%	0.0%	0.0%	52.9%
Accel.	92.5%	97.9%	64.6%	51.8%	73.0%	64.0%
Linear	23.0%	71.2%	49.8%	58.3%	25.2%	73.6%
S + A	93.0%	98.3%	65.7%	54.0%	75.6%	67.4%
S + L	31.1%	71.4%	53.7%	58.8%	28.6%	74.0%
A + L	93.7%	97.6%	63.7%	58.8%	71.7%	72.2%
S + A + L	94.4%	97.6%	65.3%	59.9%	72.5%	72.7%

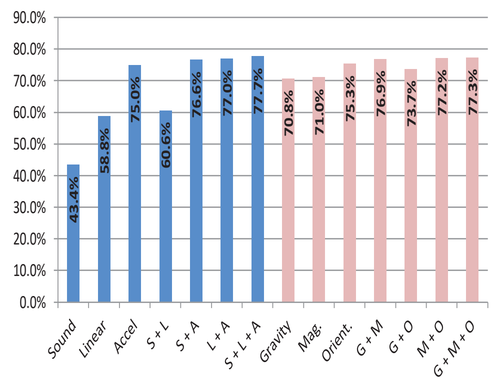

Fig. 1: Classification accuracy for manual (blue) & ranker (red) sensors

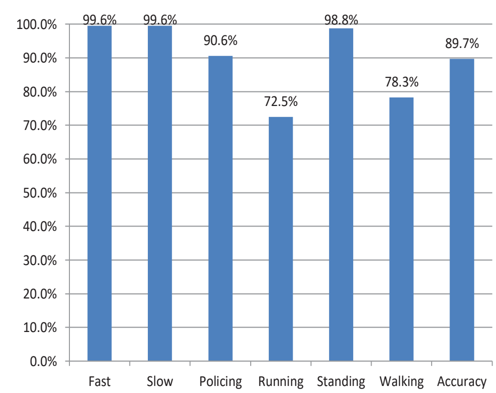

Fig. 2: Score and classification accuracy for every sensor combined

as seen in Figure 2. While this provides a 12% increase in accuracy, it requires about 2.5 times as much data compared to three sensors with X Y and Z axis data.

VI. CONCLUSIONS

By combining samples from different sensors within a common smartphone, the accuracy of gunshot detection within the realm of HAR improved over individual sensor performance. The two different shooting conditions examined showed that not only can gunshots be detected, but the sensors are able to capture enough unique data to accurately classify them. This can improve upon the different detection methods mentioned previously, where relatively few and simple detection methods are employed. The pervasiveness of these smartphone sensors can also provided a better context to the data. With the accelerometer and sound sensors, they could prove to better at distinguishing which user is shooting since they can feel the recoil, and hear the gunshot. Figure 3 illustrates this within one of the training samples. Beyond the training environment, these sensors are still able to pick up on this trend as seen in one of the larger testing samples, Figure 4.

Taking the context of the sensor placement into account, the behavior of the person can improve accuracy since there is more feedback when different sensor data is collected. While Figure 3 and Figure 4 only have data from two of the sensors used for classification, it can be useful for determining if the user wearing the device was the shooter or simply near them. The expected behavior of taking the time to remain still long enough to aim before shooting results in distinguishable spikes in both sensor data for recoil and sound of the gunshots. While it can not be assumed that users will always be shooting under these ideal conditions it provides a baseline for how these and other sensor data might behave under both test and more realistic conditions.

The availability of more than one sensor can also allow for the implementation of better classifiers that can perform both effectively and efficiently. It was shown that volume alone in terms of how many sensors are used is not a good indicator of how well the classifier will perform. However, update rate and number of axis had an impact on sensor performance.

One of the signatures of a gunshot is the transition from low dB level associated with the activity standing still or aiming, with a very rapid and potentially short lived peak in dB level. Depending on how many shots occur, the peak lasted longer since the sound sensor's 0.32 second update rate is unable to distinguish the peaks of each individual gunshot if they occur in quick succession. The detection of recoil occurring at the same time as the gunshot sound provides options for further research as it gives better context.

VII. LIMITATIONS

Limitations of this study include the use of higher sampling rates without the use of smoothing or cleaning of data. Since individual sensor update rates are only estimates, the sampling rate can only be adjusted to the fastest sensor, producing excess valueless data. This excess data also greatly increases the computational cost for apply a classifier, especially since some sensors collect for the X Y and Z axis. Examining how to balance collection rate can reduce the processing power needed to both collect and examine the data. A recent study examining the use of an accelerometer instead of sound for smartphone hotword detection [24] illustrates how battery usage can be reduced through sensor/ data management, and online classification within smartphones.

Another limiting factor is that the sound sensor only used a relative decibel level and not actual sound recordings. Since phones are designed to transmit human voice ranges, it has trouble dealing with 160 dB gunshots. Building a customized application for this type of data collection could greatly improve accuracy. The individual sensors can be better tailored in a custom application as compared to AndroSensor where there is less control over each individual sensor.

The ambiguous conditions of shooting also create a problem since conditions are not always the same. A day shooting at the range could consist of 30 straight minutes sitting at a bench shooting, standing, or laying down shooting dozens or even hundreds of times. It could also include a hunting trip where the user is sitting for three hours and only shoots once. The 25 samples used to label before and after the gunshot is misleading since the assumption is that a user is aiming before a shot. There is the potential however for this behavior to appear no differently then standing. Device location could potentially differentiate the action of aiming and standing better, and the implementation of change point detection and a time series classifier could solve these issues.

With the purpose of this study being a proof of concept, the Nave Bayes classifier can be greatly improved with better classifiers. A SVM classifier with KDA features has the ability to classify 15 different activities with an accuracy of 94% [8] for an offline system and 92% with an online system. Applying feature extraction to each sensor can also be examined in order to account for the fact that the data needs to be processed as time series, and how the data from each sensor behaves.

VIII. FUTURE RESEARCH

This study has shown that the sensors within modern smartphones have the ability to detect different features of gunshots. This has been exploited with stand-alone mobile and stationary devices in the past, and now can potentially be adopted for use with mobile phones. Smartwatches can be the focus of another study examining how recoil detection can be performed and compared to phone based detection. Recoil classification can also be examined since different firearms produce different levels of recoil. Implementation of gunshot only classifier could better increase accuracy and overcome complexities of extending current HAR due to the sampling rate required.

IX. ACKNOWLEDGMENT

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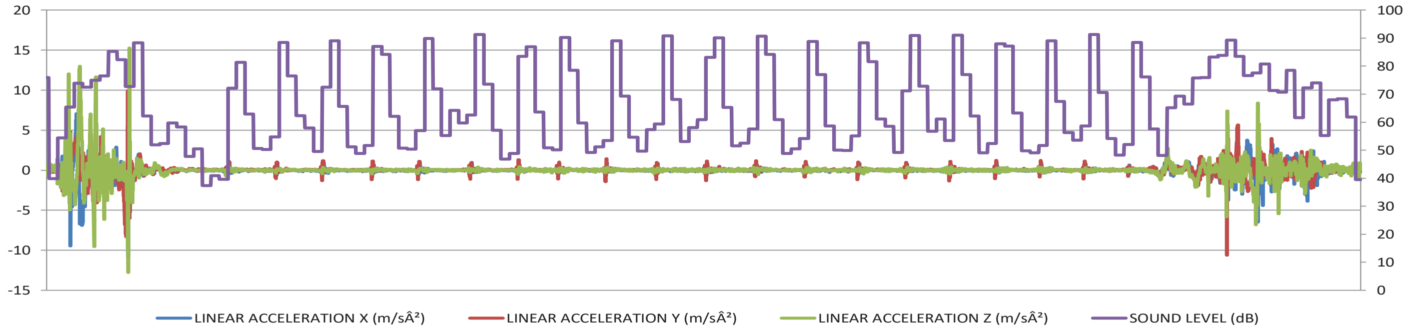

Fig. 3: Training sample, 20 slow shots phone in pocket. Linear acceleration and sound sensor data before preprocessing

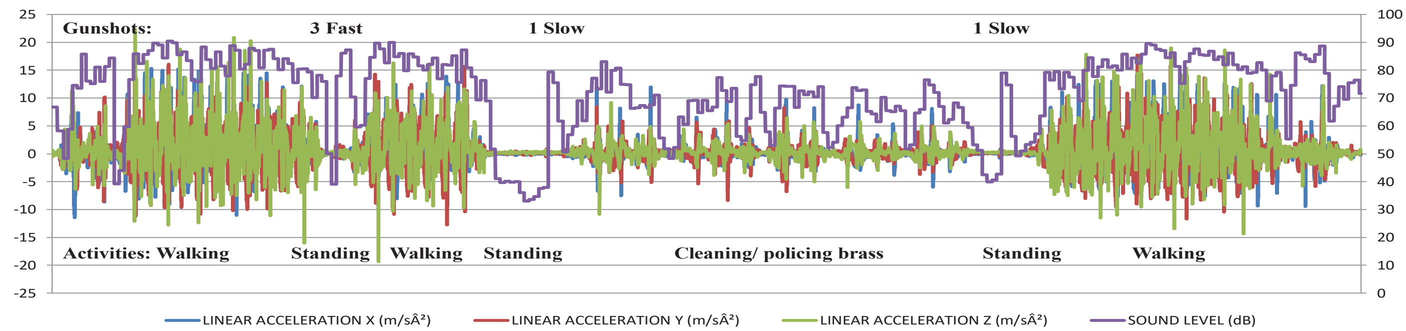

Fig. 4: Testing sample, linear acceleration and sound sensor data before preprocessing. Labeled gunshots (top) and other activities (bottom)

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