Human Physical Status detection related to Danger Situations based on Smartwatch and Smartphone

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***Abstract*—The life of an individual is characterized by daily activities such as going to the office or to school, working, doing sport. Alongside them, unpleasant situations related to criminal events, such as to be robbed, can take place. In this cases, it is difficult to ask for help or to contact the authorities about the ongoing criminal situation. In this context, on the basis of the behavior related to the human physical status, it is possible to exploit specific data, in order to extract relevant information that characterizes danger situations. Based on such idea, a model centered on three main aspects related to the human body posture, level of stress and geolocation, is proposed. The experimentation is based on a smartphone and a smartwatch, as they support both the data extraction its local computation centered on machine learning techniques. The paper presents the proposed approach along with a first evaluation.**

***Index Terms*—Body posture detection, Criminal event identification, Geolocation, Machine learning, Smartphone, Smartwatch, Stress level detection**

I. Introduction

Taking the bus, going to the bank or shopping, doing sport, working and so on, represent typical activities that characterized the life of individuals. Alongside these normal daily activities, one can come across by unpleasant situations, such as to be robbed on the street, to be held hostage during a robbery in a bank, or even being involved involuntarily and accidentally in the midst of terrorist events as it happened in Paris, in Nice, and in Berlin [1].

Due to the unpredictability of such events, the implementation of preventive measures, which are primarily based on the management of human resources (e.g. the allocation of police officers to specific locations, who can react promptly when an event occurs), is generally unthinkable. Indeed, classic mechanisms adopted by the Law Enforcement Agencies (LEAs) and Police Forces (PFs) for the detection of situation of dangers represent a weak link in the emergency service chain [2]. Such a weakness is generally due to the time between the identification of a danger and the necessary intervention time to deal with it, because of lack of proper and effective technologies.

In this scenario, the citizens play an important role, as they represent the main actors in such situations. Thanks to the advancements of the Internet, along with the growing diffusion of connected mobile devices mediated by the network, the citizens can move from a passive role of being victims to a more active role, by supporting both PFs and LEAs to fight the criminality as well as by helping each other.

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According to [3] [4], smartphones and smartwatches are nowadays among the most popular IoT social devices. They are equipped with a different set of features and functionalities, that allow to extract user-related data, perform local computation, process information related to different activities or situations, transmitting data through the network etc. They represent enabling tools to support pervasive computation as they touch on mobile computing, location computing, mobile networking, sensor networks, human–computer interaction, and so on [5] [6]. As a consequence, they are promising candidates for performing tasks ranging from the detection, notification and communication of events in a pervasive way.

In this context, this paper focuses on the analysis of human aspects that deals with the behaviors and actions of human beings in different situations [7]. The following research questions have been tackled: (i) which aspects characterize the human physical status under conditions of danger and (ii) how those aspects can be exploited to detect a danger situation. To deal with it, a model for the detection of the human physical status related to situations of danger has been proposed. It is defined by considering three main aspects: (i) the *human posture*, which is the position, that is held from the human body while standing, sitting, or lying down combined with the arms posture (ii) the *physical geolocation*, which is a site or a place where someone or something can be located, and (iii) the *level of stress*, which is the response of the human body to pressures from a situation or life event. A set of specific features, which are identified for each aspect, are used to train a classifier, built on the top of a smartphone and a smartwatch, that characterizes the human physical status related to situations of danger, by using machine learning techniques.

The rest of the paper is organized as follows. The proposed model as well as the selected features are defined in Section II. The data computation process is presented in Section III, whereas, the implementation details and the preliminary results are discussed in Section IV. Section V concludes the paper by highlighting potential future directions.

II. A Human Physical Status model

In this Section, the conceptual model for the detection of human physical status related to situations of danger is proposed. In particular, the main characterizing aspects (i.e. class of features) have been identified, and their related features have been presented.

More specifically, the proposed *Human Physical Status model (HPSM)* concerns of three main aspects, which are depicted in Figure 1: *Body Posture*, *Stress level* and the *Location* of a person, which are described in the following.

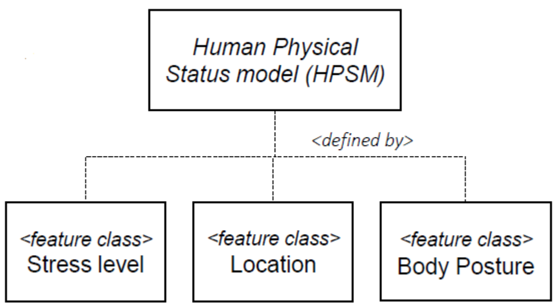


Fig. 1. Examples of body postures related to situations of danger

a) Body Posture: it represents the position in which one holds the body. On one side, a set of characteristics, related to general position of the individual's body, have been considered, such as *LyingOnTheGround*, *Sitting*, and *Standing*. On the other side, other features linked to the position of the arms have been modelled, that is to say, *HandsUp*, *HandsOnHead*, and *HandsBehindTheBack*. From their combination a set of 9 features have been defined and analyzed:

- *HandsUp - Sitting:* this activity corresponds to having the hands up while sitting on a chair or on a bench, which can happen for example during a robbery.
- *HandsOnHead - Sitting:* this activity corresponds to having the hands on head while sitting on a chair or on a bench, which can happen for example during a hostage situation.
- *HandsBehindTheBack - Sitting:* this activity corresponds to having the hands tied behind the back while one is sitting on a chair or on a bench, which can happen for example during a hostage situation.
- *HandsUp - Standing:* this activity corresponds to having the hands up while standing, which can happen for example during a bank robbery.
- *HandsOnHead - Standing:* this activity corresponds to having the hands on the head while one is standing, which can happen for example during a hostage situation.
- *HandsBehindTheBack - Standing:* this activity corresponds to having the hands tied behind the back while standing, which can happen for example during a hostage situation.
- *HandsUp - LyingOnTheGround:* this activity corresponds to having the hands up while lying down on the ground, which can happen for example during a robbery.
- *HandsOnHead - LyingOnTheGround:* this activity corresponds to having the hands on the head while lying down on the ground, which can happen for example during a hostage situation.
- *HandsBehindTheBack - LyingOnTheGround:* this activity corresponds to having the hands tied behind the back while lying down on the ground, which can happen for example during a hostage situation.

The details about their data extraction and preprocessing are presented in next subsection.

b) Stress level: this aspect, which is related to the level of stress of a person, is detected on the basis on the heart rate. It provides an information that, in accordance with the pulse rate and based on its speed variation, can be used to discriminate among different situations. A previous research study about the stress level detection was conducted and described in [8]. The results demonstrated that the highest levels of stress occur just prior to and during critical incidents, and the people do not fully recover from that stress right after the event due to the shock. Instead, by practicing sport activities, the change of the pulsation takes place gradually, while in situations of pleasant surprises, a sudden change with short-term peaks occurs. In contrast, a situation of stress due to a danger leads to an increase in sudden pulsating with a duration of the prolonged peak. On the contrary, a lowering of the heart rate could indicate either a situation of tranquility, such as rest or sleep, or a situation of extreme danger such as the loss of consciousness due to blood loss. On the basis of such research a further investigation has been reported in [9], by identifying specific threshold values related to shock due to criminal scenarios.

By exploting the insights gathered from such previous researches, a threshold approach has been adopted. The threshold values have been calculated on the basis of the heart rate data of different people, that have been collected from July 1, 2016 until December 31, 2017 [10]. The collection was conducted on women and men with an age ranging from 20 up to 80 and belonging to different countries (ie. Australia, Canada, China, France, Germany, Ireland, Italy, Japan, New Zealand, Norway, Singapore, Spain, Switzerland, United Kingdom, United States). From such analysis and according to the study conducted from the "Harvard Medical School" [11] for male persons with an age between 20 and 80 the avarage resting heart rate is between 59 BPM (Beats Per Minute) and 65 BPM, whereas for female persons with the same age the avarage resting heart rate is between 63 BPM and 67 BPM. Moreover, values up to 90 BPM are still considered normal, whereas values higher than 100 BPM are considered related to anomaly conditions, which can be either physical or mental.

As a consequence, in this work, the following thresholds have been choosen as avarage values of the previous studies, i.e. *HeartRateLowerBound* $< 59BPM$ and *HeartRateUpperBound* $> 100BPM$, in order to detect the stress level of an individual by relying on the *optical heart-rate sensor* of a smartwatch.

c) Location: this aspect is related to the geolocation of a person. A related work based on machine learning regarding the identification of high risk crime areas is presented in [12]. Its main drawback, as raised from the authors themselves, is that it is limited to moderate sized cities, furthermore the used dataset is neither provided nor mentioned.

In this context, a more general location mapping approach has been proposed. In particular, we analyzed and combined (i) previous research results regarding physical location of crimes [13], as well as (ii) statics gathered from the "Bureau of Justice Statistics" regarding places of occurrence for violent and property crimes [14], by categorizing them as *high crime risk places* (i.e. those places that are mostly related to money or valuables) and *low crime risk places*, as it is depicted in Figure 2.

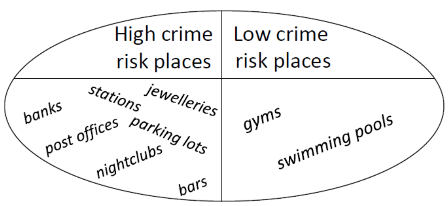


Fig. 2. Categories of high and low crime risk places

The information for matching the human location with high or low crime risk places relied on the data coming from the smartphone on the basis of the current user's geolocation. Thanks to a sensor which is able to retrieve the longitude and the latitude of the device based on the GPS coordinates, a request is made to resolve the current location into a place. Starting from such coordinates, Fouresquare APIs have been used to get the information and, in particular, the *place name* and the *place type*. An example of request along with the input paramters (ie. client id, client secret, latitude, longitude, version and radius) to the URL *https://api.foursquare.com/v2/venues/search* [15], is shown in Figure 3.

```
private val URL = "https://api.foursquare.com/v2/venues/search"
private val SEARCH = "ll=$lat,$lang&radius=20&
client_id=4NRWRKYJTMLL1GJ2QYDG4APPL3IIT2D3XSVGKO4MBXTRTAPN&
client_secret=1ZZ5QTWR2Z5T4HLDSOXNW3PRYGQJ0GTA3IKKX02DBXBF3YJS&
v=20190323"
private val COMPLETE_URL = "$URL?$SEARCH"
```

Fig. 3. Example of request to retrive information related to the Location

The response, after executing the above request, provides the data related to the geolocation such as: (i) *id*, which identifies a place, (ii) *name*, that represents the name of the place, (iii) *location*, which is the raw location of the place in terms of latitude and longitude, (iv) *category*, which describes the category it belongs to, is used for the matching in order to discriminate between low and high crime risk places according to the proposed categories.

In the following Section, the adopted approach for collecting and computing data is described.

III. Data computation

The collection and elaboration of the data related to the body posture has relied on the exploitation of smartwatch and smartphone sensors, both equipped with: (i) an *accelerometer*, which allows to measure the acceleration and the movement of an object, and (ii) a *gyroscope*, that allows to retrieve rotational data, in order to measure the orientation and the angular velocity of the considered object.

Two algorithms, for both the devices, have been defined and implemented as Apps: (i) one has been deployed on a smartphone for collecting the data regarding the body posture; (ii) the other one has been deployed on a smartwatch to collect the data regarding the hands/arms related positions. The smartwatch was worn on the left wrist (as many people wear it), while the smartphone was placed in the right front pocket of the trousers (as it was done in other related studies).

Figure 4 represents the smartphone GUI design of the system which shows the data colleted from the smartphone and coming from the smartwatch by using a Blutooth connection. In particular, it shows two graphs, one for the accelerometer signals at the top and a the second one for the gyroscope signals at the bottom. The green line shows the x-axis value, the blue line represents y-axis values and the red line shows z-axis value for both graphs. On the top of the screen it is shown, instead, the information about the "Heart Rate" as well as the current "Location". Moreover, the "Position" indicates which body posture or activity is detected through the smartphone, whereas "Position Watch" shows which arms-related posture is detected through the smartwatch.

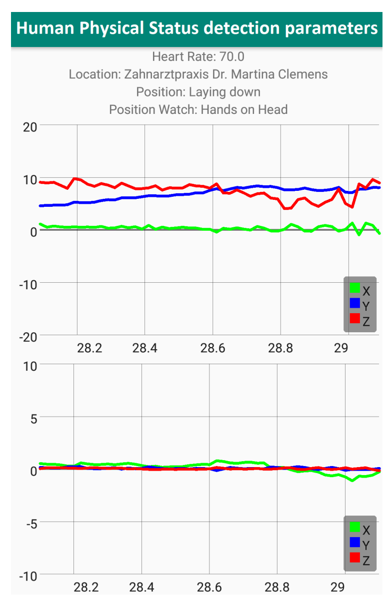


Fig. 4. Smartphone GUI

The data were collected on a sample of 40 people with an age between 18 and 40 years old, men and women, who performed the different activities by holding each position for 7 seconds.

The raw data which came from the device sensors was not directly suitable for the machine learning process, due to the noise. As a consequence, it has been pre-processed by applying a median filter [16], which was used to remove noise from the signal that can affect the results of the activity recognition. Additionally, each trace has been also normalised using low pass butterworth filter to remove the remaining noise [17]. The Butterworth filter was used to remove the gravity components, which is a low frequency signal, as it has not been considered as a feature of the proposed model. As a consequence, a linear acceleration has been obtained, that has been exploited according to the approach proposed in [18].

The data regarding the body posture have been organized in different files on the basis of the different activities and structured in rows of 128 values. This window size is obtained using a frequency of 50Hz and a time of 2.56 seconds, that produces 128 values per row for each file. When the window was filled the values were stored into the respective file. An example of row is shown is Figure 5.

```
0.6466553 0.7161109 0.49097902 0.7711963 1.3915064 1.5184424 2.2513185 2.579436 ↩
    ↪ 0.87897223 −0.3784131 −1.6357985 −1.4465919 0.42870852 2.0549269 1.8226099 ↩
    ↪ 0.33290774 −1.2597803 −1.8776954 −1.5687379 −2.9458742 −4.6750784 ↩
    ↪ −3.8655617 −2.6656568 −2.1100123 −0.57959473 −0.977168 −1.2358302 ↩
    ↪ −1.0346485 −0.9532178 −1.0106983 −1.1927198 −1.0466236 −1.2981006 ↩
    ↪ −2.308799 0.29698244 0.19878663 −1.4010864 −2.3878345 −1.1448194 ↩
    ↪ −0.033530276 −0.17962648 −0.24908204 −0.55324954 −0.4023633 0.23231691 ↩
    ↪ 0.47181886 0.06466553 −0.7568262 −0.36164796 0.07664063 0.17004639 ↩
    ↪ 0.41194338 −0.33769777 0.5364844 2.2177882 1.710044 −0.37362307 −0.855022 ↩
    ↪ −0.21794678 0.17004639 0.37122804 0.011975098 −0.059875492 −0.05269043 ↩
    ↪ 0.1580713 0.51492923 0.33290774 0.49337405 0.35925296 1.6860938 0.41912845 ↩
    ↪ 1.1376343 0.8669971 0.6658155 1.0777588 0.7927515 0.7448511 0.74245610. ↩
    ↪ 97237796 0.9651929 0.70174074 0.30416748 0.73048097 1.0729688 0.5508545 ↩
    ↪ 0.4239185 0.5843848 0.75203615 0.6490503 0.37362307 0.39278322 0.81191164 ↩
    ↪ 0.91010743 0.6514453 0.59156984 0.62749517 0.49097902 0.37601808 ↩
    ↪ 0.49097902 0.7759864 0.6011499 0.48139894 0.33290774 0.6011499 0.9699829 ↩
    ↪ 1.0418335 0.81191164 0.8167017 1.0466236 1.3651612 0.8286768 0.74724615 ↩
    ↪ 1.0705738 1.0130934 0.95561284 0.79035646 0.45984375 0.6179151 1.1448194 ↩
    ↪ 0.6682105 0.4622388 0.63707525 0.90771246 0.9412427 1.0202783 0.98435307 ↩
    ↪ 0.728086 0.76161623
```

Fig. 5. Example of data collection trace

Figure 6, instead, shows a trace, that has been generated from the data collected via smartphone. Each trace has been annotated with labels according to the activities it is related to. In particular, the marked range between A-B represents the *Sitting* position. The values between C-D represent the *Standing* position and the range between E-F represents the position *LyingOnTheGround*. Whereas, the values between B-C, D-E, and from F-end represent transition values between two consecutive activities.

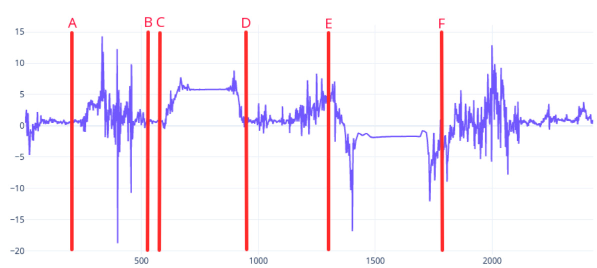


Fig. 6. An example of trace collected through the Smartphone

A similar labelling task has been done for the traces collected by using the smartwatch.

IV. Preliminary results and discussion

The main evaluation was focused on the Body Posture identification, as the Stress level and Location identification are basically centered respectively of threshold values and location mapping. In particular, regarding the body posture aspect, a training dataset and test dataset have been constructed by using a standard approach based on 5-fold cross validation, so as to reduce both the risk of losing important patterns/trends in data set and the error induced by bias. In more details, 70% of all body posture's traces have been exploited to build the training set extracted from the collected data (see Section III), whereas the remaining 30% of the data to build the test set, which have been employed respectively to train and test the above-mentioned classifiers.

The experimentation of the model was done for each single body posture in order to get the prediction of each of them separately (i.e. at single posture level), and then the accuracy of all the postures were averaged, in order to calculate the overall accuracy of the trained models. Moreover, as different traces of certain body postures were available, the construction of the training set and the test set took into account that the traces collected from a person were used only in the training set or in the test set only. This is important to ensure that the proposed features are able to recognize even new traces with a certain degree of similarity, in terms of body posture.

Figure 7 shows a qualitative representation of the confusion matrix related the human posture detection through the classifier deployed on the smartphone.

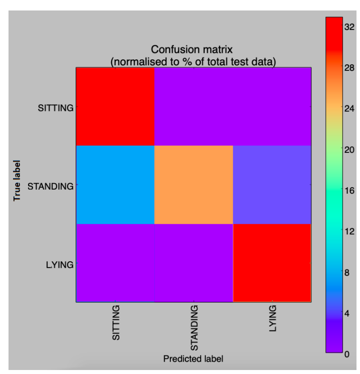
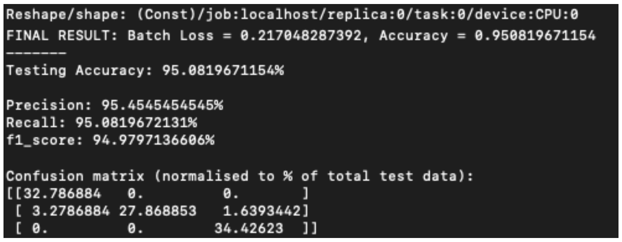


Fig. 7. Smarphone confusion matrix qualitative representation

Whereas, Figure 8 shows the related quantitative confusion matrix representation in percentage. As it is possible to see from this evaluation, the classifier deployed on the smartphone is able in most cases to distinguish between the different positions of *Standing*, *Sitting*, and *LyingOnTheGround*. Only in few cases the position of Standing is misclassified. However it shows good performaces of around 95.08% in terms of accuracy, 95.45% precision, 95.08% recall and 94.97% f1-score. In the same way, the evaluation process regarding the identification of the hands-related postures via the classifier deployed on the smartwatch, have been conducted, by showing around 94.74% accuracy, 94.07% precision, 94.74% recall and 93.63% f1-score.



```
Reshape/shape: (Const)/job:localhost/replica:0/task:0/device:CPU:0
FINAL RESULT: Batch Loss = 0.217048287392, Accuracy = 0.950819671154
-------
Testing Accuracy: 95.0819671154%

Precision: 95.4545454545%
Recall: 95.0819672131%
f1_score: 94.9797136606%

Confusion matrix (normalised to % of total test data):
[[32.786884   0.          0.        ]
 [ 3.2786884 27.868853   1.6393442]
 [ 0.         0.        34.42623  ]]
```

Fig. 8. Smarphone confusion matrix quantative values

The overall results for both the classifiers and they avaraged value are summarized in Table I.

TABLE I
CLASSIFICATION RESULTS GATHERED FROM THE SMARTPHONE- AND SMARTWATCH-BASED CLASSIFIERS

Device	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Smartphone classifier	95.08	95.45	95.08	94.97
Smartwatch classifier	94.74	94.07	94.74	93.63
Avarage value	94.91	94.76	94.92	94.30

As we can see, even though the performace of the smartwatch classifier is slightly lower than that related to smartphone classifier, both of them show very high results.

V. CONCLUSION

The paper focused on the detection of human physical status related to situations of danger enabled by smartwatch and smartphone technologies. A model, based on three main aspects related to the body posture, the stress level and the geolocation, has been identified, and for each aspect, specific features have been elaborated.

Machine learning techniques were used to evaluate the features related to the body postures, by training 2 classifiers for mobile devices: one of them deployed on a smartphone and the another one on a swartwatch, in order to detect body and arms related postures. From the evaluation both the classifiers reached an accuracy higher than 94%, as a symptom of goodness of the proposed features. The other two aspects related to the stress level and the geolocation have been involved, as triggering factors, in the general process of danger situation identification, based respectively on threshold values and location mapping.

However, through the use of such parameters, possible false positives related to the overall detection of situations of danger can be generated, due to factors that have not been considered in the current version. For example, if a user is doing sport in a park, and the activities that he is performing are similar to those we faced with, and if those activities require a physical effort that can be captured as a stress level condition, then, the the proposed model might detect a false situation of danger.

This problem is currently mitigated through a local notification mechanism that activates the vibration of the devices based on a time countdown. If the user is not in a dangerous situation, he can manually deactivate the process, thus preventing the generation of a false alert.

Future work foresees to extend the proposed model by identifying other characterizing elements and their relationships, such as other body postures like *ArmsDown - Standing*, *CrossedArms - Standing and Sitting* and *HandsOnTheLegs - Sitting*, which are not related to situations of danger and that have not been investigated in this context yet.

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