Discovering and Understanding Android Sensor Usage Behaviors with Data Flow Analysis

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Abstract Today's Android-powered smartphones have various embedded sensors that measure the acceleration, orientation, light and other environmental conditions. Many functions in the third-party applications (apps) need to use these sensors. However, embedded sensors may lead to security issues, as the third-party apps can read data from these sensors without claiming any permissions. It has been proven that embedded sensors can be exploited by well designed malicious apps, resulting in leaking users' privacy. In this work, we are motivated to provide an overview of sensor usage patterns in current apps by investigating what, why and how embedded sensors are used in the apps collected from both a Chinese app market and official market called Google Play. To fulfill this goal, We develop a tool called "SDFDroid" to identify the used sensors' types and to generate the sensor data propagation graphs in each app. We then cluster the apps to find out their sensor usage patterns based on their sensor data propagation graphs. We apply our method on 22,010 apps collected from AppChina and 7,601 apps from Google Play. Extensive experiments are conducted and the experimental results show that most apps implement their sensor related functions by using the third-party libraries. We further study the sensor usage behaviors in the third-party libraries. Our results show that the accelerometer is the most frequently used sensor. Though many third-party libraries use no more than four types of sensors, there are still some third-party libraries registering all the types of sensors recklessly. These results call for more attentions on better regulating the sensor usage in Android apps.

Keywords Android system; Sensor usage; Data-flow analysis; Clustering

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1 Introduction

Android-powered smartphones have become more and more popular for both personal and business use. According to a report from the International Data Corporation (IDC) [18], Android-powered smartphones dominate the market with a 87.6% share in the second quarter of 2016. At the same time, the smartphone's hardware is more and more advanced. Various sensors have been embedded in smartphones, such as the motion sensor (*e.g.*, accelerometers, gravity sensors, gyroscopes, rotational vector sensors), the environmental sensor (*e.g.*, temperature, illumination) and the position sensor (*e.g.*, orientation sensors and magnetometers) [1]. These sensors are used by some third-party applications (apps) to support their novel features, such as the Spirit Level in some Camera-related apps.

Android is designed without considering the security issues that may be led by the embedded sensors. The third-party apps can use embedded sensors without claiming any permissions on Android platform. However, embedded sensors can be exploited by well designed malicious apps (malapps), resulting in leaking users' privacy. For example, tapping different positions on the touchscreen will cause different motion changes of the smartphone. If the correlations between the tap events and the data collected by the motion sensors are learned, one can successfully guess users' input through the data collected by the motion sensors. Related work [7, 8, 25, 28, 30] has already demonstrated that smartphones' embedded sensors can expose users' privacy data. In particular, Xu *et al.* [36] designed and implemented "TapLogger", a trojan app that uses obtained sensor data to log user inputs on touchscreen stealthily. "TapLogger" was reported by various media [26, 32] due to its high threat to users' confidential information. Besides, other researchers [20, 22, 40] proposed many user identity recognition mechanisms based on embedded sensor data. Their work indicates that embedded sensors' data can not only be used to identify whether a user is the smartphone's owner, but can also leak users' identity information.

Although these studies still remain in the experimental stage, they attract us to discover the sensor usage patterns in the current Android apps. According to a statistical result from AppBrain [5], the number of apps in Google Play has reached 2.4 million, while according to the Android API Guides [1], Android system supports more than ten types of sensors. Since embedded sensors can expose confidential information on smartphones, curiosities are aroused on understanding what, why and how the embedded sensors are used in current apps. Previous work does not answer this questions, since the related work usually focuses on Android permission analysis [33], Android malware detection [31] or user privacy protection in Android platform [24]. In order to better answer these questions, we extend our previous work [23] by additionally analyzing 7,601 popular apps from Google Play and discuss the experimental results in depth. We design and implement a tool called SDFDroid (Sensor Data Flow Droid). It first disassembles the apk files to smali code files, and then performs two kinds of data flow analysis. One is backward tracking analysis, which starts from the API that registers a sensor listener in the system to find the used sensors' types. The other is forward tracking analysis, which starts from the API that reads sensor data from the system to generate sensor data propagation graphs. We calculate the similarity between each pair of sensor data propagation graphs that are generated from many apps, and then cluster the graphs with DBSCAN [13], a well known clustering algorithm. Sensor

usage patterns are thus constructed from the clustering results. We analyze 22,010 apps collected from AppChina (one of the main Android app markets in China) and 7,601 apps from Google Play. We find that almost all the apps implement sensor related functions with the help of the third-party libraries. We also find that accelerometer is the most-used sensor and that the used sensor type has a clear association with the app’s function. We make the following contributions in this paper:

- We design and implement SDFDroid that fast and accurately analyzes Android apps to identify the types of embedded sensors used by the apps and to generate the apps’ sensor data propagation graphs.
- We employ SDFDroid to analyze all the apps in AppChina and some popular apps in Google Play. We reveal sensor usage patterns in apps at a large scale.
- To the best of our knowledge, our work is the first attempt to discovering the sensor usage behaviors on the view of a complete Android app market.

The remainder of this paper is organized as follows. Section 2 describes the background of Android sensor system and smali code files. Section 3 gives our system design. Section 4 presents experimental results and limitations. Related work is given in Section 5. Section 6 concludes our work.

2 Background

2.1 Android Sensor System

Today’s Android-powered smartphones are equipped with various embedded sensors. These sensors are used to monitor the device’s movement, position or other surrounding environmental conditions. The Android system supports many types of sensors (see Table 1). Some sensors are hardware types, which means that the sensor data is directly read from physical sensors built in the smartphone. Other sensors are software types, which means that the sensor data is read and calculated from one or more of the hardware sensors [1]. The embedded sensors are widely used in the third-party apps. For example, a navigation app may use the magnetic field sensor to determine the direction.

The embedded sensors are managed by Android Sensor Framework. Different from the Camera, GPS and Bluetooth which are protected by Android permission mechanism, the embedded sensors can be directly used by the third-party apps without any requirement of permissions. With the help of Android Sensor Framework, a third-party app can read a sensor’s data by the following steps (as shown in Figure 1).

- First, instantiate an object of *SensorManager* class (Line 12). In this step, an app creates an instance of the sensor service. This class provides many methods for using sensors, such as accessing specified sensors and listing all available sensors, registering and unregistering sensor event listeners.
- Second, instantiate an object of *Sensor* class by calling the *getDefaultSensor()* (Line 14). In this step, an app gets an object of *Sensor* with a specific type. The type of the sensor can be specified by the method’s parameter. As shown in this example, *Sensor.TYPE_ACCELEROMETER* is a constant describing an

Table 1 Some sensor types supported by the Android platform

Sensor	Type	Description
Accelerometer	Hardware	Measures the acceleration force
Ambient_Temperature	Hardware	Measures the ambient room temperature
Gravity	Software or Hardware	Measure the force of gravity
Gyroscope	Hardware	Measures a device's rate of rotation
Light	Hardware	Measures the ambient light level
Linear_Accelerometer	Software or Hardware	Measures the acceleration force, excluding the force of gravity
Magnetic_Field	Hardware	Measures the ambient geomagnetic field
Orientation	Software	Measures degrees of rotation that a device makes around all three physical axes
Pressure	Hardware	Measures the ambient air pressure
Proximity	Hardware	Measures the proximity of an object relative to the view screen of a device
Relative_Humidity	Hardware	Measures the relative ambient humidity
Rotation_Vector	Software or Hardware	Measures the orientation of a device
Temperature	Hardware	Measures the temperature of the device

```

1 //SensorActivity.java
2 public class SensorActivity extends Activity
3 {
4     float accx;
5     private SensorManager sensorManager;
6     private Sensor sensora;
7
8     public void onCreate(Bundle paramBundle)
9     {
10         super.onCreate(paramBundle);
11         setContentView(R.mainview);
12         sensorManager = (SensorManager) getSystemService(Context.SENSOR_SERVICE);
13         Log.d("sensor", "Get sensorManager Success");
14         sensora = sensorManager.getDefaultSensor(Sensor.TYPE_ACCELEROMETER);
15         SensorEventListener accelerometerListener = new SensorEventListener()
16         {
17             public void onAccuracyChanged(Sensor arg0, int arg1)
18             {
19             }
20             public void onSensorChanged(SensorEvent arg0)
21             {
22                 accx = arg0.values[0];
23                 .....
24                 // Do something with this sensor value
25             }
26         };
27         this.sensorManager.registerListener( accelerometerListener, sensora, SENSOR_DELAY_NORMAL);
28     }
29     .....
30 }

```

Fig. 1 Code example to use sensor

accelerometer sensor type. If light sensor is needed, one can set the method's parameter as *Sensor.TYPE_LIGHT*. All available constants can be found in the Android developer website [2].

- Third, instantiate an object of *SensorEventListener* interface (Line 15) and override two callback methods which are *onAccuracyChanged()* (Line 17) and *onSensorChanged()* (Line 20). These two methods are used to receive sensor events when sensor accuracy changes or when sensor values change. Android

system will invoke *onSensorChanged()* when sensor data changes automatically, and a *SensorEvent* object is put in the methods' parameter. The *SensorEvent* object is created by the system. It contains the following information: the raw sensor data, the sensor's type, the accuracy of the data and the timestamp of this event. Developers can read sensor data from this object (Line 22).

- Last, register a sensor event listener (Line 27). By invoking the method *registerListener()*, app registers a *SensorEventListener* into the system. The sensor that will be registered is specified by the method's second parameter. When a sensor's value changes, the system will only notify the apps that have registered this sensor. The third parameter of this method is used to set the data delay. The data delay controls the interval at which sensor events are sent to the app. In this example, the default data delay (*SENSOR_DELAY_NORMAL*) let this app receive the raw sensor values every 0.2 seconds.

2.2 Smali Code

Smali code is a kind of programming language used by Dalvik, Android's JVM implementation. A given app's smali codes can be retrieved with Apktool [4], a tool for reversing Android apps. An app's smali codes obtained by disassembling are matched with the app's source codes. Hence, analyzing the smali codes directly is reasonable. We provide the corresponding disassembled smali codes of Figure 1 in Figure 2 and Figure 3. Figure 3 is the smali codes associated with the interface class *SensorEventListener*. Apktool generates individual smali files for interface classes and inner classes. In the smali files, all instructions are based on registers. Local registers are represented with the symbols start with *v*, parameter registers are represented with the symbols start with *p*. Operations on the registers are determined by the Opcodes, such as {*const-string*, *invoke-static*, *iput-object*, ...}. For example, *const-string v2, "sensor"* (in Figure 2 Line 16) means creating a new string whose value is "sensor" and putting it in register *v2*. Detailed information about the meanings of different Opcodes can be found in [3].

3 System Design

3.1 High-level Overview

We design and implement a tool called "SDFDroid" that performs static analysis on Android apps to identify the apps' used sensor types and to generate the apps' sensor data propagation graphs. SDFDroid supports automated analysis and is efficient to process a large number of apps. After we get all the apps' sensor data propagation graphs, we calculate their similarity. We convert the similarity into distance between each pair of graphs before we cluster the graphs. In this work, DBSCAN [13] is employed to cluster the app samples based on the distances between each pair of graphs, as DBSCAN is a widely-used clustering algorithm based on density estimation that can describe the behaviors of various apps. The sensor usage patterns of each cluster are then analyzed based on the clustering results. We illustrate the system's overview in Figure 4.

```

1 .super Landroid/app/Activity;
2 .source "SensorActivity.java"
3
4 # instance fields
5 .field accx:F
6 .field private sensorManager:Landroid/hardware/SensorManager;
7 .field private sensora:Landroid/hardware/Sensor;
8
9 # virtual methods
10 .method public onCreate(Landroid/os/Bundle;)V
11     .parameter "savedInstanceState"
12
13     invoke-super {p0, p1}, Landroid/app/Activity;-> onCreate(Landroid/os/Bundle;)V
14     const/high16 v2, 0x7f03
15     invoke-virtual {p0, v2}, Lcom/my/sensorgravity/SensorActivity;-> setContentView(I)V
16     const-string v2, "sensor"
17     invoke-virtual {p0, v2}, Lcom/my/sensorgravity/SensorActivity;-> getSystemService(Ljava/lang/String;)
        Ljava/lang/Object;
18     move-result-object v2
19     check-cast v2, Landroid/hardware/SensorManager;
20     iput-object v2, p0, Lcom/my/sensorgravity/SensorActivity;-> sensorManager:Landroid/hardware/SensorManager;
21     const-string v2, "sensor"
22     const-string v3, "Get sensorManager Success"
23     invoke-static {v2, v3}, Landroid/util/Log;-> d(Ljava/lang/String;Ljava/lang/String;)I
24     iget-object v2, p0, Lcom/my/sensorgravity/SensorActivity;-> sensorManager:Landroid/hardware/SensorManager;
25     const/4 v3, 0x1
26     invoke-virtual {v2, v3}, Landroid/hardware/SensorManager;-> getDefaultSensor(I)Landroid/hardware/Sensor;
27     move-result-object v2
28     iput-object v2, p0, Lcom/my/sensorgravity/SensorActivity;-> sensora:Landroid/hardware/Sensor;
29     new-instance v0, Lcom/my/sensorgravity/SensorActivity$1;
30     invoke-direct {v0, p0, v1}, Lcom/my/sensorgravity/SensorActivity$1;->
        <init>(Lcom/my/sensorgravity/SensorActivity; Landroid/widget/TextView;)V
31     .local v0, accelerometerListener: Landroid/hardware/SensorEventListener;
32     iget-object v2, p0, Lcom/my/sensorgravity/SensorActivity;-> sensorManager:Landroid/hardware/SensorManager;
33     iget-object v3, p0, Lcom/my/sensorgravity/SensorActivity;-> sensora:Landroid/hardware/Sensor;
34     const/4 v4, 0x3
35     invoke-virtual {v2, v0, v3, v4}, Landroid/hardware/SensorManager;-> registerListener(
        Landroid/hardware/SensorEventListener; Landroid/hardware/Sensor;)Z
36     return-void
37 .end method

```

Fig. 2 Smali code for SensorActivity

```

1 # virtual methods
2 .method public onAccuracyChanged(Landroid/hardware/Sensor;)V
3     .parameter "arg0"
4     .parameter "arg1"
5     .prologue
6     return-void
7 .end method
8
9 .method public onSensorChanged(Landroid/hardware/SensorEvent;)V
10     .parameter "arg0"
11     .prologue
12     const/4 v3, 0x0
13
14     iget-object v0, p0, Lcom/my/sensorgravity/SensorActivity$1;-> this$0:Lcom/my/sensorgravity/SensorActivity;
15     iget-object v1, p1, Landroid/hardware/SensorEvent;-> values:[F]
16     aget v1, v1, v3
17     iput v1, v0, Lcom/my/sensorgravity/SensorActivity;-> accx:F
18     ...
19     return-void
20 .end method

```

Fig. 3 Smali code for SensorActivity\$1

Fig. 4 Overview of SDFDroid

3.2 Static Analysis

In this Section, we describe the static analysis method used in this work. Complete code is statically analyzed without the need of its execution. Therefore, static analysis can be done at app market level efficiently.

An Android app is packaged as an Android application package (APK) file with compiled bytecode, additional metadata and resources in it. SDFDroid disassembles an APK file into smali code files with the help of Apktool. Then, SDFDroid parses the smali files and creates corresponding java objects of their contents.

Based on the previous step, SDFDroid performs two kinds of static analysis. One is backward tracking analysis that specifically focuses on analyzing *registerListener()*'s second parameter to find out which sensors are used by an app. The other is forward tracking analysis that focuses on generating an app's sensor data propagation graph. We describe the detail of these two kinds of static analysis as follows (we use the codes in Figure 2 and Figure 3 for examples):

- **Backward tracking analysis.** In the backward tracking analysis, the analysis begins at the method *registerListener()*, whose second parameter specifies the used sensor. SDFDroid first finds out the corresponding smali code of *registerListener()* in the smali code files, then begins to track the register *v3* that stores the value of this method's second parameter (see line 35, Figure 2). SDFDroid searches the smali codes in reverse order to find the value of *v3*. Then, SDFDroid finds that *v3* obtains an object value at line 33. This object is a class field defined in Line 7. In the next step, SDFDroid searches the corresponding setters of this field. One setter can be found in Line 28. The value in register *v2* is assigned to this field. After this, SDFDroid backtracks register *v2*, and finds that *v2* stores the result of invoking method *getDefaultSensor* (see Line 26-27). This method is provided by Android system, and we know the return value of this method is decided by the method's parameter. Hence, the register corresponding to this method's parameter is backtracked (See register *v3* in Line 26). If a register obtains a constant value, the tracking of this register will be terminated, and the tracking result will be reported. As shown in this example, register *v3* gets a constant value in Line 25. This result will be reported, and we will realize the sensor type is 1. Hence, the sensor used by this

app is an accelerometer. The relationships between the numbers and the real sensor types are listed in Android Developer Website [2].

- **Forward tracking analysis.** The forward tracking analysis is similar with the backward tracking analysis. SDFDroid first creates an empty graph and finds out the register that needs to be tracked in the smali codes. Then, it determines whether the value of this register is assigned to another object, or is overwritten by another value. In the forward tracking analysis, if the value of a tracked register is assigned to another object, the target object that receives the value is added into the track queue. Otherwise, if the register is overwritten, the tracking of this register will be stopped. For example, in Figure 3, sensor data is obtained from the system through the *SensorEvent* object: *Landroid/hardware/SensorEvent;->values:[F* and is assigned to the register *v1* (See Line 15). SDFDroid searches the smali files in order in forward tracking analysis. Finally, SDFDroid finds the value of register *v1* is assigned to a class field *accx* in Line 17. At the same time, the search process reaches the end of this method. Hence, the tracking of register *v1* is stopped, and SDFDroid will search at where the class field *accx* is used in all other smali code files of the same app in the next step. Each time SDFDroid finds a new line of smali code that propagates the sensor data, it adds the smali code into the graph as a node. The directions of sensor data propagation are represented by the directed edges between each pair of nodes.

Both backward tracking analysis and forward tracking analysis have a queue to store objects that need to be tracked. Once the tracking process finds an object that needs to be tracked, it puts the object in this queue. When the tracking of the current object is finished, SDFDroid gets an object from the top of the queue and starts to track it. The static analysis of an app is finished when the queue is empty. An app’s used sensor types are reported in a *.xml* file while its sensor data propagation graph is reported in a *.gexf* file. GEXF(Graph Exchange XML Format) is a language for describing complex network structures. Gephi[15] can open a *.gexf* file and show the graph (See Figure 5). Nodes in the graph are smali code lines, while edges represent data propagation directions.

3.3 Clustering Analysis

Once the used sensor types and sensor data propagation graphs of all the apps are generated, we perform clustering analysis on these graphs to construct their sensor usage patterns.

3.3.1 Distance calculation

The first step to perform clustering analysis is to calculate the similarity between each pair of graphs. Calculating the edit distance between two graphs is an effective way of calculating the similarity between these two graphs. Graph edit distance measures the minimum number of graph edit operations (including insert or delete a node, insert or delete an edge or change the label of a node or edge) to transform one graph to another. However, calculating the edit distance between two graphs is NP-hard [37]. It is only applicable to graphs that have a small number of nodes.

Fig. 5 Sensor Data Propagation Path Graph.

Although many researchers have modified the basic algorithm of graph edit distance to improve its efficiency, it cannot be applied to the sensor data propagation graphs that may have hundreds of nodes. Besides, an Android app market may have more than ten thousand apps that need to be analyzed. Since we need a fast algorithm to calculate the similarity between each pair of graphs on a large-scale, in this work, we compute a *graph hash* for each graph and calculate the similarity between each pair of graphs based on their hash values. This procedure is inspired by Neighborhood Hash Graph Kernel (NHGK) that is originally proposed by Hido and Kashima [16].

NHGK is a kernel operation over labeled graphs. It has high expressiveness of the graph structure, and fast execution speed on graphs with large number of nodes. Hence, it is applicable to process graphs with hundreds of nodes such as the sensor data propagation graphs. The main idea of NHGK is to integrate the information of a node and its neighbor nodes into a hash value. The calculation of a node's hash value is defined as follows:

$$H(v) = R(l(v)) \oplus (l(v_1^{NE}) \oplus \dots \oplus l(v_n^{NE}))$$

where $l(v)$ represents the binary label that is transformed from the node's real label. $\oplus$ represents a bit-wise XOR. R means a one-bit rotation to the left. v^{NE} is the neighbor nodes of node v . This algorithm can also be used k times iteratively to integrate information across neighbors up to a path with length k . The hash value of a graph G is obtained by calculating the hash values of all the nodes in graph G . Then the similarity between two graphs is computed based on the number of nodes that have the same hash values (Algorithm 1). In this algorithm, the binary hash values are treated as integer. Hence, they can be sorted and compared.

Algorithm 1 Calculate the similarity between two graphs

Input: G_1, G_2
Output: Similarity between G_1 and G_2

```

1:  $G_1^{hash} \leftarrow G_1.hash()$ 
2:  $G_2^{hash} \leftarrow G_2.hash()$ 
3:  $V_1 \leftarrow G_1^{hash}.nodes()$ 
4:  $V_2 \leftarrow G_2^{hash}.nodes()$ 
5:  $V_1^{sort} \leftarrow V_1.sort()$ 
6:  $V_2^{sort} \leftarrow V_2.sort()$ 
7:  $n_1 \leftarrow V_1^{sort}.length()$ 
8:  $n_2 \leftarrow V_2^{sort}.length()$ 
9:  $c \leftarrow 0$ 
10:  $i \leftarrow 0$ 
11:  $j \leftarrow 0$ 
12: while  $i < n_1, j < n_2$  do
13:   if  $V_1^{sort}[i] == V_2^{sort}[j]$  then
14:      $c \leftarrow c + 1$ 
15:      $i \leftarrow i + 1$ 
16:      $j \leftarrow j + 1$ 
17:   else if  $V_1^{sort}[i] < V_2^{sort}[j]$  then
18:      $i \leftarrow i + 1$ 
19:   else
20:      $j \leftarrow j + 1$ 
21:   end if
22: end while
23:  $s = \frac{c}{n_1 + n_2 - c}$ 
24: return  $s$ 

```

In our work, when we calculate the similarity between each pair of graphs, we simplify the labels of nodes in the graphs at first to ensure the method's robustness. The labels of nodes are entire small code lines in original graphs (as shown in Figure 5), and we relabel the nodes only with the operation codes. For example, node label *mul-float v1,v2,v3* is relabeled as *mul-float*. For some special operations, such as invoking a method, we also reserve the names of the invoked methods. Then we count the number of distinct labels in all graphs, and relabel them with different binary labels. Finally, each node's hash value is computed. By doing this, we can calculate the similarity between each pair of sensor data propagation graphs with the algorithm above.

3.3.2 Clustering

After we have calculated the similarity between each pair of graphs, we cluster the graphs to find their common characteristics and thus to discover the sensor usage patterns of different apps. The algorithm we used is Density-based spatial clustering of applications with noise (DBSCAN) [13]. DBSCAN is one of the most widely-used clustering algorithms based on density. The main idea behind this algorithm is that, for a set of points in a given space, it clusters points that are closely located together and make outliers for points that lie alone in low-density regions. In a DBSCAN clustering, the points are classified as core points, reachable points and noise. A core point p is a point that has at least m neighbor points within distance d from it, and these neighbor points are considered to be directly reachable from p . A point q is a reachable point of p if there is a path from p to q

Fig. 6 The number of apps in each category

where each point on the path can be directly reached from the point before it. The points are neither core points nor reachable points are noise. After the clustering, each cluster consists of some core points and their reachable points. The points that are reachable but not core points form the cluster's edge [35].

DBSCAN only needs two parameters: m and d to confirm core points. It does not need to specify the number of clusters. Therefore, it is suitable on our app set, as we do not know how many clusters the apps will be associated with.

In our work, we transform the similarity between each pair of graphs generated with SDFDroid to a distance between each pair of graphs. For two graphs, the more similar they are, the smaller distance they have. We measure the distance by:

$$d = \frac{1 - s}{1 + s}$$

where s is the similarity between two graphs and d is the distance.

4 Evaluation

4.1 Dataset

The dataset in the experiments is collected from two app markets. One is AppChina, a famous Android app market in China. We download all the 22,010 apps available in AppChina in December 2014. The apps from AppChina belong to 14 subcategories under “Software” category and 14 subcategories under “Game” category. The other one is Google Play. We download 7,601 popular apps available in Google Play in July 2016. The apps from Google Play belong to 25 subcategories under “Apps” category and 14 subcategories under “Games” category. The number of apps in each subcategory is shown in Figure 6. For each app, we get its apk file, size, developer and description.

4.2 Analysis Results

Except some apps that cannot be disassembled by Apktool, we successfully analyzed 19,914 apps from AppChina and 7,601 apps from Google Play. We find

10,976 apps (55.1%) from AppChina and 3,179 apps (41.8%) from Google Play contain code snippets that are used to read sensor data. We present the detailed cluster and analysis results as follows.

4.2.1 Clustering results

In order to ensure the robustness and representative, in the process of clustering, we set the parameter d and m of DBSCAN to 0.1 and 10 respectively. Apps from AppChina and apps from Google Play are clustered separately. After the clustering, 8,319 apps from AppChina are clustered into 98 clusters and 1,468 apps from Google Play are clustered into 35 clusters. We compare the samples in the same cluster and find the main reason why their sensor data propagation graphs are similar is the using of the same third-party libraries. Table 2 shows the sensor related third-party libraries used in the AppChina’s clusters that have more than 100 apps. Some third-party libraries’ methods are obfuscated with different names in different versions, which makes their sensor data propagation graphs different, hence they are clustered into different clusters. The table shows *Tencent*, *Cocos2dx*, *Unity3d* are the Top 3 frequently used third-party development libraries which contain sensor related codes in the apps from AppChina. *com.tencent.mm.sdk* is a Jar package used to share the moments with one’s friends in *WeChat* (The most widely-used IM tool in China). *Cocos2dx* is a framework for building 2D games and other graphical apps. *Unity3d* is a game development toolkit that helps developers to build 3D games and real time 3D animations. Table 3 shows the sensor related third-party libraries used in the Google Play’s clusters that have more than 20 apps. This table displays *Unity3d*, *Tapjoy*, *Google ad* are the most frequently used sensor related third-party libraries in the apps from Google Play. *Tapjoy* is an advertisement (ad) library. *com.google.android.gms.ads* is also used for ad purpose. We also manually check the other libraries and find most of them are ad libraries and game development libraries. These results show running games and displaying ads are the main reasons for apps using embedded sensors.

Figure 7 is a matrix describing clustering results by category for apps from AppChina. This figure illustrates that different category usually has different sensor usage patterns. Category IME, Browser and Theme have few apps that have sensor related codes. Most apps in Category Game_Trivia, Game_Shoot, Game_Strategy and Game_Adventure are classified into Cluster 15 and Cluster 16. It indicates that most apps in these categories are developed with the help of *Cocos2dx* and *Unity3d*. Each category contains some apps that have sensor related code snippets. Figure 7 also shows some clusters only contain apps in “Software” category while some other clusters only contain apps in “Game” category. This reveals the different sensor usage behaviors between apps and games. This figure also shows “Game” apps are more likely to use sensors. Figure 8 is a matrix characterizing clustering results by category for apps from Google Play. This figure demonstrates that *Unity3d* and *Cocos2dx* are usually used in “Game” apps because most apps in cluster 1 and cluster 5 are games. Figure 8 also shows most apps in cluster 6 are “Apps” apps and most apps in cluster 19 are “Game” apps, which indicates that *Google ad* is usually used in “Apps” apps and *Tapjoy* is commonly used in “Game” apps. We also study the reason why some clusters contain many apps from the same category. We find the apps in the same combination of cluster and category are usually developed by the same developer based on the same template. For

Table 2 The sensor related third-party libraries in the clusters from AppChina

ID	Cluster Number	The Number Of Apps	Sensor Related Third-Party Libraries
1	15	1097	org.cocos2dx.lib
2	16	938	com.unity3d.player
3	1	619	com.tencent.mm.sdk
4	14	398	com.tencent.mm.sdk
5	6	397	com.tencent.mm.sdk
6	3	313	org.cocos2dx.lib
7	25	214	com.adobe.air.Accelerometer
8	24	196	com.badlogic.gdx.backends.android
9	13	185	org.apache.cordova
10	43	177	com.mobi.view
11	10	166	com.tencent.mm.sdk
12	34	165	org.cocos2dx.lib
			com.unity3d.player
			com.tencent.mm.sdk
			com.millennialmedia.android.AccelerometerHelper
			com.mobclix.android.sdk
13	39	160	com.unity3d.player
14	62	137	org.andengine.engine.Engine
15	40	130	cn.sharesdk.onekeyshare.Shake2Share
16	33	112	com.adsmogo.mriad
			com.tapjoy.mraid
			org.ormma.controller
			com.adobe.air
17	9	105	com.baidu.location
18	67	104	cn.sharesdk.onekeyshare.Shake2Share
			com.umeng.socialize.sensor.UMShakeSensor
			com.unity3d.player
			com.zhuohuamg.game.util.ShakeListener
19	8	102	com.tencent.mm.sdk
			com.trid.tridad.TriDContentView
20	27	101	

Table 3 The sensor related third-party libraries in the clusters from Google Play

ID	Cluster Number	The Number Of Apps	Sensor Related Third-Party Libraries
1	1	242	com.unity3d.player
2	6	209	com.google.android.gms.ads.internal.overlay
3	5	127	org.cocos2dx.lib
4	13	109	com.adobe.air
5	19	100	com.tapjoy.mraid
6	3	60	com.ansca.corona.CoronaSensorManager
7	7	57	com.mixpanel.android.viewcrawler.FlipGesture
8	20	53	com.badlogic.gdx.backends.android
9	8	51	com.admarvel.android
10	10	49	com.tapjoy.mraid
			com.badlogic.gdx.backends.android
11	9	38	com.facebook.ads
12	22	31	com.google.android.gms.ads.internal.overlay
13	30	28	com.ideaworks3d.marmalade.LoaderThread
14	15	26	com.tapjoy.mraid
			com.unity3d.player

instance, for cluster 14 and category “WallPaper” in AppChina, 397 apps are developed by the same developer. For cluster 13 and category “Game_Educational” in Google Play, 20 apps are developed by the same developer. Since the developers only need to change some resource files (pictures, text contents, etc.) in the templates, the apps developed with the same template usually have the similar sensor data propagation graphs.

Fig. 7 Matrix for cluster result by category of apps from AppChina. Each grid corresponds to a combination of cluster and category, and the depth of the grid's color represent the number of apps in this grid. The more apps in the corresponding combination of cluster and category, the deeper the color.

Fig. 8 Matrix for cluster result by category of apps from Google Play.

4.2.2 Used sensor type

According to the backward tracking analysis results, accelerometer is the most frequently used sensor. More than 70 percent of apps from AppChina and 66 percent of apps from Google Play use this sensor as indicated in Figure 9. This is mainly because some popular functions, such as Shake in WeChat (shake your phone, then you will find a random person who shakes his/her phone at the same time with you to chat with), need this sensor. All the widely used sensor related third-party libraries, such as *Cocos2dx*, *Unity3D* and *OneKeyShare*, require this sensor. Gyroscope is often used to display the 3D model of an object. Proximity sensor almost only appears in *com.tencent.mm.sdk* while gravity sensor almost only appears in *Unity3D*. The third-party libraries that provide map function, such

Fig. 9 Percentage of apps that use each type of sensor

as *com.baidu.mapapi*, will use the orientation sensor and magnetic field sensor. Some ad libraries also need magnetic field sensor. The apps that can distinguish QR Code may use the light sensor. Linear acceleration sensor is mainly used by *Unity3D* and rotation vector sensor is mainly used by *Unity3D* and *Google ad*. Motion sensors and position sensors are widely used, while environmental sensors are seldom used except the light sensor. This is because many smartphones do not have the hardware sensors to measure the temperature or humidity. *Unity3D* can access six types of sensors. However, *madhouse*, an ad library, registers eleven types of sensors for their ad display. Although attractive ads may need the data from embedded sensors, we do not think eleven types of sensors are necessary. We find 54 apps from AppChina and only one app from Google Play use this library. We summarize the detail about the used sensor types in the most used sensor related third-party libraries in Table 4. Apps from AppChina and most apps from Google Play only use the sensors showed in Figure 9, but several apps from Google Play also use some novel sensors. For example, *WalkLogger pedometer* from Health&Fitness category used step detector sensor and step counter sensor. These two types of sensors were added in Android 4.4. *WatchMaster-Watch Face* from Personalization category used the heart rate sensor which was added in Android 4.4W.

4.2.3 Discussion

Our studies on AppChina and Google Play do not find any app that steals users' sensor data (The data read from the sensors which are not protected by Android permissions). Different from the methods of stealing users' location, contact or message, which often use Java reflection API to read data and send the data to the Internet, apps just use the sensor data in their local codes. However, since the embedded sensor can be directly used without requirement of permissions, some third-party libraries register all the sensors recklessly, no matter whether they really need. This not only leads to more power consumption, but also makes the sensors more easily be exploited by malicious apps. Though many apps contain the third-party libraries that can read sensor data, they do not functionally need

Table 4 used sensor type in each third-party library

Markets	Libraries	Accelerometer	Magnetic Field	Orientation	Gyroscope	Light	Pressure	Temperature	Proximity	Gravity	Linear Acceleration	Rotation Vector
AppChina	org.cocos2dx	✓	✓			✓				✓	✓	✓
	com.unity3d.player	✓										
	com.tencent.mm.sdk	✓										
	cn.sharesdk.onekeyshare	✓							✓			
	com.umeng...UMShakeSensor	✓	✓		✓	✓	✓	✓	✓			
	com.adsmogo.mriad	✓				✓	✓	✓				
	com.adchina.android.ads.views	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	com.madhouse.android.ads	✓										
	com.millennialmedia.android	✓										
	com.mobi.view	✓										
	com.adcocoa	✓										
	com.baidu.location	✓	✓			✓			✓			
	com.baidu.navi	✓		✓								
	com.amap.api.mapcore	✓	✓	✓		✓						
	com.google.zxing	✓				✓						
	com.badlogic.gdx	✓	✓									
	com.adobe.air	✓			✓							
	com.mobclix.android.sdk	✓		✓	✓							
	com.trid.tridad	✓										
Google Play	com.unity3d.player	✓	✓			✓				✓	✓	✓
	com.google...overlay	✓										✓
	org.cocos2dx.lib	✓			✓							
	com.adobe.air	✓										
	com.tapjoy.mraid	✓	✓									
	com.ansca...CoronaSensorManager	✓		✓								
	com.mixpanel...FlipGesture	✓										
	com.badlogic.gdx	✓	✓									
	com.admarvel.android	✓	✓									
	com.facebook.ads	✓	✓		✓							
	com.ideaworks3d...LoaderThread	✓	✓	✓								

the sensor data. Hence, we suggest the third-party libraries put the sensor related codes in a standalone package, and let the developers chose to use it or not by themselves.

Runtime Performance We conducted the experiments on a quad-core machine with Inter Core i5 CPU (3.10 GHz $\times$ 4) and 8GB RAM, running Ubuntu 16.04 LTS. Most of the apps can be processed within 3 minutes. The experimental results indicate that SDFDroid is efficient to explore sensor usage behaviors of Android applications on a large scale.

Limitations Our method may not perform very well on the Apps with heavily smali code obfuscation. The *Reflection* API may also affect the analysis results. Another important factor affecting the analysis results is the use of Native methods. Some third-party development libraries write parts of their sensor related codes in the Native functions with the help of Native Development Toolkit(NDK). The Native functions are written by C++ and cannot be disassembled to smali codes, hence they cannot be analyzed by SDFDroid. However, the state-of-art analysis tools like Flowdroid also meet these shortcomings. SDFDroid does not handle Android inter-component communication (ICC) and inter-process communication (IPC). But, since sensor data is used in highly real-time, we think it is seldom transported through ICC or IPC. SDFDroid uses the methods provided by Apktool to disassemble Android apps, hence we cannot analyze the apps that cannot be disassembled by Apktool.

5 Related Work

The related work of this paper mainly falls into two aspects: string-based static analysis on Android apps and graph-based static program analysis of Android apps.

- *String-based static analysis on Android apps.* Many efforts have been made to perform static analysis on Android apps. Androgurad [11] is a toolset widely used in analyzing decompiled Android apps. It can be used to generate method invoke graph or detect malicious apps via signature matching. Androgurad cannot perform data tracking analysis. Another well-known static analysis tool for Android apps is FlowDroid [6] which is based on Soot [29]. It conducts precise static taint analysis on Android apps and generates the propagation path for sensitive data, but the analysis result relies on the predefined source and sink API of sensitive data. William Kliebe *et al.* [19] propose a tool combined FlowDroid and Epicc [27] to track both inter-component and intra-component data flow in a set of Android apps. Wei *et al.* [34] build a general framework called Amandroid for security analysis of Android apps. Li *et al.* [21] develop IccTA which improves the precision of the apps' inter-component analysis. However, this tool needs a very long time to analyze a single app. These tools need to generate a control flow graph for the whole app before they perform analysis, which cost much more time than SDFDroid that only concern sensor related codes. In other words, these tools are too heavyweight for the purposes of our study. The work which is most similar to ours is SAAF [17], a static Android analysis framework for Android apps. The difference between SDFDroid and SAAF is the that, SDFDroid has the ability to perform forward tracking analysis.
- *Graph-based static program analysis of Android apps.* Different from string-based static analysis that mainly focuses on the code strings, graph-based static analysis considers the function calls or data flow in the apps' program. Zhang *et al.* [38] propose ViewDroid, an approach to mobile app repackaging detection based on the apps' view graphs. Subgraph isomorphism algorithm is used in their work to measure the similarity between apps' view graphs. Gascon *et al.* [14] develop a method for Android malapps detection based on function call graphs. They employ an explicit mapping to map call graphs to a feature space, then train a support vector machine to distinguish malapps from benign apps. Zhang *et al.* [39] propose a novel approach to classify Android malapps via weighted contextual API dependency graph. They assign weights to different API nodes in the graph when measuring similarity by graph edit distance algorithm. That means critical APIs, such as API requiring permission check, have greater weights and more easily to influence the classification results. Chen *et al.* [10] develop a new technique called MassVet for vetting apps at a massive scale. Massvet uses two kinds of graphs. One is the app's view structure graph and the other one is the app's control flow graph. An algorithm called Centroids which is also proposed by Chen [9] is applied to calculate the app's *v-cores* and *m-cores* based on these two kinds of graphs. Then, they use these two kinds of cores to detect potential malicious apps fast and accurately at a massive scale. Elish *et al.* [12] propose a highly accurate classification approach for detecting malicious Android apps. Their method statically extracts a data

dependence graph from a given app at first. And then they analyze how user inputs trigger sensitive API invocations based on this data dependence graph. The rate of sensitive API invocations which depended on user triggers is used to classify malicious Android apps. The difference between our work and the related work is that we use data flow graphs to do clustering while they use API call graphs for classification.

Although there exists related work on static analysis of Android apps, to the best of our knowledge, there is no work that has focused on thoroughly analyzing Android sensor usage behaviors. Different from our previous work on exploring the behaviors of sensor usage in Android apps from AppChina [23], we additionally analyze more than seven thousand apps from Google Play and present more detailed description of the system design, implementation, and experimental results, in order to better understand the Android sensor usage behaviors with data flow analysis based on all the apps from a complete Chinese Android market and popular apps from Google Play.

6 Conclusion

In this paper, we design and implement a tool called SDFDroid to analyze sensor usage behaviors in current Android apps. SDFDroid performs forward tracking analysis to generate an app's sensor data propagation graph and backward tracking analysis to find the app's used sensor types. Through extensive experiments on a widely-used Chinese App market, AppChina, and the official app market, Google Play, we find that Android apps often preform sensor related functions with the help of third-party libraries. Accelerometer is the most frequently used sensor. Though many apps only register one type of sensor, there are some apps registering eleven types of sensors. This indicates the emerging need for better regulating the sensor usage in Android apps. In the future work, we will extend the analysis to Native code, and generate more complete sensor data propagation graph to accurately characterize the app's sensor related functions. Besides, we will study on how to protect the sensors from the malicious attacks effectively with no influence on users' normal use.

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