IMPROVING GEOLOCATION BY COMBINING GPS WITH IMAGE ANALYSIS

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Abstract

The Global Positioning System (GPS) provides geolocation to a considerable number of applications in domains such as agriculture, commerce, transportation and tourism. Operational factors such as signal noise or the lack of direct vision from the receiver to the satellites, reduce the GPS geolocation accuracy. Urban canyons are a good example of an environment where continuous GPS signal reception may fail. For some applications, the lack of geolocation accuracy, even if happening for a short period of time, may lead to undesired results. For instance, consider the damages caused by the failure of the geolocation system in a city tour-bus transportation that shows location-sensitive data (historical/cultural data, publicity) in its screens as it passes by a location. This work presents an innovative approach for keeping geolocation accurate in mobile systems that rely mostly on GPS, by using computer vision to help providing geolocation data when the GPS signal becomes temporarily low or even unavailable. Captured frames of the landscape surrounding the mobile system are analysed in real-time by a computer vision algorithm, trying to match it with a set of geo-referenced images in a preconfigured database. When a match is found, it is assumed that the mobile system current location is close to the GPS location of the corresponding matched point. We tested this approach several times, in a real world scenario, and the results achieved evidence that geolocation can effectively be improved for scenarios where GPS signal stops being available.

Keywords: Computer vision, Geolocation, GPS, A-GPS, Image Analysis, Pattern Recognition.

INTRODUCTION

In recent years, the means used in the calculation of geographic location have evolved, becoming progressively more accurate. Some of the methods and technologies used in geolocation can give an accurate location on the Earth's surface, but not an exact location (Wing and Eklund, 2007). In the field of geographic location, currently, there are three main technologies: Global Positioning System (usually known as GPS), Assisted-GPS (usually known as A-GPS) and Cell tower ID. The first, GPS, is based on a set of geostationary satellites and a computation having as input the GPS signal from those satellite and as output a location on the Earth's surface. However, GPS has two main drawbacks: its signal is highly affected by noise and it requires direct vision between the GPS receiver and a set of at least four satellites (Monico, 2000). To compensate this problems, and accelerate the positioning, the A-GPS technology was developed, combining GPS information with information from the network. As the main characteristic of this technology indicates, it is internet dependant, which means that the major strength of A-GPS does not work everywhere (Diggelen, 2009). Finally, the Cell Tower ID, is a GPS-free technology, that uses only cellular network to reference a position. This technology uses cell coverage to determine the position of some device, but it is not much accurate (Figueiras and Frattasi, 2010).

The geolocation technologies above presented perform well for most of the cases. However, for some situations, GPS and A-GPS may not be able to provide geographic location. For instance, when a vehicle suddenly enters a long urban street cutting through skyscrapers, the GPS signal may be affected by the metal structures of the buildings and the lack of direct vision from the receiver to the satellites.

Our approach tries to overcome this problem by combining computer vision (CV) with GPS, regarding the scope of geolocation, where CV is used to help in the geolocation process when GPS signal is weak or not available.

Computer vision has evolved in the last decade and its applications are becoming more comprehensive. As Bernal stated (Bernal, Vilariño and Sánchez, 2010), when we think about computer vision, it is impossible not to think about using features. In CV, many feature descriptors have already been proposed and tested. According to Bernal, feature descriptors can be divided into four main groups: texture descriptors, colour descriptors, shape descriptors and motion descriptors (Bernal, Vilariño and Sánchez, 2010). For the purpose of the current work, a study of several descriptors was previously performed and three main descriptors were selected as being most promising: Scale Invariant Feature Transform (SIFT, Lowe, 1999), Speeded-up Robust Features (SURF, Bay, Tuytelaars, and Van Gool, 2006) and Histogram of oriented gradients (HOG, Dalal and Triggs, 2005). The three algorithms present good results, in terms of analysis success rate and response time, but the HOG was slightly inferior to SIFT and SURF. Besides this fact, both SIFT and SURF are Scale invariant, which means that both can detect features for images captured from different distances (affecting the size of a target, in a picture). The HOG does not provide this important feature. The SIFT algorithm provides another critical feature for our purposes: it is rotation invariant, meaning that it can contour rotation problems. Due to this second invariance feature it takes a little more time to process an image, compared to the SURF algorithm (Bernal, Vilariño and Sánchez, 2010).

Our approach relies on a set of characteristic points stored in a reference database. Each point is designated by Point of Interest (POI) and consists of one or more geo-referenced model images of a building, road or monument. In our approach we assume that a mobile system is near the location of a POI if the POI is recognized in one of the captured images assigned to it. Hence, whenever GPS signal fails, the CV system takes over the geolocation data feed process: summarizing, captured frames of the mobile system surrounding landscape are analysed by a CV algorithm, in real-time, trying to recognize POIs (from the database) in the captured frames. To the extent of the test cases, the current work demonstrates that, without GPS signal and with the help of simple computer vision algorithms, it is possible to obtain conclusive answers about a mobile system current location based on the proximity to a well-known (POI) location.

In chapter 2, the proposed approach is described and explained in more detail and, in chapter 3, the prototype used for tests is presented. In chapter 4, the achieved results are reported and discussed. Finally, chapter 4 presents the conclusions.

IMPROVING GEOLOCATION BY COMBINING GPS WITH IMAGE ANALYSIS

The following method is based on the described approach which combines computer vision with GPS (CV-GPS): conceptually, if we consider that the GPS function is to assign coordinates to a location then, by using an inverse logic, if we see a particular geo-referenced POI, then we can assume that we are near to the GPS coordinates of that POI. In the city sightseeing tour example previously mentioned, the “near” concept to a POI can be the line of sight proximity inside an urban canyon.

CV-GPS method

GPS alone cannot provide an accurate positioning in situations where the receiver fails to see the required satellites. Feature recognition through computer vision algorithms cannot be used as a solo geolocation method because it would imply to compare millions of images, trying to identify a feature (with geolocation previously associated). For current microcomputers, such task is not possible to be performed in real-time. If we want to use computer vision to “geo-reference” a location, it is necessary to reduce the set of images to compare. Both these technologies (feature recognition from CV and GPS) can complement each other, in order to create a valuable new geolocation method, able to compensate the complete or partial lack of positioning information.

The main idea of the CV-GPS method is to use coordinates sent by the GPS receiver and, when the GPS signal is weak or absent being impossible to accurately reference the current location, to start the image analysis process which tries to compensate this lack of location information. To achieve it, the image analysis process tries to identify a POI in the current captured images. If one is found, the corresponding GPS location is used. The set of POIs is kept in a database where, for each POI, one or more images can be kept. Furthermore, in the database, each image of the POI has the corresponding GPS coordinates associated.

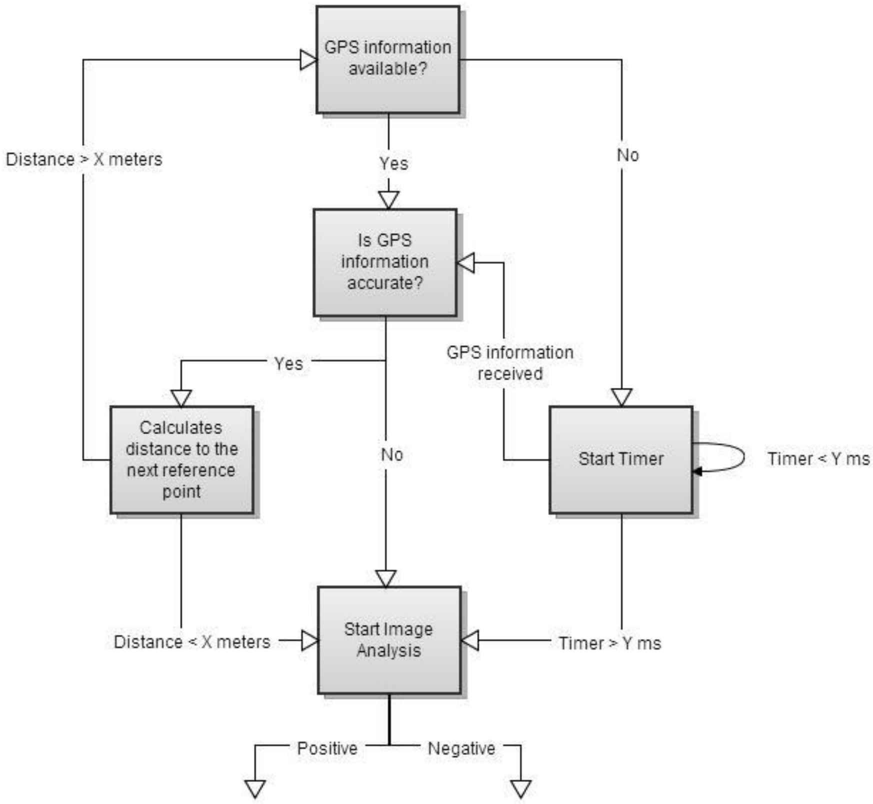

Figure 1 CV-GPS system operation.

The operation of this method is depicted in Figure 1, where X is the limit distance, in meters, from which the image analysis process starts being executed, and Y is the maximum time, in milliseconds, that the system may be absent of GPS data before starting the image analysis process. A system implementing this method receives and uses the GPS data acquired from the GPS receiver for geolocation. If the GPS sensor can determine its own accuracy (value in meters correspondent to the approximate error of the coordinates) then the accuracy information is also used. In this case, if the GPS information is accurate enough for the geolocation, then the latitude and longitude coordinates may be used to calculate the distance from the current position to the closest set of reference points. This calculation has the purpose of discarding the more distant POIs, reducing the number of valid POIs for image comparison, at any time. If, on the other hand, the received GPS information is not accurate enough to be reliable, then the image analysis is started, to compensate that lack of accurate geolocation information. If the system suddenly stops receiving GPS information, a timer is started. This timer stops either because GPS data is available again or because a maximum time Y is exceeded. In the second situation the image analysis process is started. When this process takes over, if the result of analysis is positive - a POI has been detected in a video frame - the system knows that it is close to the geographic coordinates associated to the matched POI.

The Image Analysis component

The image analysis process requests images from two sources: an external camera, placed near the GPS receiver, capturing frames in real-time (observed image) and a database of POIs (model images). From the database, only the images of POIs closer than a threshold X to the actual location are considered. In order to obtain good performances, the number of image comparisons should be the lowest possible, avoiding unnecessary image analysis. To analyse the images, a feature descriptor is used, which detects characteristic elements (features) between two images and compares them trying to find similarities. In our approach, the SURF (Speeded-up Robust Features) algorithm has been used, due to its scale invariance property, which is an important factor to consider when capturing images at distinct distances, affecting the scale of the point to detect (Bernal, Vilariño and Sánchez, 2010). The performance of SURF has also been taken into account, compared to other feature descriptors (Juan and Gwun, 2009). The necessary time to analyse each captured frame is an important factor to consider in order to be able to process regions with a higher density of POIs. To guarantee better results, it is important that every reference point has more than one associated reference image, captured from distinct points of view. Ideally, for every POI the database should hold at least three images, one frontal and two lateral, in which case only one match would be necessary to obtain a positive result. This three images allow us to contour the partial lack of rotation invariance of the SURF algorithm. The following Figure show outputs generated by the image analysis process.

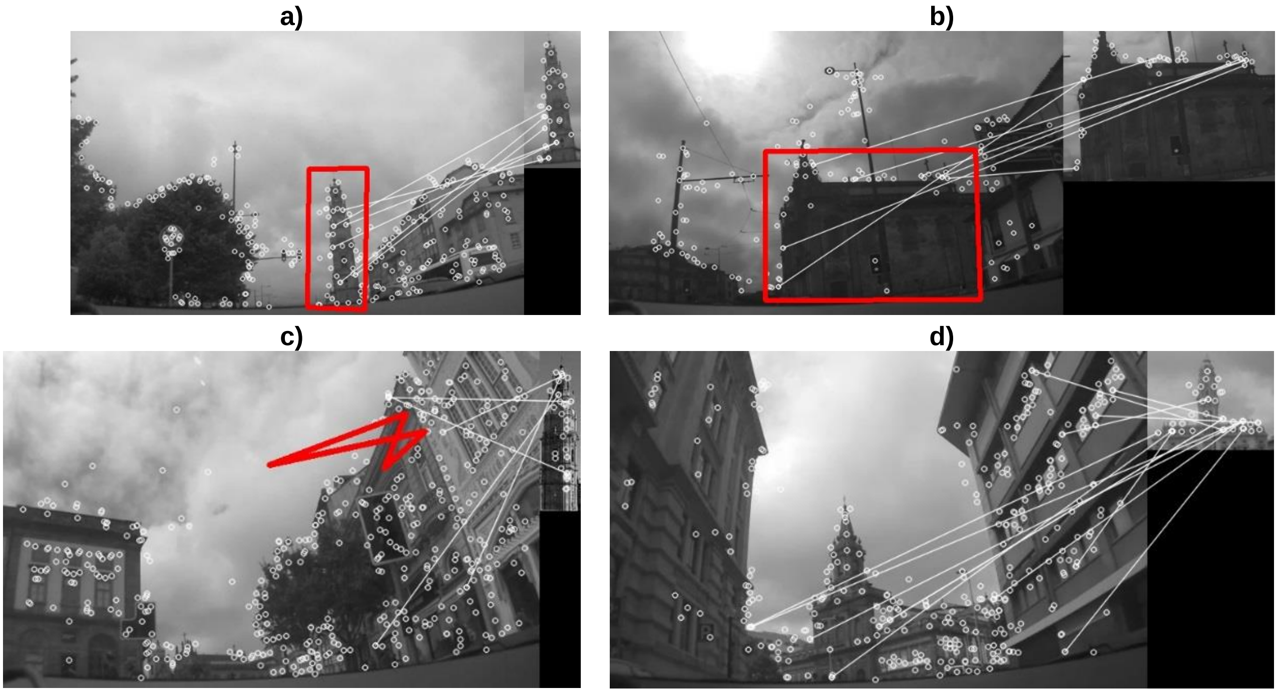

Figure 2 Image Analysis Results. a) and b) are True Positives; c) is a False Positive; d) similar buildings could generate mistakes but the algorithm performed correctly.

As it is possible to see in Figure 2a, the image analysis process found a match, but clearly (red line shape depicts result from algorithm) it does not correspond to a POI, generating a false positive situation. In order to provide better results and discard situations like this, it is important to implement a filter for False Positive discarding. The false positive detection was based in the analysis of the red quadrilateral (more specifically of the 4 points returned by the algorithm). If the points do not represent a quadrilateral (as depicted in Figure 2c), the system considers it as a false positive and discards it, because in true positives, the shape resembles a quadrilateral (as observed in Figures 2a and 2b). In this method context, it is acceptable to discard a true positive, because over a route and for a single POI it is expected several true positive detections, but it is not so good not to discard a false positive, because over a route only one positive is necessary to confirm the geolocation (the method trusts the CV component).

TESTING PROTOTYPE

Architecture overview

Conceptually, the proposed method was instantiated through a system architecture composed of three logical modules: media, GPS and server modules. Figure 3 illustrated the three modules as well as the interaction between them.

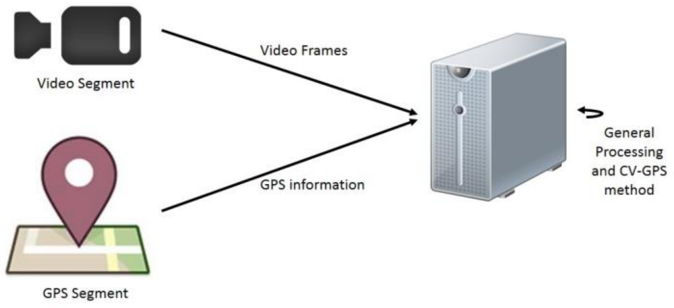

Figure 3 *System architecture*

The Media module is composed by a camera (or set of cameras), properly configured to provide access to one or more video streams (sets of video frames). It is important that these cameras are strategically placed in the vehicle, in order to obtain a clear view of the outside landscape. If this module is composed by only one camera, it should be positioned in the front of the vehicle and pointing forward, so the requested images may display a reference point before passing by it. If this module is composed by more than one camera, then only one of these cameras must be placed as above described, and the others may be placed in order to complement the video capture of the first one. In our prototype, the media module used a video camera Axis M3114-R. The GPS module is composed by a GPS receiver. This receiver must be steady, in order to guarantee that an eventual lack of accuracy of the GPS information is only resultant of the signal reception itself, and not from the bad adjustment of the receiver. Besides the signal reception, this module must be capable of sending the information to the server module, where it is properly analysed. In the current implementation, an Android Smartphone was used to instantiate the GPS module, running a simple application that captures the GPS coordinates and periodically sends them to the server module. Finally, the server module, implemented as a desktop application, is responsible for most of the processing activity: it receives the video frames from the media module, and the GPS information from the GPS module, and processes the information in order to obtain a valid and accurate positioning of the system. The CV-GPS processing is performed in this module.

Figure 4 *System assembled in the vehicle*

This architecture was implemented and tested using a personal vehicle, as illustrated in Figure 4. In this Figure, it is possible to see the camera and the GPS steady placed over the vehicle's dashboard, and the laptop, running the server application.

TESTING AND RESULTS

In order to properly evaluate the CV-GPS method, a set of experiments was performed, evaluating if the proposed method can provide geolocation improvements, and if the image analysis system is working as expected in different light conditions (which varies, for instance, with the atmospheric conditions), vehicle velocities or road pavement conditions. It is expected, though, that the system fails in situations where is not possible to get a clear picture of the elements to detect (for instance, under heavy rain). The next sections present the test scenarios used for evaluating the system and the routes and Points of Interest used for performing the experiments. After that, the obtained results are presented and discussed.

Test Routes and Points of Interest

In the development of the test scenarios three test routes were used, all in the Porto downtown, Portugal. The routes were chosen according with specific characteristics like different distances, road pavements, illumination conditions, and the distance and line of visibility from the road to the Points of Interest expected to be detected.

a) **b)** **c)**

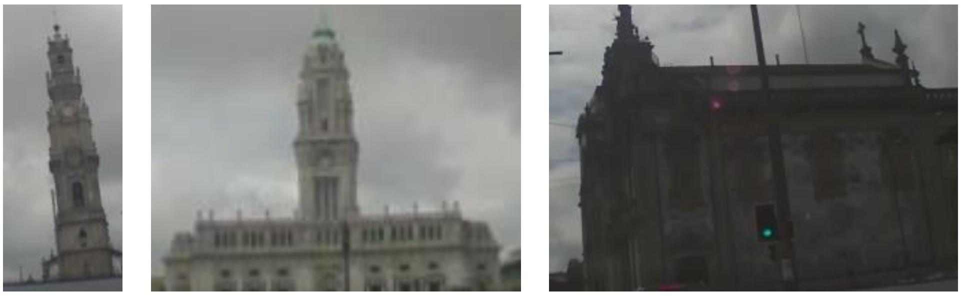

Figure 5 Points of Interest used in the detection: a) POI1; b) POI2; c) POI3.

Also three POIs were used, specifically, POI1 (GPS coordinates 41.145669, -8.614728, two model images associated in the database), the POI2 (GPS coordinates 41.149594, -8.610303, two model images associated in the database) and POI3 (GPS coordinates 41.1475314, -8.6165759, one model image associated in the database). These POIs have distinct shape and textures and as we can see in Figures 5, their model images were captured under less favourable light conditions (in order to test the system under the worst conditions).

Experiments

To correctly validate the system, eight experiments were performed, some of them inclusively repeated, in a total of 13 tests. In order to provide enough information to replicate the same conditions of these experiments, this tests were performed without rain but with a very cloudy sky (difficult illumination conditions) at 9 of June 2013, between 1h30pm and 4h30pm. In these experiments the CV-GPS method was configured to trigger the image analysis inside a threshold distance of 300 meters of the POI (X parameter), or after two seconds without GPS information (Y parameter).

Some of the experiments had similar goals, although performed in different routes and different Points of Interest. This way, the first, second and third experiments had the goal of simply detect the POIs. The first and third experiments were repeated three times (referred as 1.1, 1.2, 1.3 and 3.1, 3.2, 3.3 in the results table). The fourth and fifth experiments targeted the detection of false positives. In the fifth experiment the error was inclusively provoked, by searching for a POI that did not belong to the performed route. The fifth experiment was executed twice (5.1 and 5.2 in results table). The sixth and seventh experiments targeted the simulation of urban canyon situations. To test this situation, we turned off the GPS signal during partial or total time of the route. Finally, the eighth experiment had the purpose of testing a situation where a vehicle is close to a POI, but without seeing it. This happens for instance in single way roads, where the POI is only visible in one way. This way, the vehicle may be passing very close to the POI, but the system only should target it when it is visible (this is not possible by a GPS only solution, because the distance to the POI would probably be the same (or approximately) in both ways of the road, but is possible with the CV-GPS method because the system only returns a valid geolocation when the POI is detected in the image.

Results

The execution of the set of experiments described in the previous section allowed us to extract results and take conclusions about the correctness and validity of the CV-GPS system. Table 1 summarizes the results achieved.

Table 1. Experiments Results

Test #	Duration	Km	Av. Speed	IAPT	NAI	NP	NFP	POI Detected
1.1	3.45min	1	25	100%	122	6	0	Yes
1.2	3.40min	1	35	100%	124	7	1	Yes
1.3	3.40min	1	40	100%	129	6	1	Yes
2	3.25min	1	35	100%	268	2	0	Yes
3.1	2.15min	1.2	30	90%	72	5	0	Yes
3.2	2.25min	1.2	30	90%	76	6	1	Yes
3.3	2.05min	1.2	35	90%	69	4	0	Yes
4	9.55min	2.5	35	18%	102	*6*	*0*	Yes
5.1	2.05min	1.2	35	90%	70	1	1	No*
5.2	2.15min	1.2	30	90%	70	0	0	No
6	9.40min	2.5	30	35%	187	5	0	Yes
7	3.50min	1.2	25	100%	107	10	0	Yes
8	3.25min	1.2	25	90%	76	5	0	Yes

The evaluated parameters were the *Duration*, *Number of kilometres* of the route (km), *Average Speed* in which the route was performed (Av. Speed), *Image Analysis Percentage Time* (IAPT) which is the percentage of time in which the image analysis method was running, *Number of Analysed Images* (NAI), *Number of False Positives* (NFP) and finally if the POI was detected in time or not (before the vehicle with the assembled system passes by it). Some of the parameters measured and presented on the table are influenced by the traffic conditions (traffic, semaphores, crosswalks, etc.). All the tests were performed in an urban environment with the limit speed of 50km/hour and with normal traffic conditions. The routes were performed in different average speeds and during an approximated period of 3 hours between 1h30pm and 4h30pm. During that period a slightly change of atmospheric conditions occurred, causing a slight increase of the luminosity, but maintaining a very cloudy sky. The test 5.1 is marked with an asterisk because building detected in the false positive was not correspondent to the one we were trying to provoke in this test, but to another building in that route (was a regular false positive). This false positive detection was not seen in the other repetition performed in the same route. It is important to refer that the false positives in 1.2, 1.3, 3.2 and 5.1 were detected at a considerable distance of the intended POI (from 180 to 220 meters).

Discussion

The analysis of the achieved results makes it possible to verify that, for all the performed tests, the target POI was successfully detected in time, and more than once per repetition.

In the first experiment (1.1, 1.2 and 1.3), the POI was detected 6, 7 and 6 times respectively, but also 2 false positives were found. The false positives were detected with the vehicle stopped at a semaphore, which discards the possibility of being caused by the road conditions or velocity. In the second experiment (2), a single image was available in the database (the POI only had one image associate) for the image analysis matching. For this reason there were performed a lot of more matches than in other experiments. On the other hand, only two positives were detected, because the road where the POI is visible for the camera is only around 50 meters long (short time available for detection). In the third experiment (3.1, 3.2 and 3.3), only 90% of the route was covered by image analysis, because the 10% remaining were off the analysis maximum distance perimeter. This allowed us to verify that the combination of both technologies was working well, and that the image analysis was being triggered in the right time. Only one false positive was detected in the third experiment, and it was similar to the one detected in the first experiment. The fourth experiment was performed over a bigger route (2.5km), but only 18% of it was covered by image analysis. In this experiment it was possible to verify that the GPS information was properly working together with the image analysis, in order to minimize the detections in places where no POI was available for detection. At the same time, it was possible to verify that no false positives were detected in this route. The fifth experiment had the deliberate objective of mislead the system. By introducing incorrect information in the database it was possible to verify if the image analysis component would mix up the POIs and detect a not existing POI in the image (the POI did not even belonged to that route). This experiment was repeated two times. In the first repetition, 5.1, a false positive was detected, but not where it was expected. The false positive was detected around 180 meters of the coordinates of the target POI, which means that the system did not confused the POI1 with POI2, but failed in a common detection as in the false positives detected in the experiments number one and three. In the second repetition, 5.2, the experiment went as expected and no POI was detected. The sixth experiment tried to simulate an urban canyon situation, where suddenly the GPS coordinates stop being available. In order to simulate this, as explained in the previous sections, the GPS was turned off which increased the percentage time of image analysis of this route to 34%, because the image analysis was started after 2 seconds without GPS input. The experiment returned positive results, and POI1 was detected in time, without false positives. In the seventh experiment the goal was once again to simulate an urban canyon situation by deactivating the GPS information, but using a different route. The results were as expected and POI2 was detected in time. The eighth and last experiment, evaluated a problematic situation that could not be solved by a GPS only solution. A method using GPS information only would consider that the vehicle was passing by the POI in a situation where the POI would not be visible yet but with this system, the POI was detected in the proper time, and no false positives were detected.

Summarizing, we verified that the system performed as expected in most cases. The light conditions in which the system was tested were not ideal at all, and nevertheless the system responded quite well. With better atmospheric conditions, it is expected that the results are at least this good, because the quality of the captured images would be superior. The false positives detected in tests 1.2, 1.3, 3.2, and 5.1 occurred relatively far from the expected POIs, at variable distances from 180 meters to 220 meters, and can be discarded by simply reducing the threshold distance used to trigger the image analysis (which is clearly too high), or by fixing the problem in the image detection stage, by adding another filter to the results obtained from the image analysis algorithm. This filter would discard the concave quadrilaterals returned in the detection, pattern verified in all the false positives detected. Furthermore, the 300 meters distance threshold used in the experiments proved themselves to be an overkill, because in most cases the POIs were not even visible at that distance. Nevertheless, by using that distance was possible to keep the image analysis running for a longer period of time, allowing a better study of the false positive detections and guaranteeing that the number of false positives was already satisfactory. In future tests, perhaps it would suffice to use the image analysis within a distance threshold of 100 to 150 meters to the POI. Finally, regarding performance of the system, concerning the image descriptor, although the results of the image analysis are very good (considering the number of analysed images and the number of false positives detected) the time that each analysis took might still be improved by using a faster image descriptor. An example of a faster algorithm is ORB (Oriented BRIEF) detector (Rublee, Rabaud, Konolige, and Bradski, 2011). Theoretically, this new detector can perform more analysis per second, keeping the same success rate than SURF detector.

CONCLUSION

This work presents an innovative approach for keeping geolocation accurate in mobile systems that rely mostly on GPS, by using computer vision to help providing geolocation data when the GPS signal becomes temporarily low or even unavailable. For some applications, for instance, a city tour-bus transportation that shows location-sensitive data in its screens as it passes by a POI, the lack of GPS data, even for a short period of time, may lead to undesired results.

The main contribution of this work is a method that enables geolocation by using feature recognition from computer vision and GPS technology in a complementary fashion. When available, GPS signal is used in order to know the distance from the mobile system where the CV-GPS is assembled, to the nearer POIs. This way, it prevents the CV system of trying to find a match with the entire set of POIs available in the database. When GPS signal is unavailable the CV module (feature recognition) is used to identity POIs in video frames, captured by a video camera placed on a mobile system. If a POI is matched to one of the POIs available in the database containing model images, then it is assumed the mobile transport is known to be near GPS coordinates associated to the matched POI. As soon as GPS data becomes available again, the computer vision system stands by.

To test our method we defined a set of experiments (appropriate variables and test scenarios). The resulting set consisted of 8 experiments, some of which were repeated more than once. The experiments targeted different goals: to test the simple detection of POIs, to test false positive situations by forcing these situations, to simulate situations of lack of GPS signal and simulate urban canyon situations (no GPS signal). Three distinct routes and three distinct POIs were used in our experiments, with different characteristics, such as, different road conditions or POIs texture or shape. The atmospheric conditions under which the tests were conducted were not ideal (cloudy day), with less favorable light conditions.

The results achieved with the performed tests were positive for almost every experiment: only few false positives were detected. Good results were achieved with different floor conditions, vehicle velocities and with or without GPS information available, returning only four bad result instances. The four false positive detections are acceptable if we consider that 1472 images were analyzed. Furthermore, we detected a pattern in the identified false positives (the pattern recognition result returns a concave quadrilateral), which allows us to hereafter develop a new filter capable of discard a larger set of false positives.

With the achieved results, we can validate the proposed method for scenarios similar to those we experienced with. Other improvements can be performed, which are defined in the next section.

FUTURE WORK

Future work will address issues related to system performance, POI match outcome and further experiments. Regarding performance, although the SURF algorithm has presented good results, it would be important to test the ORB detector, which theoretically can perform more analysis per second with the same success rate. Regarding POI match outcome, a new filter should be tested that detects the current false positive situations by discarding concave quadrilaterals. Finally, further experiments are recommended with distinct light conditions, for instance, higher luminosity, and a higher density of POIs to detect, in order to verify the system accuracy and performance.

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