A proposal for obtaining 3D tracks based on multiple non-geodesic GNSS.

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Extended Abstract

With the increasing number of mobile phones and other devices with GNSS capabilities, the number of geopositioned information is growing (Oxera, 2013). This geopositioned information is not obtained only about points of interest but related to other activities like walking, trekking, etc, a great number of applications to use these geocapabilities has been developed creating a great opportunity for benefits (Henttu et al., 2012). However, the data captured using these low cost GNSS devices (integrated or standalone) has not high positional accuracy. For this reason, several techniques to combine multiple tracks have been developed (Lima and Ferreira, 2009). All these techniques are developed in two dimensions and use different approaches to remove outlier points (Long and Trisalyn, 2013). A brief review of the parameters and values used to remove these outlier points can be seen in Table 1.

Authors	Parameter	Values	Action
Agamenomi et al. (2010)	Delta time	3 seconds	Split track
	Maximum distance from other tracks	100 meters	Discard point(s)
Cao and Krumm (2009)	GPS Precision (deduced from minimum attractor distance)	5 meters	No action
Fathi and Krumm (2010)	Maximum delta time	10 seconds	Split track
	Speed	5 – 90 mph (8 -145 km/h)	Split track
	Distance between points	5 meters	Points interpolated to 5 meters

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Authors	Parameter	Values	Action
Lima and Ferreira (2009)	Minimum number of satellites	5 satellites	Discard point
	Maximum delta of time	7 seconds	Split track
	Minimum distance to trace (Douglas-Peucker Algorithm)	1 meters	Discard all intermediate points
Liu et al. (2012)	Maximum speed	180 km/h	Discard last point
Niehöfer et al. (2010)	Minimum distance between points	5 meters	Merge point below threshold
	Maximum speed	200 km/h	Discard last point
	Acceleration	4 m/s^2	Discard point
	Direction change	Function depending on velocity (not specified)	Discard last point
Zhang et al. (2010)	Maximum speed (highway/urban)	250 / 100 km/h	Discard last point
	Maximum distance	300 meters	Split track
	Maximum direction change	45º	Split track

Table 1. Filtering criteria as indicated by different authors (Own preparation).

As the previous table indicates, there are different criteria and different actions applied, even if the same criteria are employed. This is the reason that has leaded us to analyze the correlation between parameters and how these parameters interact with the resulting tracks.

Following that, in this work, we propose a methodology to create a set of 3D filtered tracks from raw GNSS position data using different parameters and adjusting them to reduce correlation and handle differences between two and three dimensional data. The followed methodology can be briefly defined by these stages:

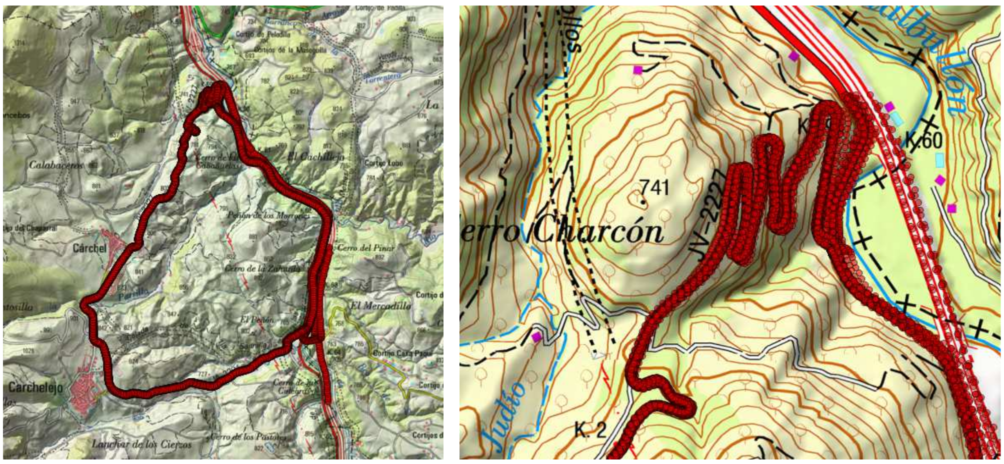
1. Extract points and attributes from captured tracks of GNSS.
2. Order these points by timestamp to create a time sequence.
3. Enrich information by determining new attributes like distance from previous points to the next, angularity of the displacement vector, etc. in a 3D space.
4. Remove points with no additional information, e.g. points captured while user is stopped.
5. Filter the points using approaches of Agamenomi et al. (2010), Cao

and Krumm (2009), Lima and Ferreira (2009), Liu et al. (2012) and Zhang et al. (2010) but having different thresholds for ascending and descending parts of the tracks, for sinuous parts of the track, etc.

6. Reconstruct tracks using algorithms based on Fathi and Krumm (2010) and Cao and Krum (2009)
7. Maintain continuity of aligned tracks.

The methodology have been tested using several approaches to create tracks from a set of low cost GNSS devices and compared to another GNSS data that have not been used as a surveying system. The set of low cost devices are three standard datalogger GPS with up to 1.5 meters precision (as described by manufacturer) and a frequency of 1Hz. While the other surveying system is a Racelogic VBox GPS with DGPS correction deactivated and having up to 0.50 meters precision including IMU data with a frequency of 100Hz. The devices were installed inside a standard car using an external antenna.

The test site was a set of roads (Figure 1.a), all outside any city and in a sloppy zone having different ranges slopes, curvatures, sinuosity and even possibility of multipath error due to embankments (Figure 1.b). All the tracks are composed by points having, at least general information like the one defined in NMEA protocol. The points, captured with the described devices, were continuous (not stopped at the beginning or end of the each section), can be self-intersected (if joined in tracks) and covers the selected roads several times in both directions.



(a) (b)

Figure 1. (a) Motorways and captured points represented by red circles (b) Detail of the captured points in the north part (Basemap: IGN Raster - http://www.ign.es/wms-inspire/mapa-raster?SERVICE=WMS& -, Points: GPS captured by the standard device).

Once the points were captured, following the first stage of our methodology, we have approximately 128000 points with the standard dataloggers and 1724000 points with the VBox GPS. Both datasets have information about position and timestamp. However, while dataloggers have DOP information, VBox GPS has no precision information because of the use of IMU that interferes with the GPS original precision calculation. These points were ordered using timestamp (grouped by device) to assure continuity of the point sequence, as indicated in methodology's second stage.

With the previous point sets from the GNSS devices, we selected several parameters among the described in Table 1, the chosen set was: time delta, distance, velocity, angularity, acceleration and precision (PDOP for the dataloggers and number of GPS satellites for the VBox GPS). Furthermore, in order to include 3D information we determine increment of height and slope. All points were enriched, following the third stage of the method, with these parameters and then they were filtered by removing points with a zero delta time or distance. All distances were calculated in 3D and the angles are determined in the plane defined by three consecutive points. The number of these removed points was marginal (less than 0.1%). However, it was necessary to simulate track division by assigning an allowed maximum delta of time in order to remove parameters between stops in the devices and data captured between different days. The chosen value was 3 seconds following the most restrictive value defined by Agamenomi et al. (2010).

After that, we apply the correlation coefficient to determine basic correlation between parameters, the results show almost a perfect correlation between distance and velocity parameters (see Table 2 and Figure 2.a & 2.b). With regards to the other parameters, Table 2 indicates the direct relation between slope and delta of height that is obvious based on its equation and a medium correlation (0.40) between both distance and velocity versus angle (Figure 2.c & 2.d). However, the last correlation does not represent a parameter that can be avoided when filtering because it constricts the tracks' sinuous parts. With respect to the rest of parameters, both point sets have a similar behavior even with a more reduced correlation in the case of VBox with IMU.

		accel.	angle	ΔZ	distance	Δtime	precision	Slope
Standard datalogger	angle	-0.0226						
	ΔZ	-0.0154	0.0204					
	distance	0.0678	-0.5355	0.1424				
	Δ time	-0.0192	0.1672	0.0215	0			
	precision	0.0022	0.0311	-0.0079	-0.0775	0		
	slope	-0.0222	0.0410	0.8917	0.1051	0.0298	-0.0028	
	velocity	0.0700	-0.5451	0.1400	0.9866	-0.1032	-0.0792	0.1046

		accel.	angle	ΔZ	distance	Δtime	precision	Slope
VBox GPS	angle	-0.0006						
	ΔZ	-0.0103	-0.0100					
	distance	0.0079	-0.4092	0.1269				
	Δ time	0.0005	0.0556	0.0002	-0.0176			
	precision	0.0003	-0.1842	-0.0146	-0.0016	-0.0070		
	slope	0.0231	0.0238	0.8384	0.0925	0.0026	-0.0307	
	velocity	0.0079	-0.4092	0.1269	1	-0.0176	-0.0016	0.0925

Table 2. Correlation coefficients between point parameters using both devices (Own preparation).

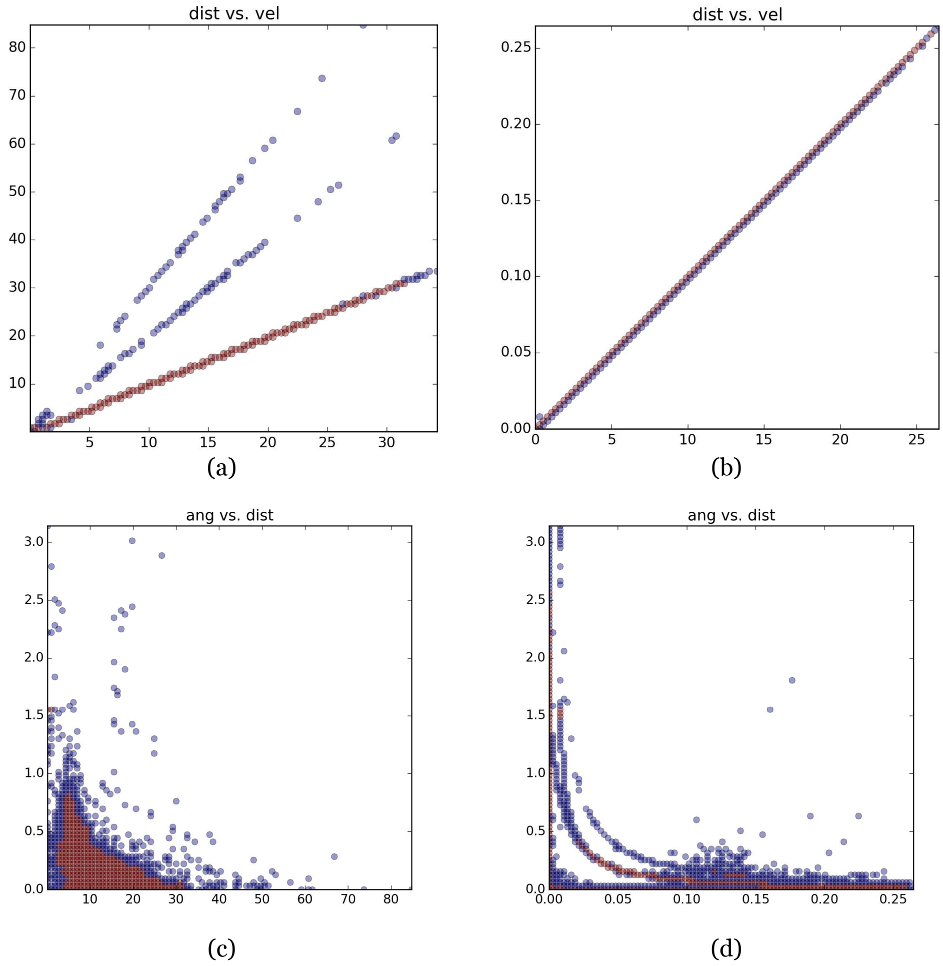


Figure 2. (a) & (b) Scatter plot of distances (meters) versus velocity (m/s) (a – Standard dataloggers, b – Vbox GPS). (c) & (d) Scatter plot of angle (radians) versus distance (meters) (Own preparation).

Taking into account the correlation described in the previous paragraph, we remove the velocity as a filter value and selected the following pair of values and parameters: (i) Maximum distance: 100 meters (Agamenomi et al, 2010), (ii) Acceleration: 4 m/s^2 (Niehöfer et al, 2010), (iii) GPS precision, based on number of satellites with a minimum of 5 satellites (Lima & Ferreira, 2009) and (iv) Delta time: from 1 to 3 seconds (previously used). The percentage of removed points is shown in table 3. The results show different number of points filtered for the high frequency GPS and the standard datalogger GPS. While the first tends to overvalue acceleration, even with IMU correction, the last tends to reduce precision.

Filtering parameter	Standard Datalogger	VBox GPS
Maximum Distance	0%	0%
Acceleration	0.00%	13.49%
GPS Precision	1.30%	0.15%
Delta time	0.36%	0.00%

Table 3. Percentage of removed points based on the filtering parameters (Own preparation).

On the other hand, we analyze the differences between points in ascending and descending zones (zero-slope points are ignored) in order to determine if both dataset are similar. The results of applying Kolmogorov-Smirnov test show that both sets of data are clearly different. For the purpose of these tests we have not used height change nor slope because the two point sets are selected using these parameters (ascending and descending parts of tracks). Moreover, we have not tested differences in time because it is a discrete value equal between points.

After that, we created the tracks from points ordered by time and filtered as it was described in previous paragraphs. The filtering has been applied using only one set of parameters because the differences shown by Kolmogorov-Smirnov test are lower than the range of values accepted for all the parameters. On the other hand, we have tried to recover some points from the filtered set using Lima & Ferreira (2009) limit, 1 meter in the normal direction, as it was indicated in the last stage of the methodology. However, there was not possible to recover any because the distance is too short and increasing this value should interfere with other parameters like local angle.

In table 4 we present the statistics of reconstructed tracks, for both devices using the points previous to the filtering process (pre-filtering) and after the filtering process. The results show that high frequency capturing devices like VBox are very interesting because they recover faster than low frequency devices. For this reason, minimum distances of VBox GPS are very significant versus the same distances in the standard datalogger devices. This frequency also affects the maximum distance per track and the number of tracks reconstructed, that are too fragmented in the case of using a standard datalogger. Moreover, the low minimum distance in standard dataloggers indicates the need to use a threshold value for this parameter that we propose to be equal to the precision of the GNSS.

	Standard datalogger		VBox GPS	
	Pre-filtering	After filter	Pre-filtering	After filter
Max	72709.44	51393.73	122420.29	121871.29
Min	0.09	0.09	677.98	673.25
Mean	6467.68	3173.89	81663.17	61217.46
Number of tracks	287	576	3	4

Table 4. Distance statistics of created tracks, all distances are in meters. (Own preparation).

The results showed in this work indicate that several of the approaches for filtering point data from GNSS use similar parameters and these parameters are correlated, even using 3D information. This correlation makes very difficult to tune threshold values in each stage of the methodology thus forcing to choose different sets of original parameters. Even though choosing only a non-correlated set of parameters, the differences in sinuosity and slope of the roads change some threshold values like acceleration and others like maximum angularity or maximum distance. These changes cut tracks in several parts reducing total distance of the track, that is another parameter that could not be directly determined as correlated.

In this work, we have presented a methodology and a set of parameters and threshold values to reconstruct 3D tracks from GNSS devices observing different types of motorways. The used algorithm is based on several previous algorithms modified to include the Z dimension and has been tested with this new dimension and changes in slope or direction of the track and to remove both direct and indirect correlation of the parameters. Finally, the chosen zone has samples of different slopes, sinuosity and is surveyed several times by different types of GNSS devices (non-geodesic) in order to be equivalent to the ones used by common users. In our ongoing work, the methodology will be applied to more positional accurate observations using geodesic GNSS devices and will be extended to cover roads inside cities to filter multipath errors.

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