Motion Estimation from Map Quality with Millimeter Wave Radar

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***Abstract*— Simultaneous Localization and Mapping (SLAM) builds maps of *a priori* unknown environments. Whilst this key mobile robotic competency continues to receive substantial attention, less attention has been paid to assessing the quality of the resulting maps. This paper proposes a way to quantify the intrinsic quality of point-cloud maps built from a stream of range bearing measurements. It does so by considering both the temporal and spatial distribution of the points within the map. One of the causes of unsatisfactory maps is the execution of un-modelled or poorly sensed vehicle manoeuvres. In this paper we show that by maximizing the quality of the map as a function of a motion parameterization, the vehicle motion can be recovered while correcting the map at the same time. In contrast to typical scan matching techniques, we do not rely on segmentation of the measurement stream into two separate "scans"; Instead we treat the measurement sequence as a continuous signal. We illustrate the efficacy of this approach by processing range data from a $77GHz$ millimeter wave radar that completes 2 rotations per second. We show that despite this acquisition speed being commensurate with vehicle rotation rates, we are able to extract the underlying vehicle motion and yield crisp, well aligned point clouds.**

I. Introduction

We are familiar with Simultaneous Localisation and Mapping (SLAM) algorithms as a technique that is commonly used for building maps of *a priori* unknown environments. Indeed SLAM has been, and continues to be, the focus of an immense amount of research in the mobile robotics community [11][12][15]. Fine progress has been made in understanding the fundamentals of the problem and in building modest implementations. There also exists prior work [14][13][9] on modelling of the environment for learning maps as well as assigning distinctiveness measure to various portions of the map to aid tasks such as localization. However, relatively less attention has been paid to actually measuring the quality of these maps. This paper seeks, in part, to address this imbalance and proposes a quality metric which can be applied to point-cloud maps — one of two contributions this paper makes. A good map can be measured by how well it conveys information about the environment. Assuming the world is made of sharp edges, normal incidence of the sensor's beam should yield a sharp representation of the environment. We define a good map as one where the rendered point-cloud produces a well-defined and unblurred "image" of the environment. The quality metric proposed scores low for crisp, well-formed maps and high for blurred, confused renderings. The temporal distribution of the constituent points in the point-cloud is introduced as a contributing factor towards the quality metric along with the spatial properties.

A common cause of unsatisfactory mapping is the execution of un-modelled or poorly sensed vehicle manoeuvres. For example a land-based vehicle may experience excessive wheel slippage while turning or a marine vehicle may undergo un-modelled lateral drift. The second contribution of this paper is to take the map-quality metric and use it to annul the effects of unknown or incorrect short-term vehicle motion by estimating new or improved vehicle motion parameters. This is achieved by first expressing the map quality metric as a function of a parameterization of vehicle motion. Since the map quality metric scores low for good maps, minimizing this metric will maximizes the map quality. The vehicle motion parameter set is then found by maximizing map quality.

The motivation for this work is an ongoing project to utilize a 77-GHz millimeter wave radar sensor. The sensor has an angular acquisition rate substantially below that of the common-place SICK laser range finder. The combined effect of measuring ranges up to $400m$ and swift vehicle rotations make it hard to justify the adoption of a scan matching technique[1]. To illustrate, if we were to chop the radar measurement stream into "scans" corresponding to one complete sensor revolution, one would observe intra-scan distortion (particularly at large distances) caused by the vehicle motion during the scan. In this work we suggest an alternative to scan matching in which the radar measurement stream is considered as a whole and used to estimate vehicle motion during various vehicle manoeuvres.

This paper is divided into the following sections. Background on mapping using radar is covered in section II. Section III develops and describes the quality metric of maps we utilize in this paper. Section IV describes the implementation and evaluation of the technique as a motion estimator using data gathered from a mobile robot equipped with a millimeter wave radar.

II. Background

Millimeter wave radars have been successfully used in the area of outdoor autonomous navigation [7][6]. Radars are long range sensors and hence are well suited for outdoor applications and large scale mapping. They are also known to be little affected by weather and lighting conditions[2].

Durrant-Whyte[7], [4], [5] implements the navigation of an autonomous guided vehicle designed to transport standard cargo containers in port environments using millimetre-wave (MMW) radar sensors. The sensors are used to detect the range and bearing of a number of fixed known beacons located in the environment. Two radar units, at 77GHz, are mounted at the front and rear of the vehicle. The navigation system works by detecting the range and bearing to a set of beacons placed at known, mapped locations about the environment. The beacons are radar trihedrals, effectively internal corner reflectors. Clark and Durrant-Whyte [4], [5] use the radar returns either for location determination, or to build a terrain map in front of the vehicle. Location determination is achieved by matching and triangulating pre-placed beacons to a map of their known co-ordinates. Polarisation information is used to distinguish location beacons from terrain reflections.

Dissanayake et al[6] use MMW radar to implement the simultaneous localization and mapping algorithm on a vehicle operating in an outdoor environment. The radar returns the range and bearing to a landmark. The number and location of the landmarks is not known *a priori*. Landmark locations need to be initialized and inferred from observations alone. The radar receives reflections from many objects present in the environment but only the observations resulting from reflections of stationary point landmarks should be used in the estimation process. In their implementation landmark quality implicitly tests whether the landmark behaves as a stationary point landmark. Range and bearing measurements which exhibit this behavior are assigned a high quality measure and are incorporated as a landmark. Those measurements that do not are rejected.

Foessel-Bunting [10] uses the evidence grid approach for three dimensional map building with a radar sensor model. The evidence grid approach divides the space of interest, which can be two-dimensional or three-dimensional, into regular cells. Each cell stores the accumulated evidence of occupancy for the corresponding area or volume as provided by the sensor observations. The technique takes into account the uncertainty of sensor data through a probabilistic sensor model.

The framework of evidence grid or occupancy grid[8] has been used in the area of adaptive robotic exploration to maximize map accuracy[3]. The spatial representation of the environment is used to calculate the entropy of the map and hence the accuracy. The disadvantage of this metric is that the method is highly dependent on accurate estimation of the robot's location. Since the observations are taken in sensor space which is relative to the robot's absolute location, the correct cells can be updated only when the correct location of the robot is known.

III. Quality Metric of Map

This paper proposes a quality metric or score ψ, for point cloud maps. A cost function,$\psi(\cdot)$, is proposed such that 'good maps' map to a lower value than 'bad-maps'. What constitutes a 'good' or 'bad' map is to a degree a subjective qualification. We consider a crisp map with sharp, non-self-intersecting object borders to be 'good' [1].

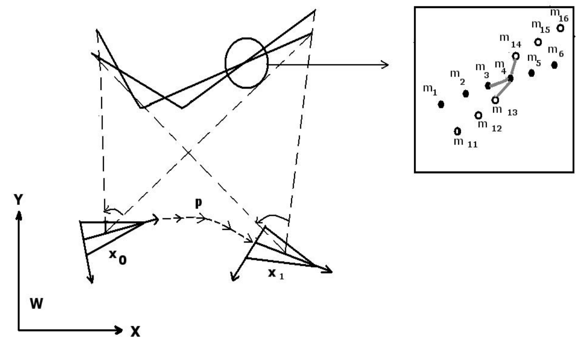


Fig. 1. Figure illustrates the motion of the robot, the generation of (x, y) points in the map set M and explains the selection of spatial-temporal nearest neighbors. Given the initial position, x_o and the motion parameter p of the vehicle, the pose of the vehicle at time t can be calculated. Using the pose and the observation data, the point m_i can be generated in the World (W) frame. The magnified points are numbered according to the time stamp. Consider point m_4 taken at time stamp 4. Points m_3, m_{13} and m_{14} are all spatially close. However, we are not interested in point m_3 as it is a return from the very next measurement and hence too close temporally. Points m_{13} and m_{14} are important as they are sufficiently far away temporally yet spatially close.

The score is calculated as the sum of squared weighted distance between *selected* points in the map. The question that arises is how to make this selection to obtain a score that reflects our concept of map quality. We do this by considering both the spatial and temporal property of the observation data.

We posit that spatially close sensor returns, that are not so close temporally, are likely to be generated by spatially close real world objects. The radar system rotates at the rate ω_r rad/sec and it can be assumed that the radar will see at least some portions of the world again after a complete rotation. Hence we might expect the minimum time difference between points that represent the same portion of the world to be $1/\omega_r$ seconds. Distance between points that are spatially close to a query point but are temporally more than $1/\omega_r$ seconds away should contribute the most to the score as it is these points that most likely represent the same world objects. This is illustrated in Fig[1]. Considering the time difference between points and selecting only those that are temporally not too close, ensures that points from consecutive radar returns do not contribute much to the score.

We now describe the method to obtain the score of the map. Consider a vehicle mounted with a radar scanning system. The radar returns an observation set consisting of the time, t, at which this observation was taken, the angle of the radar, θ, and an array of return energies corresponding to the ranges, $E = \{e_i\}$ where e_i is the energy in the i^{th} range bin, (ie) the energy at $i \times dr$ m away where dr is the range resolution of

[1] Implicitly, for the radar sensor we discuss later, this assumes we will not encounter strong grazing reflections whose range changes wildly with vehicle roll and pitch

the radar. Let this observation set be called Z.

$$Z : z_1, z_2, ...z_N = \{\theta_1, E_1, t_1; .... \theta_N, E_N, t_N\} \quad (1)$$

Given the position of the vehicle, x_o, at time, t_o, we parameterize the local motion (in the near future) of the vehicle as

$$x(t) = g(x_o, t, p) \quad (2)$$

where x_o is the initial position of the vehicle, t is the time and p is a vector of parameters that describe the motion of the vehicle, for example the coefficients of a spline. This is described in Fig[1].

A map M can now be generated as a set of N, (x, y) points by composing $x(t)$ with $z(t)$ where $z(t)$ is the array of all returns in Z that have a time stamp of t.

$$M : m_1, m_2, ...m_N = x(t) \oplus z(t) \quad (3)$$

where m_i is the i^{th} (x, y) point (see Fig[1]).

The score is defined as the double sum of squared weighted distances between each point in the map and its spatial-temporal nearest neighbors.

$$\psi(Z, p) = \sum_{i \in M} \sum_{j \in M_s^i} S_{ij}^2 \quad (4)$$

where S_{ij} is the weighted distance between points i and j. The details of obtaining the set of points M_s^i and then the calculation of the weighted distance will be discussed shortly.

Consider a point i in the map. We are interested in finding all the points that are spatially close to this point, but temporally not too close, so that we can assign higher weights to the distance between these points. Hence the first step is the process of selecting the points whose distance from point i contributes to the score and the next step is the process of assigning weights to these distances based on the spatial-temporal closeness.

M_s^i is the set of all points that are spatially close to the query point i. We define the operator, ρ, that returns the indices of the set of points that are close (less than an acceptable distance,s) to query point i in the map set M.

$$M_s^i = \rho(M, i, s) \quad (5)$$

Now for point i, we have a set of spatially close points in the point set M_s^i. Next, we define two functions, ϕ_s and ϕ_t that return the distances and time differences respectively between the query point i and the point set M_s^i.

$$s_{ij} = \phi_s(i, M_s^i) \quad (6)$$

$$t_{ij} = \phi_t(i, M_s^i) \quad (7)$$

For every point j in M_s^i, the distance and time difference is calculated using the functions ϕ_s and ϕ_t. Hence, s_{ij} and t_{ij} are the distance and time difference respectively between query point i and the j^{th} point in M_s^i. Having found the spatial and temporal distances between point i and the point set M_s^i, we define the spatial-temporal distance selector, κ_{ij}. The spatial-temporal distance selector κ_{ij} has the following properties:

- low for points that are close in distance but less than $1/\omega_r$ seconds away in time
- low for points that are very far in distance irrespective of time
- high for points that are close in distance and at least $1/\omega_r$ seconds away in time

We define this functionally in the following manner:

$$\kappa_{ij} = e^{-(\frac{s_{ij} - \alpha_s}{\beta_s})^2} \times e^{-(\frac{t_{ij} - \alpha_t}{\beta_t})^2} \quad (8)$$

where s_{ij} and t_{ij} are the distance and time difference respectively between point i and point j, α_s is the mean point separation that is considered best for a crisp map, α_t is the minimum time difference that is expected between points $(1/\omega_r)$, β_s is the average point density and β_t is average time density.

κ_{ij} now assigns highest value to points that are spatially close and temporally more than $1/\omega_r$ seconds away. Hence the points in the map set M_s^i that have a high value of κ_{ij}, above a threshold ξ, are selected and the weighting function is centered around the point that has the highest value of κ_{ij}. To circumvent the inadvertent assigning of correspondence between points, a set of points, instead of only one point, is deliberately selected.

The Lorentzian Apodization function is used for weighting the distances based on the spatial-temporal closeness of points. This is a singly peaked function given by

$$L(s_{ij}) = \frac{1}{\pi} \frac{\frac{\tau}{2}}{(s_{ij} - s_o)^2 + (\frac{\tau}{2})^2} \quad (9)$$

where s_o is the center around which the weighting is done and τ is the parameter that specifies the width of tapering.

The distance between point i and the point corresponding to the maximum value of κ_{ij} needs to be assigned the highest weight. The rest of the distances need to be weighted based on their κ_{ij} values and the weighting needs to be smooth. Hence the Lorentzian Apodization function is a good choice. The distance between point i and the point corresponding to the maximum value of κ_{ij} is assigned to s_o. Therefore, s_o is given by the equation, $s_o = \arg\max_{s_{ij}}(\kappa_{ij})$. The weighting is then calculated for all points with a value of κ_{ij} greater than threshold ξ, and this gives the weight vector $L(s_{ij})$.

The weighted distance, S_{ij} can now be defined as

$$S_{ij} = L(s_{ij}) \times s_{ij} \quad (10)$$

where s_{ij} is the distance between point i and point j, $i \in M$, $j \in M_s^i$ and $L(s_{ij})$ is the weight for the j^{th} point. S_{ij} is the required weighted distance between query point i and the j^{th} point in map set M_s^i.

The algorithm can be summarized in the following steps as shown in algorithm [1].

The algorithm proposed gives the score for a map generated using the observations Z and the motion parameters, p. Figs[2(a), (b), (c)] show three simulated maps. The score for the relatively bad map is high while the score for the relatively good map is low. Hence the subjective good map gets the least score when scored by the algorithm proposed in this paper.

/* Algorithm to calculate the map quality score of a map given the observation data from the sensor */

input : Observation Data Z
output: Map Quality score

begin

/* Initial Position of vehicle, x_o, and Motion Parameters, p, are selected */

$\{$Initialize x_o, $p\}$;

/* For a given time the vehicle pose, $x(t)$, is calculated and the map set, M, generated using the observation data */

$x(t) = g(x_o, t, p)$;
$M = x(t) \oplus z(t)$;

/* Assume map set M has N points. For each point in M, a sub-set M_s^i is generated as, all the points close to current point less than s distance away, using KD trees */

for $i \leftarrow 1$ ***to*** N **do**

$M_s^i \leftarrow \rho(M, i, s)$

/* Assuming M_s^i has n points, distance and time difference for each point is calculated and using this the spatial-temporal distance selector, κ_{ij} is calculated */

for $j \leftarrow 1$ ***to*** n **do**

$s_{ij} = \phi_s(i, M_s^i)$;
$t_{ij} = \phi_t(i, M_s^i)$;
$\kappa_{ij} = e^{-(\frac{s_{ij}-\alpha_s}{\beta_s})^2} \times e^{-(\frac{t_{ij}-\alpha_t}{\beta_t})^2}$;

end

/* Select points that have a κ_{ij} value greater than threshold, ξ, and calculate weight vector centered around point with highest κ_{ij} value */

$s_o = \arg\max_{s_{ij}}(\kappa_{ij})$;
$L(s_{ij}) = \frac{1}{\pi} \frac{\frac{\tau}{2}}{(s_{ij}-s_o)^2 + (\frac{\tau}{2})^2}$;
$S_{ij} = L(s_{ij}) \times (s_{ij})$;

end

/* S_{ij} is weighted distance between query point i and point j in map set M_s^i. The score is calculated for every point i in map set, M */

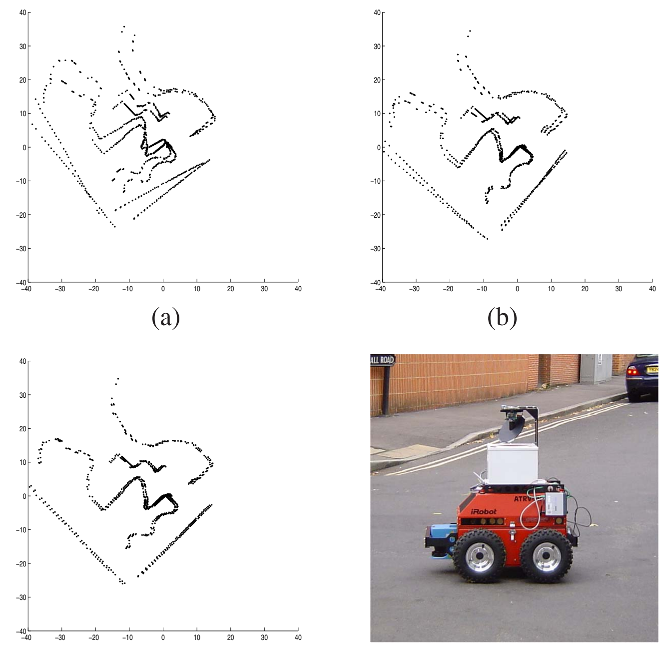
$\psi(Z, p) = \sum_{i \in M} \sum_{j \in M_s^i} S_{ij}^2$;

end

Algorithm 1: Map Quality Score

A case to note would be the algorithm scoring a perfect map that has been generated, (ie) points are perfectly aligned and separated in time. In this case, the score returned by the algorithm would not be zero. This is because as stated earlier, a set of distances are taken to avoid the correspondence problem. Hence even if all the points are aligned correctly, the neighboring points would contribute to the score. Hence this algorithm never scores zero.

In this algorithm temporal information plays an important role in scoring the map quality. This leads to the obvious question of whether errors in the absolute sensor time will affect the scoring. However, it should be noted that the algorithm considers only the difference in time between points and not the absolute temporal information.



(a) (b) (c) (d)

Fig. 2. Scores obtained for maps of various qualities (a) Bad Map - scores 1650.2 (b) Better Map - scores 1300 (c) Good Map - scores 1125.5 and (d) The ATRV-JR robot with Radar system on top.

Noting the generation of the map is dependent on the observations Z and the motion parameters, p (refer Eq[3]), it can be concluded that the score of the map is indirectly dependent on these as well. Hence maximizing the quality of the map as a function of a motion parameterization, the actual vehicle motion can be recovered while correcting the map at the same time. This is discussed in the next section.

IV. Motion Estimation from Map Quality

The map quality is a function of the observations, Z and the motion parameters, p. We can now pose the problem of motion estimation as one of maximizing map quality by a judicious choice,$\hat{p}$, of p.

$$\hat{p} = \arg\min_{p}(\psi(Z, p)) \quad (11)$$

As stated earlier, the score obtained from the algorithm in the previous section is low when the quality of the map is good. Hence minimizing the score using the motion parameters of the vehicle as the variable, will maximize the quality of the map. We now go on to show the estimation of the robot's motion parameters using the map quality score on real radar data.

The experiment was performed on a ATRV-JR mobile robot from iRobot, Inc. On this was mounted a 77GHz millimetre wave radar scanner from NavTech Electronics as shown in the Fig[2(d)]. The radar system has a maximum range of $400m$ with a range resolution of $0.25m$. It produces returns at every 0.5^o and has a complete rotation of 360^o. The radar returns the azimuth, an array of energies corresponding to the ranges at which returns have been spotted and the time at which the observation was taken. The odometry information was also logged.

Data was gathered in a realistic outdoor urban environment. The robot's motion parameters, p, are defined as the set, velocity v and steering rate ω. Motion parameters are poorly sensed when vehicle manoeuvres have large rotational components. Hence data was gathered for high values of ω.

Three cases were considered. Case 1, having $v = 0m/s$ and $\omega = -0.3840rad/sec$; Case 2, having $v = 0.1m/s$ and $\omega = 0.2967rad/sec$ and Case 3, having $v = 1m/s$ and $\omega = -0.1920rad/sec$. The observation set, Z in each case was given as input to the minimization function proposed in Eq[11]. An exhaustive search was then performed over the entire parameter space to obtain the minimum score. The vehicle's motion parameters obtained from this minimization are shown in Table[I]. It is seen that the motion parameters obtained are close to the actual motion parameters of the vehicle.

Fig[3] shows the maps drawn before any motion parameter correction is applied and after the correction suggested by the minimization is applied. It is seen that the map quality was significantly better after the correction was applied.

V. Conclusion

Two contributions are made in this paper. First a method to quantify the quality of point-cloud maps is proposed. The map built from a continuous stream of range measurements from a radar is given a score based on how crisp it is, with crisp maps getting a lower score. One of the key ideas in calculating the score is the selection of weights for points contributing to the score. This is done by considering temporal and spatial distribution of the points in the map. The second contribution is the estimation of motion parameters of the vehicle using this map-quality metric. The actual vehicle motion is recovered by maximizing the quality of the map. The effectiveness of the approach is illustrated using data obtained from a millimeter wave radar. The results show that the vehicle motion parameters obtained using the approach is comparable to the actual parameters and the maps drawn with these obtained parameters are crisp.

TABLE I

Table shows the actual motion parameters of the vehicle and the parameters obtained by minimizing the score function of the map quality. The vehicle's motion parameters, p, are defined as the set, velocity v and steering rate ω.

	Velocity (m/sec)		Steering Rate(rad/sec)	
Case	Actual	Obtained	Actual	Obtained
1	0	0	-0.3840	-0.3665
2	0.1	0.1	0.2967	0.3194
3	1	0.9	-0.1920	-0.1833

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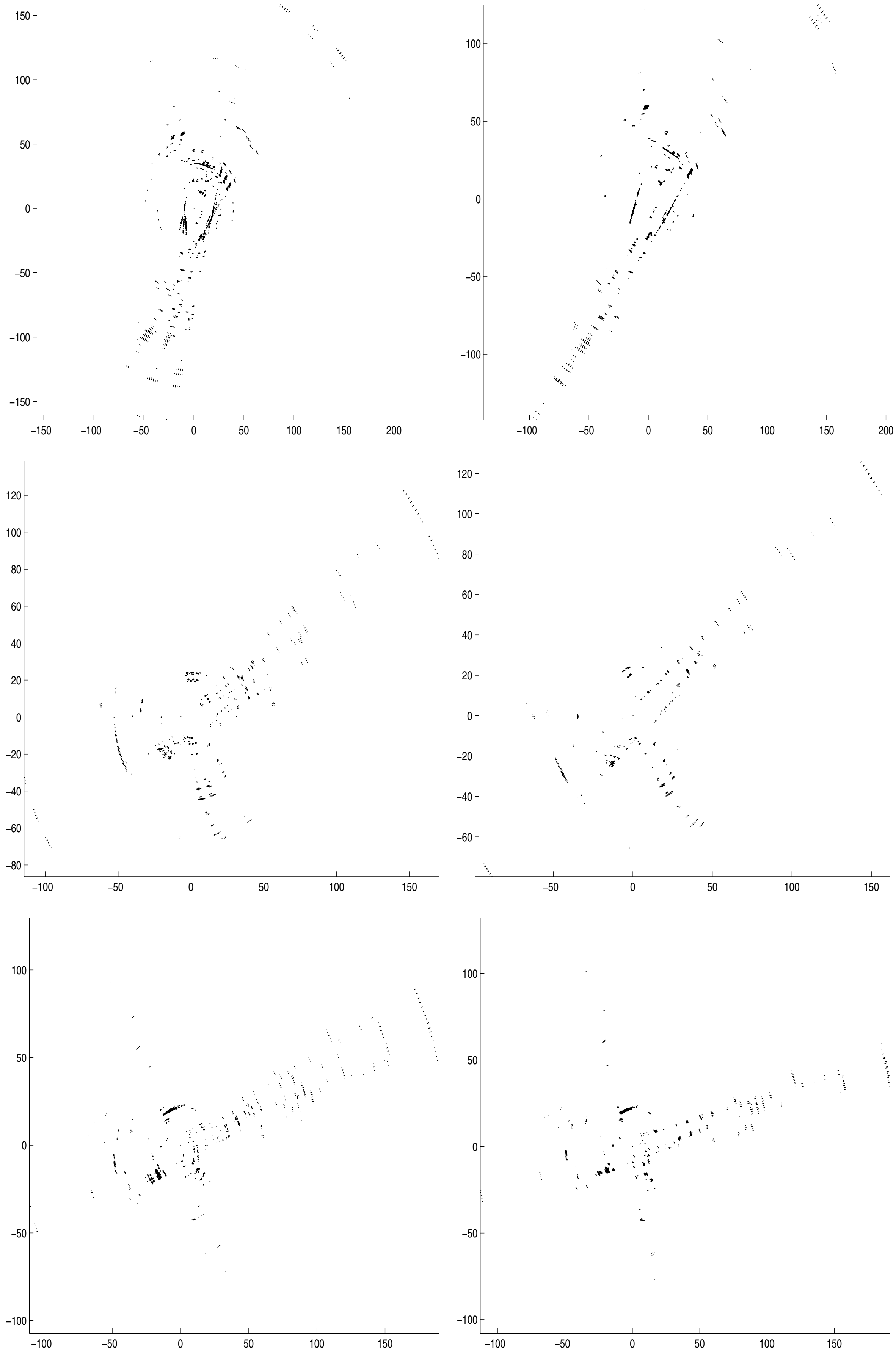

Fig. 3. Figures on the left are maps drawn before any motion parameter correction is applied. Figures on the right are maps drawn after the minimization function yields a motion parameter and that is then applied to the map drawing. The 3 cases that have been considered all have a high steering rate ($\omega = -0.3840 rad/sec; 0.2967 rad/sec; -0.1920 rad/sec$) with different values of velocity ($v = 0m/s; 0.1m/sec; 1m/s$)