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Bayesian Location Identifier
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Abstract

Location Generators cannot always provide exact measures of particular locations. Instead, they estimate the location of objects. More precisely, they use filters to aggregate noisy sensor data and to calculate probability density distributions of estimated positions. In location tracking applications, typically Kalman-type, Gaussian-Sum, and Particle Filters are used.

We believe that it is reasonable to use the outputs of those filters to describe a location estimate and its uncertainty, because they are the natural result of location tracking algorithms. In addition, the results of those filters can be feed into sensor fusion and decision making engines easily.

Geometric representations such as polygons or ellipses might be demanded by an application. The output of filters can be converted to those application demanded shapes. However, these conversions come at the loss of precision and are not well understood scientifically. Thus, we think that transmitting filter results is a solution that is easier to implement.

In this draft, we present a transmission format for PIDF-LO, which is based on the output of Kalman-type, Gaussian-Sum, and Particle Filters.

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1. Introduction

The location of an object cannot be measured precisely always. Especially, in an indoor environment numerous sources of measurement errors lead to measurement results, which are uncertain in a high degree. To represent this uncertainty, a previous draft [1] defines how uncertainty and its associated datum and confidence is expressed and interpreted. To simplify the representation, the draft limits the description of uncertainty to a number of well defined shapes, e.g. one point, a centroid, an arc-band centroid, or polygons. However, state of the art multimodal location tracking algorithms do not provide any location results of the above mentioned shapes. Instead, they typically applied some sort of Kalman or Particle Filters, which assume a Gaussian or an arbitrary error distribution. Thus, in this draft we propose to transmit as location information the results of Gaussian distributions or Particle Filters to present uncertainty.

This has the following advantages:

1. Any kind of uncertainly can be transmitted. More precisely, any form of probability distribution, which represents uncertainty, can be represented.

2. A conversion from particles to shapes is not required, which maintains precision and eases implementations.

3. Kalman and Particle filters are well understood statistical tools based on research of control theory, signal processing, Monte-Carlo simulations and Bayesian statistics. Numerous location tracking algorithms have been developed that work with those filters. Thus, the transmission format defined in this draft is based on a profound scientific basis.

2. Overview on Filters

Location tracking is based on physical measurements, which estimate time of flight, signal strength, angle of arrives, motions, objects in images, and many other forms of sensor input. All these sensor measurements are subjected to measurement noise. Because of that, filters are used to estimate the real value of the measurement despite the fact of measurement results that are subjected to noise.

Many filter types have been developed. However, in location tracking typically only a few are applied. These include different types of Kalman-Filters, filters that work with one or multiple Gaussian

Normal distributions, and Particle Filters. These filters are briefly described in the following.

2.1. Kalman Filters

A Kalman Filter uses a system model to estimate the probability of changes. This data is combined with a model of measurement data and control input, if any, to estimate the true value of the parameters under study. It only allows linear relations between filter variables and assumes Gaussian noise distributions. Despite that, it is very robust in many applications.

The result of a Kalman filter is a posteriori state vector (for example a location) and a posteriori estimated covariance. The state is given by a vector $\hat{x}_{k|k}$ and the covariance by $P_{k|k}$. Both estimates are given for the time index k [2]. If the vector has a dimension of d (for example 3 for xyz), then the covariance matrix has a size of d*d.

We suggest that, as PIDF-LO object, all these three variables shall be transmitted to indicate a position estimate, its distribution, and the time of measurement.

Also, this format should work well for non-linear filters such as the Extended or Unscented Kalman Filter.

2.2. Particle Filter

Particle Filter, also called sequential Monte Carlo methods (SMC), have the advantage that arbitrary distributions can be approximated [3]. As such, they approximate Bayesian models, which consist of probability distribution functions, which define the degree of "believe" to which a particular value is true.

Particle filters approximate probability distribution function with a number of particles. More particles are placed at positions that are more likely. Each particle has Dirac shape.

The a posteriori state of a particle filter is approximated by M particles called $x_i^{(M)}$, which are weighted with $w_i^{(m)}$.
The PIDF-LO transmission object should contain the particles, their weights and again the time index k.

2.3. Gaussian Sum Particle Filters

Here we assume that the probability distributions are described by the sum of normal distributions [4]. As such, it can be seen as the combination of two previously mentioned filtering approaches.

The a posteriori state of a Gaussian Sum Filter is approximated by M Gaussian distributions called $\hat{x}_k^{(M)}$, which are weighted with $w_k^{(m)}$ and have distributions described by covariance matrices $P_{k|k}^{(M)}$.

Again, all those parameters shall be transmitted.

3. Coordinate System and Datum

Any location is relative to a frame of reference. The frame of reference defines the position, orientation and other properties of a coordinate system, in which an object is located. A number of geodetic reference frames have been defined such as WGS84, ETRS89, or ITRF2005. Typically, they define the reference point and the orientation of the coordinate system.

In robotics, reference frames are used, too. They are referencing to a zero point, have an orientation, and may be scaled, mirrored, rotated. For example, a so called transformation matrix can be applied to the location vector to transform coordinate systems.

Commonly in navigation, besides Carthesian also Polar coordinate systems are used. In addition, a polar coordinate system has the benefit that - for example - circular bands can be described easily if the rotating angles have a high uncertainty or are not defined.

In summary, to describe the location of an object, the reference frame has to be named or defined, and the type of coordinate system must be given.

4. Examples

This section shows examples on how to transmit the location ID described above.

4.1. Kalman Filter Results

Assuming, a Kalman filter estimates a position and assigns an uncertainty to this estimate. Then

```
<gp:geopriv>
  <gp:location-info>
    <gs:Kalman srsName="urn:ogc:def:crs:EPSG::?????>
      <gml:pos>-34.407242 150.882518 34</gml:pos>
      <gml:covariance>
         1 0 0
         0 4 0
         0 0 16
       </gml:covariance>
       <gms:timestamp>
         102000
       </gms:timestamp>
    </gs:Kalman>
  </gp:location-info>
</gp:geopriv>
```

defines a point at [-34.407242, 150.882518, 34] that has a Gaussian distribution with the standard deviation of 1, 4 and 16 for the X, Y, and Z-axes.

In addition, it states that the location has been estimated at a time stamp defined by the time index 102000.

4.2. Particle Filter Results

Next, we assume that a Particle Filter has calculated three particles. Then

```
<gp:geopriv>
  <gp:location-info>
    <gs:Particle srsName="urn:ogc:def:crs:EPSG::?????>
      <gml:particleList>
         -34.407242 150.882518 34 0.5
         -34.500000 150.000000 34 0.25
         -34.400000 151.000000 34 0.25
      </gml:particleList>
    </gs:Particle>
  </gp:location-info>
</gp:geopriv>
```

defines a point at [-34.407242, 150.882518, 34] with a weight of 0.5, a point [-34.5,150,34] with a weight of 0.25, and a point at [-34.4,151,34] with a weight of 0.25.

4.3. Gaussian Sum Filter

Next, we have a Gaussian Sum Filter with two Gaussian distributions. Then

```
<gp:geopriv>
  <gp:location-info>
    <gs:Particle srsName="urn:ogc:def:crs:EPSG::?????>
      <gml:particleList>
         -34.407242 150.882518 34 0.25
         -34.500000 150.000000 34 0.25
      </gml:particleList>
      <gml:covarianceList>
         1 0 0
         0 4 0
         0 0 16
         1 0.5 0.5
         0.5 1 0.5
         0.5 0.5 1
       </gml:covariance>
      <gml:particleList>
    </gs:Particle>
  </gp:location-info>
</gp:geopriv>
```

defines a multi-vector Gaussian distribution with the center at [-34.407242, 150.882518, 34], a weight of 0.25, and standard deviations of 1, 4 and 16. In addition, a second distribution is at [-34.5, 150, 34] with a weight of 0.25 and a covariance matrix of [[1 0.5 0.5] [0.5 1 0.5] [0.5 0.5 1]].

In addition, because the sum of weights is lower than 1, we assume that the position estimate has only a belief of correctness (according to Bayesian network theory) of 0.5.

4.4. Well-know Reference Frame

Now, we extend the example given in Section 4.1. to well define a reference frame that is based on the UTM coordinate system.

```
<gp:geopriv>
  <gp:location-info name="Reference Point ID=0123456789">
    <gs:ReferenceFrame>
       UTM zone=32U
       EVRS2000
    </gs:ReferenceFrame>
    <gs:Kalman srsName="urn:ogc:def:crs:EPSG::?????>
```

```
         <gml:x>-34.407242</gml:x>
         <gml:y>150.882518</gml:y>
         <gml:z>34</gml:z>
         <gml:covariance>
            1 0 0
            0 4 0
            0 0 16
          </gml:covariance>
          <gms:timestamp>
            102000
          </gms:timestamp>
       </gs:Kalman>
     </gp:location-info>
   </gp:geopriv>
```

Here, the reference frame for the X and Y axes is given by an UTM map in the zone 32U (western part of Germany) and the height (Z axis) is given by the European Vertical Reference System (EVRS) based on the Normaal Amsterdams Peil (NAP).

In addition, we name this location "Reference Point ID=0123456789".

4.5. Relative Datum

Next, we assume that a reference frame is defined. This example is based on the particle filter given in Section 4.2.

```
   <gp:geopriv>
     <gp:location-info name="Reference Point ID=0123456789">
       <gs:ReferenceFrameDefinition>
          "Reference Point ID=0123456789"
          1 0 0 0
          0 0 -1 0
          0 1 0 0
          0 0 0 1
          carthesian
       </gs:ReferenceFrameDefinition>
       <gs:Particle srsName="urn:ogc:def:crs:EPSG::?????>
         <gml:particleList>
            -34.407242 150.882518 34 0.5
            -34.500000 150.000000 34 0.25
            -34.400000 151.000000 34 0.25
         </gml:particleList>
       </gs:Particle>
     </gp:location-info>
   </gp:geopriv>
```

The new coordinates are based on the reference point given in the previous section but it is rotated by 90 degree about their common normal, from old Z axis to new Z axis.

5. Security Considerations

Security issues have not yet been identified.

6. IANA Considerations

Well-known reference systems must be named or numbered. Thus might require a registration at IANA.

7. Conclusions

This initial draft presented a transmission format for uncertain, relative and transformed location estimates.

It is aim as a basis of discussion, because we believe that uncertainty shall be directly presented by the results of algorithms that determine uncertainty.

Questions that need to be address are:

- o Are the most common filter types covered?

- o Is the transmission format efficient? Especially, if many particle needs to be transmitted an XML description might cause too much overhead. Instead, a generic XML compression such as Binary XML can be used or an application-specific compression algorithm can be defined.

- o Does the representation of relative and transformation reference systems fit into the GEOPRIV framework?

- o Shall the time be given as an index or as a fourth dimension?

Any comments to enhance this draft are highly welcomed.

8. References

8.1. Informative References

[1] M. Thomson, J. Winterbottom, "Representation of Uncertainty and Confidence in PIDF-LO", draft-thomson-geopriv-uncertainty-05, work in progress, June 1, 2010.

[2]   Wikipedia contributors, "Kalman filter", Publisher: Wikipedia, The Free Encyclopedia, Date of last revision: 7 October 2010 15:52 UTC, http://en.wikipedia.org/w/index.php?title=Kalman_filter&oldid=389338611

[3]   Wikipedia contributors, "Particle filter", Publisher: Wikipedia, The Free Encyclopedia, Date of last revision: 24 September 2010 22:18 UTC, http://en.wikipedia.org/w/index.php?title=Particle_filter&oldid=386830379

[4]   J.H. Kotecha, P.M. Djuric, "Gaussian sum particle filtering", IEEE Transactions on Signal Processing, Volume: 51, Issue:10, pages 2602 - 2612, Oct. 2003.

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