Spatiotemporal lightmorphic computing for Carpathian roads

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Abstract

Energy consumption optimization by predicting vehicle behaviour in a dynamic environment represents an active research topic for the automotive industry. As vehicles are increasingly being equipped with driving assistance systems that function under dynamic driving conditions, a trajectory specific energy saving strategy must consider the trajectory particularities and predict in real time the opportunities for energy savings.

Researching and understanding the interactions between complex light intensity shapes and the trajectory spatiotemporal specificity is the main objective of the presented spatiotemporal lightmorphic computing framework for the Romanian Carpathian A1 and DN7 road network. Alternating start and stop locations are included, between the following major cities: București, Timișoara, Deva, Sibiu, Pitești.

Each trajectory segment measurement is composed from various slices defined as segmentation lengths (SL) that characterize the light signatures and trajectory profile. The light intensity variations are contained in the light distribution tensor $\Gamma_t$.

When analyzing the measured values, similarities between measurements are captured in a trajectory specific data-set $\Phi$. This spatiotemporal light distribution symmetry is used to predict the trajectory unique virtual light shape evolution.

Observing the light intensity variations offers a unique perspective on the mentioned route. Having a framework to characterize the light signature structural patterns for specific road trajectories, helps to solve several real-world problems like: achieving optimal energy balance for specific trajectories or accurate estimation of light intensity phenomena that can impact the interaction between vehicle and traveling environment.

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1. Introduction

Researching and understanding the interaction between complex light intensity morphing shapes and the traveled trajectories is the main objective of this work, with the aim at better characterizing the complex interactions between light availability and spatiotemporal specificity for the Romanian Carpathian road network formed by the A1–DN7 roads.

The basic idea is to extract the spatiotemporal lightmorphic profile from raw data by using a sensor sequence of values that are indexed in chronological order and have a structured nature, which is very common in many real-world applications. To that extent, a data collection methodology was established through a low-cost, small footprint sensor system [1] with data recording ability [2].

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Various degrees of freedom (DoF) for the light virtual shapes are considered. The energy demand can be anticipated not only from the driver’s perspective [3] but also from how the vehicle will react to its environment. Additionally by adding the trajectory specific light signature as a predictive feature of the energy management control system, it is possible to anticipate in real-time the trajectory specific energy savings potential.

By conducting the spatiotemporal lightmorphic computing for the acquired trajectory data, a unique virtual light signature is discovered. Next, by comparing historical trajectory data with the light distribution patterns, it is possible to predict the light morphing shape for certain trajectory segments.

2. Related research

With the developed framework to analyze the spatiotemporal lightmorphic shape for specific trajectories, new products and services can be derived.

Previous work to use light availability for specific trajectories include observing the vehicle swiveling headlamps and light intensity for particular highway geometric designs [4] or the effect of light intensity on flight trajectory in bumblebees [5].

Besides the energy aware engineered systems, the patterns in light intensity variation may be used to determine the light availability for roadside vegetation optimal growing conditions [6].

The selected trajectory is composed of the A1 highway and the national road DN7. Approximately 560km are covered in this research with multiple measurements for certain sections of the route. For the selected trajectory, various studies about the fauna [7], archaeological footprints or roadside geological vulnerability [8] exist.

3. Mathematical framework

The vehicle is considered to be a rigid body. As such it is possible to define in the XYZ coordinate system, a position vector for a point P that is located on the vehicle body, that will have the following vector representation:

\[ \vec{r} = x_i \hat{i} + y_i \hat{j} + z_i \hat{k} \]

The position vector for the next time-step is represented as:

\[ \vec{r}' = x_i' \hat{i} + y_i' \hat{j} + z_i' \hat{k}' \]

The dynamic relation between \( \vec{r} \) and \( \vec{r}' \) can be represented as:

\[ i' = a_{11} * i + a_{12} * j + a_{13} * k \]

\[ j' = a_{21} * i + a_{22} * j + a_{23} * k \]

\[ k' = a_{31} * i + a_{32} * j + a_{33} * k \]

A matrix that characterizes the vehicle position change for one time step will have the following representation:

\[ C = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \]

Considering the sum of multiple sequential matrices, a vehicle position trajectory can be composed:

\[ \Gamma = \sum_{i=1}^{N} C_i \quad (1) \]

By observing the light intensity variations and the distribution of measurements, a trajectory specific light tensor can be defined as:

\[ \Gamma_i = f(\Gamma_{IDT}) \quad (2) \]

where:

- \( I \) – intensity of light varies accordingly to seasons or weather conditions
- \( D \) – distribution characteristics for the same trajectory
- \( T \) – trajectory adjustments due to vehicle speed variations between departure and destination

For example, considering a predefined measurement segmentation length (SL) having the value of three, with two consecutive trajectory slices and three distributions, the light tensor can be derived as having the following representation:

\[ \Gamma_{SL_1} = \begin{pmatrix} a_{111} & a_{121} & a_{131} \\ a_{211} & a_{221} & a_{231} \\ a_{311} & a_{321} & a_{331} \end{pmatrix} \]

\[ \Gamma_{SL_2} = \begin{pmatrix} a_{112} & a_{122} & a_{132} \\ a_{212} & a_{222} & a_{232} \\ a_{312} & a_{322} & a_{332} \end{pmatrix} \]

The trajectory specific light tensor is constructed by using the three mode-n unfolding:

\[ \Gamma_{(1)} = \begin{pmatrix} a_{111} & a_{121} & a_{131} & a_{112} & a_{122} & a_{132} & a_{113} & a_{123} & a_{133} \\ a_{211} & a_{221} & a_{231} & a_{212} & a_{222} & a_{232} & a_{213} & a_{223} & a_{233} \\ a_{311} & a_{321} & a_{331} & a_{312} & a_{322} & a_{332} & a_{313} & a_{323} & a_{333} \end{pmatrix} \]

\[ \Gamma_{(2)} = \begin{pmatrix} a_{111} & a_{121} & a_{131} & a_{112} & a_{122} & a_{132} & a_{113} & a_{123} & a_{133} \\ a_{211} & a_{221} & a_{231} & a_{212} & a_{222} & a_{232} & a_{213} & a_{223} & a_{233} \\ a_{311} & a_{321} & a_{331} & a_{312} & a_{322} & a_{332} & a_{313} & a_{323} & a_{333} \end{pmatrix} \]
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\[
\Gamma_3 = \begin{pmatrix}
a_{111} & a_{211} & a_{311} & a_{121} & \ldots & a_{231} & a_{331} \\
a_{112} & a_{212} & a_{312} & a_{122} & \ldots & a_{232} & a_{332} \\
\end{pmatrix}
\]

The trajectory tensor values are considered to be included in the real numbers group, \( \Gamma \in \mathbb{R} \), where:

- \( K_i \) – modes index for the trajectory tensor
- \( \mathbb{R} \) – group of real numbers

A graphical representation with Matplotlib [9] of the trajectory specific light intensity tensor for five measurements and a predefined SL value is given in figure 1.

![Graphical representation with Matplotlib](image)

**Figure 1.** Predefined segment from the light intensity tensor

3.1. Probable light shape morphing

Values for the trajectory specific light tensor are captured in a data-set:

\[
\Theta = \sum \Gamma_{IDT}
\]  
(3)

While analyzing the data-set it is possible to discover similarities between segments of them \( \{\Gamma_{IDT,1}, \Gamma_{IDT,2}, \ldots, \Gamma_{IDT,N}\} \).

Values for the trajectory specific light tensor that show similarities are captured in a data-set:

\[
\Phi_{IDT} = \sum \Gamma_{IDT}
\]  
(4)

While observing the distribution of multiple light segments within the data-set \( \Phi_{IDT} \), it will be possible to estimate the probability for trajectory specific light tensor shape evolution:

\[
p_{\Phi} = f(p_k, p_{\Phi_k})
\]  
(5)

where:

- \( p_{\Phi_k} \) – data-base k-th segment specific probability
- \( p_k \) – prediction weight for the k-th segment takes values from 0 to 1

The obtained probability shape for the similarities data-set, will be used as baseline homogenization characterization for the virtual light morphing shapes.

3.2 Spatiotemporal lightmorphic signature

For each specific trajectory, a unique spatiotemporal lightmorphic signature function can be defined as:

\[
f_L = \int_1^D \int_1^T \int_1^\Gamma \zeta_t dt
\]  
(6)

where:

- \( \Gamma \) – trajectory tensor
- \( \zeta_t \) – point in time specificity

Since the \( f_L \) is continuous, the mean absolute error (MAE) between measured and estimated values can be considered.

\[
MAE = \frac{1}{n} \sum_i \left| m_{f_L} - e_{f_L} \right|
\]

where:

- \( n \) – number of samples for the considered trajectory
- \( m_{f_L} \) – light signature specific measured value
- \( e_{f_L} \) – light signature estimated value

3.3 Light vector field circulation

Since a point \( P \) is defined in the \( \mathbb{R}^3 \) space with the origin coordinates at \( P = \{0; \vec{i}, \vec{j}, \vec{k}\} \), for multiple trajectory measurements, there is the opportunity to define a continuous light vector field \( \vec{v} \) that describes the light morphing shape:

\[
\vec{v}(x, y, z) = M(x, y, z)\vec{i} + N(x, y, z)\vec{j} + T(x, y, z)\vec{k}
\]  
(7)

The vector field circulation for the unique light signature function \( f_L \) can be characterized as:
\[
\int_{\Omega} \theta d\tau = \int_{\Omega} [M(r(t)\dot{x}(t)) + N(r(t)\dot{y}(t)) + T(r(t)\dot{z}(t))] dt
\]

(8)

4. Experimental considerations

Previous research in computational design explain how to convert a single input mesh into a parametric model by using methods such as cages [10], linear blend skinning [11] or manifold harmonics. Such methods can generate smooth virtual deformations for shapes that seem more organic in behavior.

While observing the measured data for light shape distribution on specific trajectories it was discovered that there are symmetry patterns in the light intensity distribution values.

From the saved data it is possible to randomly select various light intensity vector shapes. As indicated above in the spatiotemporal lightmorphic equation (6) each particular driving path will have unique light signatures that are used to generate smooth virtual light evolution shapes.

4.1. Hardware components

All the measurements are done using the same vehicle, driver and propulsion system.

| Vehicle weight | m | 1523 | kg |
|----------------|---|------|----|
| ICE max. mech. power | \( P_{\text{ice-max}} \) | 51 | kW |
| Battery capacity | \( Q_0 \) | 55 | Ah |
| Drivetrain | --- | FWD | --- |
| Transmission | --- | Manual | --- |
| Number of gears | --- | 5 | --- |
| Aerodynamic drag coefficient | \( C_x \) | 0.33 | --- |
| Front suspension | --- | Independent | --- |
| Low beam lights | --- | Halogen | Active |

Table 1. Vehicle Parameters

In table 1, specific vehicle parameters are described. The sensor is placed on the windshield, inside the vehicle and facing outwards. As a result, the light intensity sensor will record the light variations due to the vehicle movement on the selected road trajectory, as it turns and bends following the road profile. Windshield tilt is not varied during the measurements. Only daytime sensor values are considered.

Data is recorded using Arduino UNO [2]. Light intensity is measured using the BH1750 [1] digital 16bit serial output type ambient light sensor.

The HW system is recording the data with same predefined recurrence for all the measurements. When analyzing the data, a median value is considered for every 100 measurements.

Measurements are done for trajectories that represent the Romanian Carpathian roads A1 and DN7, with alternating start and stop locations between the following major cities: București, Timișoara, Deva, Sibiu, Pitești. A map for the complete trajectory is drawn in figure 2.

![Figure 2. Romanian Carpathians A1-DN7 light intensity measurement trajectory](image)

4.2. Computing components

In order to analyze the measurement data, algorithms are written, that follow the equations defined in the mathematical framework.

Each trajectory can use various measurement slices defined as segmentation lengths (SL) to characterize the light signatures and trajectory profile.

For finding unique light signatures specific for each segment of trajectory, the algorithm for light signatures is used.

For finding matching light segments between measurements, the algorithm for light patterns is used.
Algorithm 1 Light Signatures

INPUT: Light measurements for the same trajectory
OUTPUT: Total segments and unique light signatures
BEGIN
  segmentation length (SL) ← value
  meas one ← light.data

  DEFINE the function light signature
  with the arguments (meas one, SL):
  FOR i ← 0 TO LEN(meas one) AND STEP(SL):
    RETURN:
    segmented data ← [SL]
  ENDFOR

  x ← 0
  light signatures ← []

  WHILEx < LEN(segmented data):
    current segment ← segmented data [x]
    x ← x + 1
    segment signs ← []
    FOR ij ← ITERATOR
      current segment(value, next value):
      IF ← i = j
        APPEND segment signs ← “="
      ELIF ← i < j
        APPEND segment signs ← “<”
      ELIF ← i > j
        APPEND segment signs ← “>”
    ENDFOR
    APPEND light signatures ← segment signs
  ENDFOR

  unique light signatures ← []
  FOR elem ← light signatures
    APPEND unique light signatures ← [segment]
  ENDFOR

END

Algorithm 2 Light Patterns

INPUT: Measurements for the same trajectory
OUTPUT: Matching light segments
BEGIN
  index ← 0
  matched pattern ← 0

  FOR pattern ← meas two:
    index ← index + 1
    FOR signature ← meas one:
      WHILE LEN(pattern) < LEN(meas one):
        REMOVE ← meas one [SL]
        IF ← pattern = meas one [SL]
        matched pattern ← matched pattern +1
      ENDFOR
    ENDFOR

END

5. Obtained results

The complete Romanian Carpathians A1-DN7 spatiotemporal lightmorphic trajectory from București to Timișoara is analyzed.

From Deva to Timișoara a total of five measurements were considered, while for the trajectory segment Timișoara to Deva, two path variations of the same trajectory segment were considered. For path I, there were four measurements, while for path II there were three.

From Deva to Pitesti via Sibiu there were three measurements considered, while for the trajectory segment Pitești to Deva via Sibiu there were two measurements considered.

For the Deva to București trajectory segment there was one measurement considered.

5.1. Deva to Timișoara trajectory segment

The specific light signature for the trajectory segment from Deva to Timișoara of highway A1 and DN7 roads is measured and analyzed.

The physical trajectory length is relatively constant while the journey duration varies between 3.5 and 5 hours.

As described in equation 2 the light intensity variations are forming the light distribution tensor $\Gamma_i$.

Figure 3. Measured light values for the trajectory segment Deva → Timișoara of A1-DN7 road network

Five light intensity measurements are considered with the trajectory tensor having the following representation along the distribution dimension:

$$\Gamma_{(DY\rightarrow TM)} = f(\Gamma_{1T}, \Gamma_{2T}, \Gamma_{3T}, \Gamma_{4T}, \Gamma_{5T})$$
As described in equation 3 a specific data-set can be constructed:

$$\Theta_{(DV\rightarrow TM)} = \Gamma_{11T} + \Gamma_{12T} + \Gamma_{13T} + \Gamma_{14T} + \Gamma_{15T}$$

From the data-set $\Theta_{(DV\rightarrow TM)}$ it can be observed that with an increasing SL, the unique light signatures and the trajectory light segments are converging towards each other.

After running the unique light signature algorithm, the results are saved in table 2.

| Segmentation length | 10 | 15 | 20 | 30 |
|---------------------|----|----|----|----|
| $\Gamma_{11T}$ trajectory segments | 4880 | 3253 | 2440 | 1627 |
| $\Gamma_{11T}$ light signatures | 2152 | 2926 | 2379 | 1625 |
| $\Gamma_{12T}$ trajectory segments | 4500 | 3000 | 2250 | 1500 |
| $\Gamma_{12T}$ light signatures | 1863 | 2619 | 2192 | 1497 |
| $\Gamma_{13T}$ trajectory segments | 4073 | 2716 | 2037 | 1358 |
| $\Gamma_{13T}$ light signatures | 1439 | 2191 | 1934 | 1352 |
| $\Gamma_{14T}$ trajectory segments | 3848 | 2323 | 1742 | 1162 |
| $\Gamma_{14T}$ light signatures | 530 | 1601 | 1472 | 1105 |
| $\Gamma_{15T}$ trajectory segments | 4217 | 2811 | 2109 | 1406 |
| $\Gamma_{15T}$ light signatures | 1285 | 2418 | 2069 | 1404 |

Table 2. Number of light intensity segments and unique light signatures with various SL for trajectory segment Deva to Timisoara

Similarities between measurements are captured in a trajectory specific light signature data-set $\Phi$ as described in equation 4.

$$\Phi_{(DV\rightarrow TM)} = \sum_{j=1}^{5} \Phi_{j}^{T}$$

For a predefined SL, after running the algorithm for light patterns between measurements, the results are saved in table 3.

| SL = 30 | $\Gamma_{11T}$ | $\Gamma_{12T}$ | $\Gamma_{13T}$ | $\Gamma_{14T}$ | $\Gamma_{15T}$ |
|---------|----------------|----------------|----------------|----------------|----------------|
| $\Gamma_{11T}$ | --- | 103 | 134 | 2009 | 21 |
| $\Gamma_{12T}$ | 15 | --- | 295 | 513 | 71 |
| $\Gamma_{13T}$ | 81 | 146 | --- | 681 | 72 |
| $\Gamma_{14T}$ | 1447 | 150 | 235 | --- | 41 |
| $\Gamma_{15T}$ | 18 | 58 | 81 | 545 | --- |

Table 3. Non-unique matching light segments between measurements for trajectory segment Deva to Timisoara with SL=30

For a future light distribution $\Gamma_{IXT}$, each probable light segment has the corresponding prediction weight $\rho_k$. If there is a probable light segments match between distributions, the $\rho_k$ will have a value of one. If there is not the $\rho_k$ will have a value of zero.

$$p_{\Phi_{IXT}} = f(\rho_1, p_{\Phi_{11T}}, \rho_1, p_{\Phi_{12T}}, \rho_1, p_{\Phi_{13T}}, \rho_1, p_{\Phi_{14T}}, \rho_1, p_{\Phi_{15T}})$$ (9)

The baseline can change between any of the recorded distributions.

Analyzing the observed similarities between $\Gamma_{11T}$ and $\Gamma_{12T}$ leads to the discovery of a unique spatiotemporal lightmorphic shape as represented in figure 5:

![Figure 5. Unique light segments between $\Gamma_{11T}$ and $\Gamma_{12T}$ for SL=30 and $\rho_k \geq 0.7$](image)

Repeating the same analysis, between $\Gamma_{11T}$ and $\Gamma_{13T}$ the unique light segments are represented in figure 6, between $\Gamma_{11T}$ and $\Gamma_{14T}$ the unique light segments are represented in figure 7 and between $\Gamma_{11T}$ and $\Gamma_{15T}$ the unique light segments are represented in figure 8.

According to spatiotemporal lightmorphic equation 6 a future distribution $X$ that considers the $\Gamma_{11T}$ as
baseline will circulate between the virtual probable shapes as in figure 9.

The baseline distribution can change between any of the measured distributions \( \Gamma_{I1T}, \Gamma_{I2T}, \Gamma_{I3T}, \Gamma_{I4T}, \Gamma_{I5T} \).

With changing baseline between distributions \( \Gamma_{I1T}, \Gamma_{I2T}, \Gamma_{I3T}, \Gamma_{I4T}, \Gamma_{I5T} \) for \( \rho_k \geq 0.7 \), the virtual probable light shapes are represented in figure 10.

According to equation 6 the unique light signature function for the trajectory Deva to Timisoara along the distribution dimension, can be represented as:

\[
\begin{align*}
  f_{L, \odot}^{(DV \rightarrow TM)} &= \int_1^D \int_1^T \Gamma_{I1T}^{\odot} \cdot c_{DV \rightarrow TM}^{\odot} \, dt \\
  f_{L, \odot}^{(DV \rightarrow TM)} &= \int_1^D \int_1^T \int_1^T \Gamma_{I1T}^{\odot} \cdot c_{DV \rightarrow TM}^{\odot} \, dt
\end{align*}
\]

Following the same analysis, it is possible to add into consideration the variability for light intensity and specific trajectory characteristics as described in equation 6 and obtain a unique spatiotemporal lightmorphic shape.

5.2 Timisoara to Deva trajectory segment

The specific light signature for the trajectory from Timisoara to Deva segment of A1-DN7, is measured and analyzed in figure 11 and 13.

Trajectory length is relatively constant while the journey duration varies between 3.5 and 4.5 hours.

Four light intensity measurements are considered with the trajectory tensor having the following
Figure 11. Measured light values for the Timișoara to Deva (path 1) segment of A1-DN7.

representation:

$$\Gamma_{(TM\rightarrow DV)_{(I)}} = f(\Gamma_{I1T}, \Gamma_{I2T}, \Gamma_{I3T}, \Gamma_{I4T})$$

As considered in equation 3 a specific data-set is constructed:

$$\Theta_{(TM\rightarrow DV)_{(I)}} = \Gamma_{I1T} + \Gamma_{I2T} + \Gamma_{I3T} + \Gamma_{I4T}$$

From the data-set $$\Theta_{(TM\rightarrow DV)_{(I)}}$$ it can be observed how with an increasing SL, the unique light signatures and the trajectory light segments are converging towards each other.

After running the unique light signature algorithm, the results are saved in table 4.

| Segmentation length | 10  | 15  | 20  | 30  |
|---------------------|-----|-----|-----|-----|
| $$\Gamma_{I1T}$$ trajectory segments | 4072 | 2715 | 2036 | 1358 |
| $$\Gamma_{I1T}$$ light signatures | 1446 | 2262 | 1945 | 1350 |
| $$\Gamma_{I2T}$$ trajectory segments | 4065 | 2710 | 2033 | 1355 |
| $$\Gamma_{I2T}$$ light signatures | 1465 | 2352 | 1994 | 1354 |
| $$\Gamma_{I3T}$$ trajectory segments | 3401 | 2268 | 1701 | 1134 |
| $$\Gamma_{I3T}$$ light signatures | 1102 | 1801 | 1592 | 1132 |
| $$\Gamma_{I4T}$$ trajectory segments | 2977 | 1985 | 1489 | 993 |
| $$\Gamma_{I4T}$$ light signatures | 1057 | 1581 | 1365 | 979 |

Table 4. Number of light intensity segments and unique light signatures with various segmentation lengths for Timișoara to Deva (I) trajectory.

As considered in equation 4, similarities between measurements are captured in a trajectory specific data-set $$\Phi$$.

$$\Phi_{(TM\rightarrow DV)_{(I)}} = \sum_{j=1}^{4} \Gamma_{IDT}^j$$

For a predefined SL, after considering the algorithm for matching light patterns between measurements, the results are saved in table 5.

| SL = 30 | $$\Gamma_{I1T}$$ | $$\Gamma_{I2T}$$ | $$\Gamma_{I3T}$$ | $$\Gamma_{I4T}$$ |
|---------|-----------------|-----------------|-----------------|-----------------|
| $$\Gamma_{I1T}$$ | — | 110 | 224 | 257 |
| $$\Gamma_{I2T}$$ | 209 | — | 57 | 58 |
| $$\Gamma_{I3T}$$ | 236 | 41 | — | 239 |
| $$\Gamma_{I4T}$$ | 345 | 67 | 173 | — |

Table 5. Non-unique matching light segments between measurements for trajectory (I) Timișoara to Deva with SL=30.

Figure 12. Virtual probable light signatures for trajectory (I) Timișoara to Deva with SL=30 and $$\rho_k \geq 0.7$$.

With changing baseline between distributions $$\Gamma_{I1T}, \Gamma_{I2T}, \Gamma_{I3T}, \Gamma_{I4T}$$ for $$\rho_k \geq 0.7$$, the virtual probable light shapes are represented in figure 12.

By selecting a different trajectory configuration between highway A1 and the DN1 roads, the specific light signature changes accordingly and is represented in figure 13.

Figure 13. Measured light values for the Timișoara to Deva (path 2) segment of A1-DN7.

Three light intensity measurements are considered with the trajectory tensor having the following representation:

$$\Gamma_{(TM\rightarrow DV)_{(II)}} = f(\Gamma_{I1T}, \Gamma_{I2T}, \Gamma_{I3T})$$

As previously, from the data-set $$\Theta_{(TM\rightarrow DV)_{(II)}}$$ it can be observed that with an increasing SL, the unique
light signatures and the trajectory light segments are converging towards each other.

After running the unique light signature algorithm, the results are saved in table 6.

| Segmentation length | 10  | 15  | 20  | 30  |
|---------------------|-----|-----|-----|-----|
| \( \Gamma_{1T} \) trajectory segments | 3835 | 2557 | 1918 | 1279 |
| \( \Gamma_{1T} \) light signatures | 1471 | 2183 | 1861 | 1275 |
| \( \Gamma_{2T} \) trajectory segments | 3272 | 2181 | 1636 | 1091 |
| \( \Gamma_{2T} \) light signatures | 1182 | 1883 | 1599 | 1088 |
| \( \Gamma_{3T} \) trajectory segments | 3369 | 2246 | 1685 | 1123 |
| \( \Gamma_{3T} \) light signatures | 1271 | 2027 | 1657 | 1122 |

**Table 6.** Number of light intensity segments and unique light signatures with various segmentation lengths for Timisoara to Deva trajectory (II)

Similarities between measurements are captured in a trajectory specific data-set \( \Phi \) saved in table 7.

| SL = 30 | \( \Gamma_{1T} \) | \( \Gamma_{2T} \) | \( \Gamma_{3T} \) |
|---------|----------------|----------------|----------------|
| \( \Gamma_{1T} \) | 400 | 255 |
| \( \Gamma_{2T} \) | 299 | 184 |
| \( \Gamma_{3T} \) | 316 | 353 |

**Table 7.** Non-unique matching light segments between measurements for trajectory (II) Timisoara to Deva with SL=30

With changing baseline between distributions \( \Gamma_{1T}, \Gamma_{2T}, \Gamma_{3T} \) for \( \rho_k \geq 0.7 \), the virtual probable light shapes are represented in figure 14.

5.3. Deva to Pitești (via Sibiu) trajectory segment

The specific light signature for the trajectory from Deva to Pitești (via Sibiu) segment of A1-DN7, is measured and analyzed.

Three light intensity measurements are considered with the trajectory tensor having the following representation:

\[
\Gamma_{t(DV\rightarrow AG)} = f(\Gamma_{1T}, \Gamma_{2T}, \Gamma_{3T})
\]

As described in equation 3 a specific data-set is constructed for the indicated trajectory:

\[
\Theta_{(DV\rightarrow AG)} = \Gamma_{1T} + \Gamma_{2T} + \Gamma_{3T}
\]

From the data-set \( \Theta_{(DV\rightarrow AG)} \) it can be observed how with an increasing SL, the unique light signatures and the trajectory light segments are converging towards each other.

After running the unique light signature algorithm, the results are saved in table 8.

| Segmentation length | 10  | 15  | 20  | 30  |
|---------------------|-----|-----|-----|-----|
| \( \Gamma_{1T} \) trajectory segments | 4939 | 3293 | 2470 | 1647 |
| \( \Gamma_{1T} \) light signatures | 1607 | 3056 | 2461 | 1647 |
| \( \Gamma_{2T} \) trajectory segments | 4928 | 3286 | 2464 | 1643 |
| \( \Gamma_{2T} \) light signatures | 1624 | 3007 | 2447 | 1643 |
| \( \Gamma_{3T} \) trajectory segments | 4238 | 2826 | 2119 | 1413 |
| \( \Gamma_{3T} \) light signatures | 1111 | 2261 | 2031 | 1413 |

**Table 8.** Number of light intensity segments and unique light signatures with various segmentation lengths for Deva to Pitești (via Sibiu) trajectory

Similarities between measurements are captured in a trajectory specific data-set \( \Phi_{(DV\rightarrow AG)} \) as described in equation 4.

The selected predefined SL is 20 segments and after considering the algorithm for matching light patterns between measurements, the results are saved in table 9.

With changing baseline between distributions \( \Gamma_{1T}, \Gamma_{2T}, \Gamma_{3T} \) for \( \rho_k \geq 0.7 \), the virtual probable light shapes are represented in figure 16.
5.4. Pitești to Deva (via Sibiu) trajectory segment

The specific light signature for the trajectory from Pitești to Deva (via Sibiu) segment of A1-DN7, is measured and analyzed.

Two light intensity measurements are considered with the trajectory tensor having the following representation:

$$\Gamma_{(AG\rightarrow DV)} = f(\Gamma_{11T}, \Gamma_{12T})$$

From the data-set $\Theta_{(AG\rightarrow DV)}$ it can be observed how with an increasing SL, the unique light signatures and the trajectory light segments are converging towards each other.

After running the unique light signature algorithm, the results are saved in table 10.

5.5. Deva to București trajectory segment

The specific light signature for the trajectory from Deva to București segment of A1-DN7, is measured and analyzed.

One light intensity measurement is available with the trajectory tensor having the following representation:

$$\Gamma_{(DV\rightarrow B)} = f(\Gamma_{11T})$$

After running the unique light signature algorithm, the results are saved in table 12.
Spatiotemporal lightmorphic computing for Carpathian roads

Figure 19. Measured light values for the Deva to București (via Sibiu) segment of A1-DN7

| Segmentation length | 10  | 15  | 20  | 30  |
|---------------------|-----|-----|-----|-----|
| \( \Gamma_{T} \) trajectory segments | 7781 | 5187 | 3891 | 2594 |
| \( \Gamma_{L} \) light signatures   | 2453 | 4631 | 3840 | 2592 |

Table 12. Number of light intensity segments and unique light signatures with various segmentation lengths for Deva to București (via Sibiu) trajectory

Analyzing the unique light signature function for the trajectory Deva to București along the measured distribution, multiple virtual light signature shapes can be derived as represented in figure 20.

Figure 20. Virtual probable light signatures for trajectory segment Deva to București with SL=30

In order to obtain the derived virtual shapes, isochronous data gaps are artificially created. The spatiotemporal lightmorphic computing framework is able to accommodate such data gaps and provide an estimated virtual shape.

6. Conclusion

The method is applied to the Romanian Carpathian A1 and DN7 road network in order to obtain virtual light shapes and determine the optimum energy saving driving strategies.

Several questions have been answered through the analysis and usage of the spatiotemporal lightmorphic computing framework:

- Can the optimum vehicle reaction be predicted for the selected trajectory when the light signature is estimated.
- What will be the optimum energy saving driving style for the predicted trajectory considering dynamic vehicle external parameters.
- What shape will the unique light signature have for the Romanian Carpathian A1 and DN7 road network.
- Is it possible to estimate the light signature for future driving scenarios.

Additional sensor measurements are planned to be added in the existing light intensity data-base like: sound characteristics, specific vibrations, unique humidity variations, temperature profile, chemical components concentration levels.

With this sensor fusion approach, the optimum energy conservation configurations can be discovered for specific trajectories.

Having this evolution of knowledge, a better understanding of the light intensity specificity for the Romanian Carpathian A1 and DN7 road network might lead to innovative vehicles and smart infrastructures.

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