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Discovering the Animal Movement Patterns using Hidden Markov Model

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Abstract— **Collars equipped with GPS/GSM device provide automated remote tracking of animal at successive time intervals. Since animal movement is complex and irregular, methods based on repetitiveness of human movement cannot be applied to animals. In this paper we propose a method for animal movement pattern discovery using Hidden Markov model. We present a prototype for pattern discovery which enables arbitrary definition of model states by an expert in the field, as well as marking the patterns for learning phase of the method. Case studies of wolf and bear movements validate the method and show promising results - up to 94.02% accuracy in detecting the patterns among foraging, travelling and bedding for wolfs, and up to 82.14% accuracy in detecting feeding, resting and travelling patterns for bears on intermediate spatio-temporal scale.**

Keywords*- moving objects; animal movement; pattern discovery; hidden Markov model*

I. INTRODUCTION

Modern technology enables remote tracking of animals wearing collars equipped with GPS/GSM device. Intense sampling of animal movements allows the insight into the interaction of animal and its environment [1, 2]. Still, the data gathered from a collar are not so intense due to the following drawbacks. Positions are often sampled in sparse time intervals due to the limited battery duration. Also, one could expect a lack of positions in tracking data as the consequence of the habitat that is not fully covered by GPS or GSM signal.

Movement patterns (movement modes, movement phases) play an important role in understanding the behavior of animals [3-6]. Depending on spatio-temporal scale, different types of patterns can be recognized: from home range selection and migration at coarse-scale, foraging and travelling at intermediate-scale to feeding and short stops at fine-scale.

The moving objects research is mainly focused on the analysis and prediction of movement of people and vehicles, rarely animals. It is often assumed to have dense position recordings (for example every second) to perform analysis and prediction algorithms, which is unlikely for animal movement recordings. Furthermore, the algorithms applicable to the human movement are mostly based on the discovery of frequent routes [7-9]. Though people have a tendency to repeat the route, which is not common for wild animals in such a significant rate. Animals may have a habit of visiting the same places, but their movement is complex and hard to predict [10].

There is no generic pattern discovery model for wild animals. Scientists are focused mainly on finding kill-sites [11, 12] with no intention on further application. The proposed methods also often require aerial or ground-monitoring [12] and cannot be done remotely. Although various statistical modeling approaches are recently stressed as valuable for animal movement [5, 6, 13, 14], they are rarely used in practice and remain challenging issue [5]. The one of reasons is that those methods are unsuited to biologist and ecologists since they require the expertise in statistical theory and programming [6].

We propose a method for animal movement pattern discovery using Hidden Markov model (HMM). Proposed method enables expert in the field to choose the parameters of the model according to the application in the preparation phase, when the model is constructed for the first time. In decoding phase, the detection of the pattern is done automatically enabling real-time performance. Beside the analysis of the movement aimed to get better insight into the animal behaviour, we found discovery of movement patterns useful to adapt the method of prediction of the animal next movement. Depending on detected movement pattern, different prediction method can be used.

The rest of the paper is organized as follows. In the section II the basic terms considering movement patterns are introduced. The section III presents the Hidden Markov model for movement pattern discovery. Case study of movement of wolfs in Croatia and prototype for movement patterns discovery is described in section IV.

II. MOVEMENT PATTERNS

A. Trajectory

For the purpose of discovery of movement patterns, trajectory is defined as follows:

Definition 1. Trajectory of the moving object is mapping

$$trajectory: [t_{begining}, t_{end}] \rightarrow space$$

where $t_{begining}$ is the starting moment of position recording, t_{end} the last moment of position recording and *space* corresponding two-dimensional space.

Thus, each trajectory (Figure 1) is represented as an ordered set of points:

$$(x_1, y_1), \ldots, (x_n, y_n)$$

where (x_i, y_i) are positions of moving object recorded in sequential moments t_i:

$$t_{begining} = t_1 < t_2 < \ldots$$

B. Movement patterns of animals

Although not precisely defined, the authors of [3] differ three spatio-temporal scales: coarse-scale, intermediate-scale and fine-scale. Depending on the scale, different types of movement patterns can be detected.

The common movement patterns [3-5, 12] at intermediate-scale (regardless on animal species) are:

- *Foraging* - activity of searching for and exploiting food resources. Commonly, it takes place in a limited geographical area. It manifests in small travelled distances and large turning angles.
- *Feeding* - activity which animal shows after finding food. For carnivores it may be a kill-site where animal use to come back and for herbivores may resemble foraging.
- *Travelling* - the goal-oriented movement. Animal is moving from one area to another. It manifests in large travelled distances and small turning angles.
- *Bedding (or resting)* - stop or gathering, whether it is because of a place such as den or kill-site where animal use to come back or a place where animal temporary stops.

In Figure 2 is given an example of the movement with identified foraging, travelling and bedding patterns.

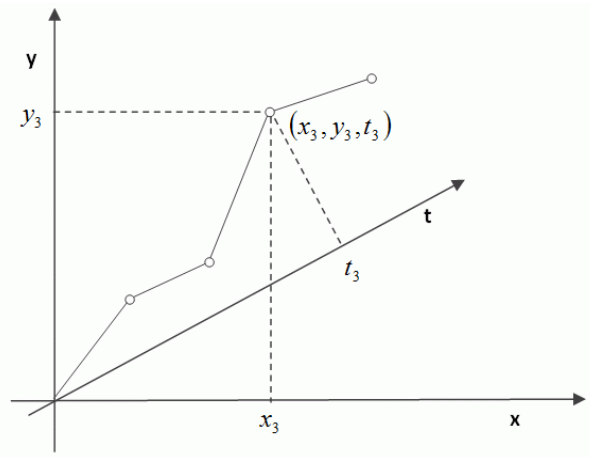


Figure 1. An example of trajectory

There are two main approaches to identify semantic patterns of trajectories: episode view of trajectory or stop and moves view.

In the first approach, authors denote an episode as a discreet time period for which the object's spatio-temporal behavior was relatively homogeneous [15]. The trajectory is presented as set of episodes, with corresponding characteristics such as meaning, description, purpose etc. This approach requires semantic annotation by hand, which cannot be applied for movement prediction in real time.

In the other approach trajectory is viewed as series of stops and moves [15-17]. Stops are the important places of the trajectory where the object has stayed for a minimal amount of time. The remaining parts of the trajectory form the moves. Stops are associated to known geographical information. The drawback of this method is that geographic information has to be known in advance, which is often not a case in study of animal movement.

We propose a method for animal movement pattern discovery using Hidden Markov model. The states of the model can be set arbitrary by the expert in the field and detection of the movement patterns can be done automatically in real-time.

III. Hidden Markov Model for Movement Pattern Discovery

Hidden Markov Model (HMM) is a stochastic model in which the system is modeled by a Markov process with unknown (hidden) parameters and the goal is to find out hidden from the sequence of observed symbols [18]. Formally, HMM is a 5-touple of state alphabet set *S*, observation alphabet set *V*, transition probability matrix *A*, observation probability matrix *B* and initial probability array *I* - *(S, V, A, B, I)*.

A. Constructing an HMM for movement pattern discovery

Assuming that the movement is represented as in *Definition 1*, structure of the HMM for movement pattern discovery is as following:

1. State alphabet set *S* is set of movement patterns:

   $$S = \{O_i: O_i \text{ is movement pattern}, 1 \leq i \leq n\}$$

2. Observation alphabet set *V* is given by:

   $$V = \{(U_i, K_j): 1 \leq i \leq n_U, 1 \leq j \leq n_K\}$$

   where $U=\{U_1, \ldots, U_{nU}\}$ is set of distance (travelled path) intervals and $K = \{K_1, \ldots, K_{nK}\}$ is set of angle intervals. Distances are considered between two sequential positions and angles are turning angles considering the prior position. These parameters are directly observed from trajectory.

3. Transition probability matrix *A* is given by:

   $$A = [a_{ij}], a_{ij} = P(S'_{t+1} = S_j | S'_t = S_i), 1 \leq i,j \leq n$$

   It holds:

   $$a_{ij} > 0, \forall\, i,j \text{ and } \sum_{j=1}^{n} a_{ij} = 1,\ \forall\, i \in \{1, \ldots, n\}.$$

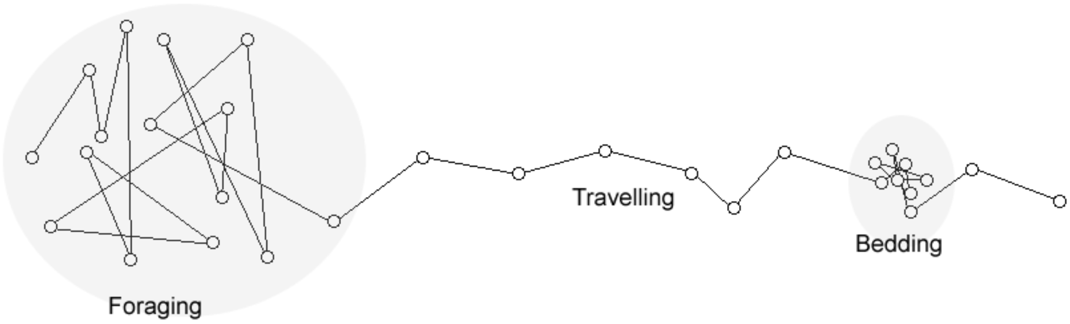


Figure 2. An example of animal movement patterns

4. Observation probability matrix B is given by:

$$B = [b_{jk}],$$

$$b_{jk} = P((U_i, K_l) \text{ in the moment } t, k=i*n_U+l \mid S'_t = S_j),$$

$$1 \leq j \leq n,\ 1 \leq k \leq n_U * n_K$$

It holds:

$$b_{ij} > 0, \forall\, i, j \text{ and } \sum_{k=1}^{m} b_{ij} = 1,\ \ \forall\, j\ \in \{1, .., n\}.$$

5. Initial probability array I is given by:

$$I = \{I_i : I_i = P(S'_1 = S_1),\ 1 \leq i \leq n\}$$

It holds:

$$I_i > 0, \forall\, i \text{ and } \sum_{i=1}^{n} I_i = 1\ .$$

Schema of Hidden Markov model for discovery of movement patterns according to above defined model components is given in Figure 3.

B. *Learning and decoding movement patterns*

HMM parameters are defined based on learning set of trajectories for which the movement pattern is known. Trajectories are translated from array of positions to array of ordered couple of angle and distance intervals.

Given a trajectory with unknown pattern and the defined model, using Viterbi algorithm [19], the most probable set of hidden states is reconstructed (Figure 4).

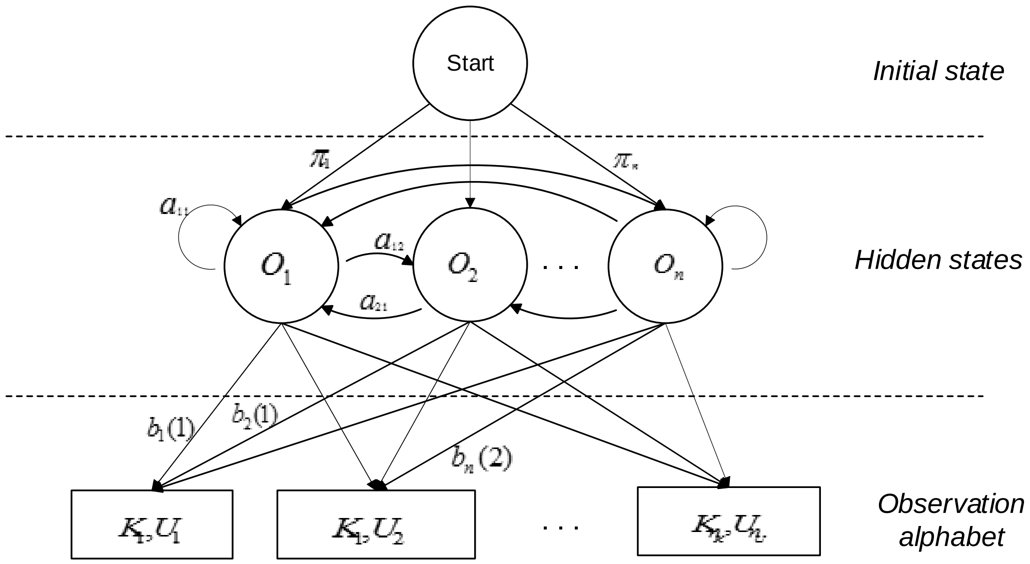


Figure 3. Schema of Hidden Markov model for discovery of movement patterns

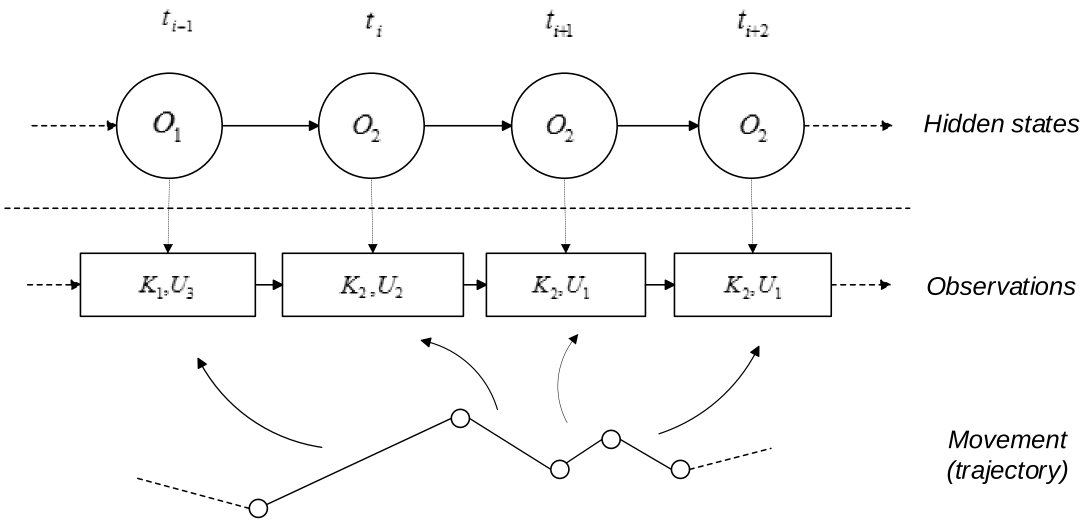


Figure 4. An example of reconstruction of movement pattern from observed trajectory

Detected patterns can be analyzed against the other variable (such as a time or moving object's characteristic) in order to give a deeper insight into the behavior of animals. For example, the analysis could show differences in behavior for male or female or dominance of certain pattern in certain time of a day or season. The other use of detected pattern is the prediction of the next movement of animal according to the pattern.

IV. CASE STUDY OF ANIMALS

A. *Prototype for movement pattern discovery*

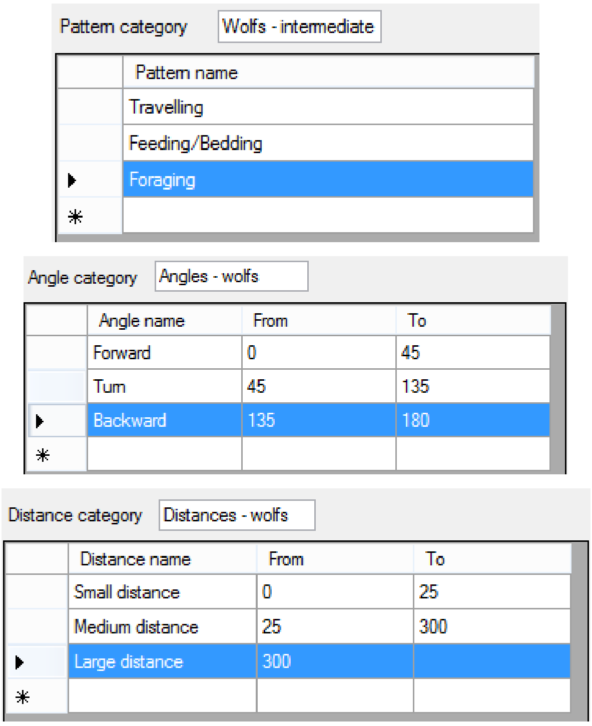
The described algorithm is validated using the prototype we developed through our research [20]. The prototype enables managing the data about moving objects, the data describing their movement and context of the movement as well as performing various algorithms. The prototype is primarily designed to manage the movement of wild animals, although we believe it can be used for other types of moving objects as well.

The prototype enables arbitrary definition of model states, as well as angle and distance intervals (see Figure 5).

Further, the prototype supports marking parts of trajectories and matching them to defined states i.e. movement patterns (Figure 6). The sets of marked trajectories are stored in knowledge base and used in learning process.

The HMM is further built according to chosen model structure (states, angle category and distance category) and training data (trajectories associated to model states by expert). The example of chosen parameters is shown in Figure 7.

Finally, given a new trajectory and model, the decoding of movement patterns is done and the patterns are marked in different colors. In is given an example of decoding of patterns of three states - blue indicating foraging, green travelling and red bedding (Figure 8 and Figure 9).



Pattern category: Wolfs - intermediate

Pattern name
Travelling
Feeding/Bedding
Foraging

Angle category: Angles - wolfs

Angle name	From	To
Forward	0	45
Turn	45	135
Backward	135	180

Distance category: Distances - wolfs

Distance name	From	To
Small distance	0	25
Medium distance	25	300
Large distance	300	

Figure 5. Defining HMM structure using prototype

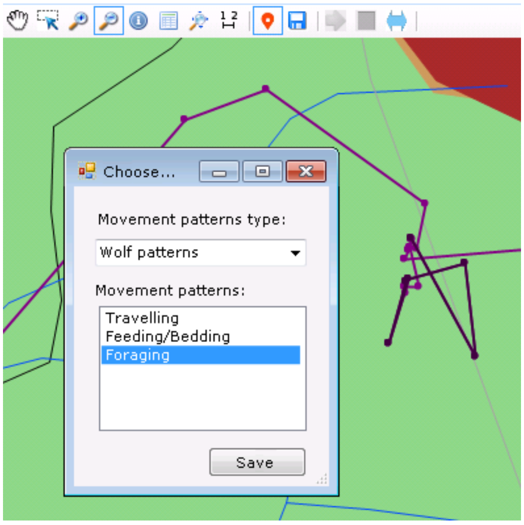


Figure 6. An example of marking parts of trajectories and matching to model states

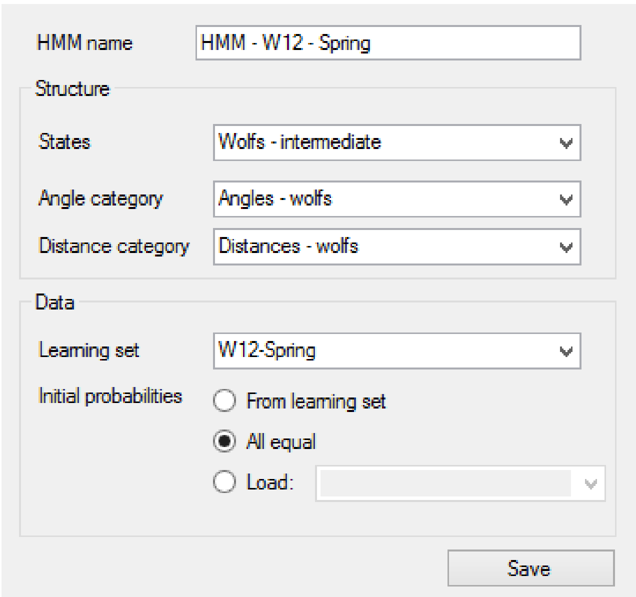


Figure 7. Choosing parameters to build HMM

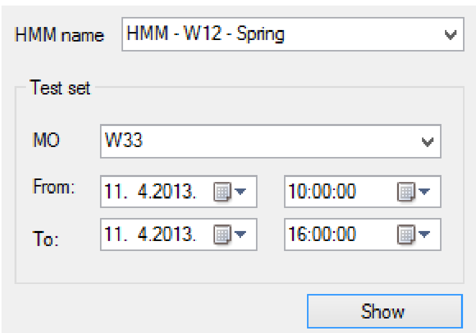


Figure 8. Choosing parameters to perform decoding of movement patterns

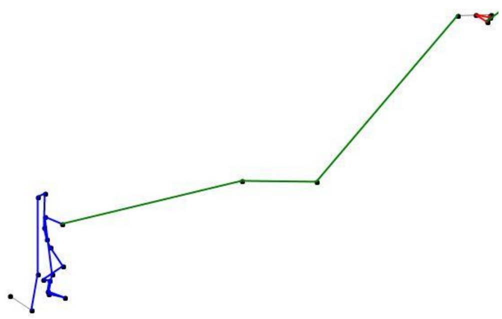


Figure 9. An example of decoding patterns

B. *Validation of the algorithm*

The algorithm is validated using the described prototype. It is validated on movements through two case studies: one case study of three wolfs and another of one bear in Croatia. Both wolfs' and bear's positions were measured every 15 minutes during several days in different periods of year. There are many missing positions according to which we segmented movement to trajectories. The movement patterns which learning sets and test sets of trajectories belong to are marked by an expert.

Case study of wolfs

Wolfs were chosen according to their differences in sex, age and social status. The following structure of HMM is chosen according to expert needs (common movement patterns are chosen) and to fit the patterns of wolf at intermediate spatio-temporal scale (set of used angles and distances is additionally shown in Figure 10):

$$S = \{foraging,\ bedding/feeding,\ travelling\}$$

$$V = \{(U_i, K_j): U_i \in \{0-25m, 25-300m, 300m+\},\ K_j \in \{0-45°, 45° - 135°, 135° - 180°\}\}$$

$$I = \{1/3,\ 1/3,\ 1/3\}$$

Matrices A and B are defined from learning set of 25 marked trajectories consisting of totally 277 segments - all belong to the movement of a female-wolf (W1) during the period from May 1st to 3rd. Since patterns of foraging, travelling and bedding/feeding are detectable from turning angles and speed (distances) of movement as described in II.B, they are recognized by HMM as well. As expected, the resulting matrix B (observational matrix) has high probabilities of observing:

- small travelled distances and medium or large turning angles ((U_1, K_2) and (U_1, K_3)) in foraging state
- small travelled distances and small or medium turning angles ((U_1, K_1) and (U_1, K_2)) in bedding/feeding state
- large travelled distances and small turning angles (U_3, K_1) in travelling state

The resulting matrix A (transition matrix) has higher probabilities of preserving the current state than switching to another state. That means that wolfs tend to stay in one pattern for certain period of time .

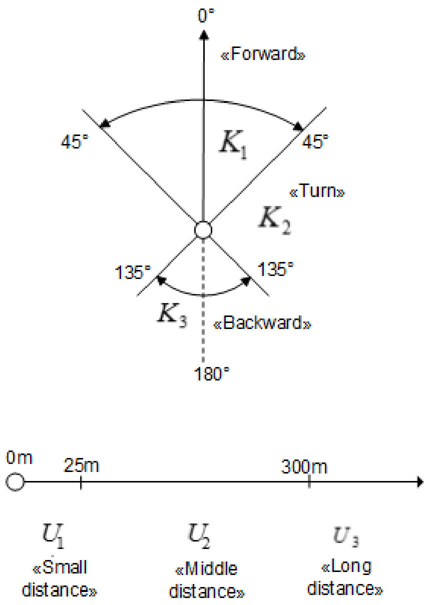


Figure 10. Set of angles and distances used in case study of wolfs

The accuracy of identification of patterns for movements of three wolfs in different periods of year is given in TABLE 1. The patterns of test datasets are not equally distributed, but no pattern is significantly different so it is not possible to priory identify certain pattern with high accuracy.

The accuracy of pattern prediction goes up to 94.02%. Accuracy is better for the movement of the same specimen (94.02% and 87.85% for W1 comparing to 85.71% for W2 and 73.37% for W3). It is also better for the movements in the same period of time as learning dataset (85.71% for W2 comparing to 73.37% for W3).

The results show that using HMM enables high accuracy discovery of movement patterns of wolfs. The possible further enhancement of the accuracy could be done by building different HMMs for different specimens and different periods of year.

Case study of bear

Unlike wolfs, bears are herbivores and their behavior patterns differ from the patterns of wolfs. The following structure of HMM for discovery of movement patterns of bears at intermediate scale:

$$S = \{feeding, resting, travelling\}$$

$$V = \{(U_i, K_j): U_i \in \{0-20m, 20-200m, 200m+\},\ K_j \in \{0-45°, 45° - 115°, 115° - 180°\}\}$$

$$I = \{1/3, 1/3, 1/3\}$$

The learning set consists of 54 trajectories with 1482 segments in total - all belonging to the movement of a male bear (B1) during the period from September 15th to October 1st.

As expected, the resulting matrix B has high probabilities of observing:

- medium travelled distances and medium or large turning angles ((U_2, K_2) and (U_2, K_3)) in feeding state
- small travelled distances and small turning angles (U_1, K_1) in resting state
- large travelled distances and small turning angles (U_3, K_1) in travelling state

The resulting matrix A has higher probabilities of preserving the current state than switching to another state.

The accuracy of identification of patterns for movements of the same bear for different periods of year is given in

TABLE 2. The accuracy of pattern prediction goes up to 82.14%. Again, the accuracy is better for the movement in the same period of time as learning dataset (82.14% comparing to 74.70% for the spring period).

TABLE 1 THE ACCURACY OF PATTERN PREDICTION FOR WOLFS

Trajectory period	**Specimen**	**Accuracy of predicting the pattern**	**Distribution of patterns in %** ***(foraging, bedding/feeding, travelling)***
04.05.-05.05.	W1	94.02%	(26.63, 54.34, 19.03)
06.09.-07.09.	W1	87.85%	(63.24, 13.52, 23.24)
01.05.-02.05.	W2	85.71%	(41.30, 41.30, 17.40)
05.12.-06.12.	W3	73.37%	(36.37, 33.68, 29.95)

TABLE 2 THE ACCURACY OF PATTERN PREDICTION FOR BEAR

Trajectory period	**Specimen**	**Accuracy of predicting the pattern**	**Distribution of patterns in %** ***(feeding, resting, travelling)***
02.10.-12.10.	B1	82.14%	(48,37,15)
15.04.-05.05.	B1	74.70%	(19,32,49)

V. Conclusion

Animal movement is complex and irregular and thus very hard to model. In order to build generic pattern discovery model for wild animals, we proposed Hidden Markov model for movement pattern discovery. The states of the model can be set arbitrary by an expert through the prototype we built. The prototype supports marking parts of trajectories and matching them to defined movement patterns and decoding of patterns using built model.

Two case studies show promising results: The accuracy of pattern prediction of common patterns goes up to 94.02% for wolfs (foraging, travelling and bedding/feeding) and up to 82.14% for bear movement (feeding, resting and travelling). The accuracy could be enhanced by building different HMMs for different specimens and different periods of year.

In the future work, we plan to use the contextual information about the terrain, climate etc. to improve detection of even more precise patterns as well as perform the experiments with other patterns.

Discovery of movement patterns can be useful not only to get better insight into the animal behavior, but to adapt the method of prediction of the animal next movement.

Although the method is developed to model the movement of wild animals, we believe that with some adjustments it could be used for other moving objects as well.

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References

[1] F. Cagnacci, L. Boitani, R.A. Powell, M.S. Boyce, Theme Issue 'Challenges and opportunities of using GPS-based location data in animal ecology' Introduction, Philos T R Soc B, 365 (2010) 2157-2162.

[2] J. Kusak, Đ. Huber, T. Gomerčić, G. Schwaderer, G. Gužvica, The permeability of highway in Gorski kotar (Croatia) for large mammals, European journal of Wildlife research, 55 (2009) 7-21.

[3] J.M. Fryxell, M. Hazell, ouml, L. rger, B.D. Dalziel, D.T. Haydon, J.M. Morales, T. McIntosh, R.C. Rosatte, Multiple movement modes by large herbivores at multiple spatiotemporal scales, Proceedings of the National Academy of Sciences of the United States of America, 105 (2008) 19114-19119.

[4] R. Nathan, W.M. Getz, E. Revilla, M. Holyoak, R. Kadmon, D. Saltz, P.E. Smouse, A movement ecology paradigm for unifying organismal movement research, Proceedings of the National Academy of Sciences of the United States of America, 105 (2008) 19052–19059.

[5] R. Joo, S. Bertrand, J. Tam, R. Fablet, Hidden Markov Models: The Best Models for Forager Movements?, PLoS ONE, 8 (2013) e71246.

[6] R. Langrock, R. King, J. Matthiopoulos, L. Thomas, D. Fortin, J.M. Morales, Flexible and practical modeling of animal telemetry data: hidden Markov models and extensions, Ecology, 93 (2012) 2336-2342.

[7] H. Jeung, H. Shen, X. Zhou, Mining Trajectory Patterns Using Hidden Markov Models, in: I. Song, J. Eder, T. Nguyen (Eds.) Data Warehousing and Knowledge Discovery, Springer Berlin / Heidelberg, 2007, pp. 470-480-480.

[8] Y. Ishikawa, Data Mining for Moving Object Databases, John Wiley & Sons, Inc., Hoboken, NJ, USA, 2010.

[9] J. Froehlich, J. Krumm, Route Prediction from Trip Observations, in: Society of Automotive Engineers (SAE) 2008 World Congress, 2008.

[10] I.D. Jonsen, R.A. Myers, J.M. Flemming, Meta-analysis of animal movement using state-space models, Ecology, 84 (2003) 3055-3063.

[11] N.F. Webb, M. Hebblewhite, E.H. Merrill, Statistical methods for identifying wolf kill sites using global positioning system locations, J Wildlife Manage, 72 (2008) 798-807.

[12] A. Franke, T. Caelli, G. Kuzyk, R.J. Hudson, Prediction of wolf (Canis lupus) kill-sites using hidden Markov models, Ecol Model, 197 (2006) 237-246.

[13] I.D. Jonsen, M. Basson, S. Bestley, M.V. Bravington, T.A. Patterson, M.W. Pedersen, R. Thomson, U.H. Thygesen, S.J. Wotherspoon, State-space models for bio-loggers: A methodological road map, Deep Sea Research Part II: Topical Studies in Oceanography, 88–89 (2013) 34-46.

[14] R. Choquet, C. Carrié, T. Chambert, T. Boulinier, Estimating transitions between states using measurements with imperfect detection: application to serological data, Ecology, 94 (2013) 2160-2165.

[15] B. Guc, M. May, Y. Saygin, C. Körner, Semantic Annotation of GPS Trajectories in: 11th AGILE International Conference on Geographic Information Science 2008, University of Girona, Spain, 2008.

[16] S. Spaccapietra, C. Parent, M. Damiani, J. Demacedo, F. Porto, C. Vangenot, A conceptual view on trajectories, Including Special Section: Privacy Aspects of Data Mining Workshop (2006) - Five invited and extended papers, 65 (2008) 126-146.

[17] L.O. Alvares, V. Bogorny, B. Kuijpers, J.A.F.d. Macedo, B. Moelans, A. Vaisman, A model for enriching trajectories with semantic geographical information, in: Proceedings of the 15th annual ACM international symposium on Advances in geographic information systems, ACM, Seattle, Washington, 2007, pp. 1-8.

[18] S.J. Russell, P. Norvig, Artificial Intelligence: A Modern Approach, Second ed., Pearson Education, 2003.

[19] L.R. Rabiner, A tutorial on Hidden Markov Models and selected applications in speech recognition, Proceedings of the IEEE, 77 (1989) 257–286.

[20] I. Nižetić, K. Fertalj, Automation of the Moving Objects Movement Prediction Process Independent of the Application Area, Computer Science and Information Systems, 7 (2010) 931-945.