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Towards Visualization of Generalized Mental Maps Representations

R.V. Chumakov[1], K.V. Ryabinin[2], K.I. Belousov[3]

Perm State University, Perm, Russia

[1] ORCID: 0000-0002-6860-1932, chumakoff.r.v@gmail.com
[2] ORCID: 0000-0002-8353-7641, kostya.ryabinin@gmail.com
[3] ORCID: 0000-0003-4447-1288, belousovki@gmail.com

Abstract

The paper is devoted to the visualization of generalized digital representations of mental maps. Digital mental map representations (DMMRs) are digital drawings of some certain spaces made by humans, reflecting their spatial experience and distinctive thoughts they have about the considered spatial places. Accordingly, DMMRs can be useful for identifying people's subjective perception of some space. If there are many DMMRs and their manual analysis is difficult, some generalized representation can be used, which can help identify general patterns or trends in the perception of space by informants.

In addition to the visualization itself, this article also describes some of the issues that arise in the process of creating a generalized representation of the DMMRs and suggests novel methods for solving these issues. However, the proposed solutions do not guarantee full objectivity; they are only an approximation attempt. The methods to assess and increase the approximation quality are the matter of future work.

In previous works, the Creative Maps Studio web application was developed to collect DMMRs. This application is also used in this work. However, now it was been enriched by an analytical module that allows performing various transformations of the DMMRs and related data. This analytical module is based on the concept of data flow visual programming. Particular data processing operators within this module are described by ontologies. This makes that module quite flexible and easy to use. With the help of this module, the visualization of the generalized map is implemented.

One more question considered in the paper is the process of data preparation and visualization. Suggestions are made for the interpretation of the results. The strengths and weaknesses of the proposed data processing and visualization methods are discussed.

Keywords: Mental Map, Digital Mental Map Representation, Mental Map Generalization, Mental Map Visualization.

1. Introduction

Almost every human has a rich spatial experience that is constantly developed while they live in a certain region. This experience summarizes the human spatial orientation skills, human perception and associations with particular places, and even human opinions about these places, including personal feelings, assessment of the quality of life, etc. Extracting and evaluating this experience is a promising yet challenging task within Digital Humanities research. To solve this task, different representations of so-called mental maps are used.

It is worth noting that the terms "representation of a mental map" and "mental map" are not well-established yet, so other authors may use different terms to denote these concepts, for example "mental map" (to refer to what is here called a "mental map representation") [1, 2], "cognitive map" [3], "sketch map" [4]. As a rule, it depends on the specifics of the scientific field and the preferences of the researchers.

For the sake of clarity and disambiguation, let us define the terminology to use hereafter. **Mental map** – a representation of a certain space in someone's mind, possibly in conjunction with some subjective representations of a non-spatial nature (if a person's map is being considered). **Mental map representation** – a reflection of a mental map on some material storage (for example, paper or computer memory). So, the **digital mental map representation (DMMR)** is a mental map representation, created and stored in a computer or another digital device. **Generalized mental map representation (or just generalized map)** – a data structure that stores information about the objects in mental maps representations from a certain set. **Generalized map visualization** – an interactive graphical representation of the generalized map in the form of a two-dimensional chart. In this paper, DMMR is used to compose a generalized map.

The methods of studying mental maps are strongly affected by the development of digital technologies. It became clear that the study of mental maps using digital technologies has a lot of advantages [5–8]. Some digital systems for working with representations of mental maps have appeared [6, 9, 10], including the Creative Maps Studio application (https://creativemaps.studio), which has been developed to allow creating digital representations of mental maps. More than 900 maps from 12 regions of Russia were collected by using this application. In order to analyze the general perception of the country by the residents of each region, an analytical module was developed within Creative Maps Studio. One of the operators of this analytical module is a generalized map visualization operator (GMV). Generalized map consists of a set of maps drawn by the residents of a certain region. GMV is the subject of this paper.

In addition to describing the operation of the GMV itself, its input and output data as well as some theoretical issues of map data processing are discussed. Several interpretations of the output data are proposed along with the discussion of pros and cons of using the GMV rendering results. Assumptions are made about possible future works.

2. Key Contributions

New analytical features are introduced to the previously developed Creative Maps Studio vector graphics editor:

1. The ability to automatically visualize a set of mental maps representations (generalized map rendering).
2. The ability to view the coordinates dispersion of objects within the generalized map and compare the frequencies of occurrence of any objects on maps (with a possibility to choose which objects will be displayed).

3. Related Work

Hypotheses about the existence of mental maps are suggested not only in relation to people, but also in relation to animals. Since there are no known cases of animals drawing representations of mental maps, as a rule, their mental maps are studied indirectly. Only assumptions can be made about how mental maps are arranged (if their existence is taken for granted) based on how animals act in space. A pioneering work in this field is [3] followed by [11, 12]. In these works, statistics are usually collected on the actions of animals and the frequency of actions that more or less contribute to the achievement of the estimated goal (usually, the foraging).

As for people, here a wider range of research tools is available. A person can be asked to draw something or fill out a survey. In the present work, we concentrate on the map drawings as a natural way to represent mental maps.

Informants can draw on ready-made maps, marking features, which are important for them [7]. They can draw maps on their own from scratch, both on paper [4, 13, 14] and on digital devices [8]. Accordingly, generalized analysis can also be carried out in traditional form [13, 15] or in digital form [6, 8]. In the latter case, as a rule, the researcher manually draws up a generalized map visualization. In other words, a qualitative assessment takes place [13, 14]. Quantitative assessment is also used, but it usually involves some expert manual steps [6].

At the same time, it is important to note that mental map representations are sustained reflections of information from the real world, albeit this information is modified by human perception [4, 16]. So, the study of representations of mental maps is considered relevant to Digital Humanities research.

4. Background

The mental map representations used in this work as a data source are collected in digital format using the Creative Maps Studio application developed earlier [10]. The analytical module (the GMV is a part of) is built using the ontology engineering principles and data flow programming paradigm. This approach was first introduced in the SciVi ontology-driven visual analytics platform and proved its efficiency in solving real-world visual analytics tasks from different application domains [17]. The analytical pipeline is being described as a data flow diagram – a chain of operators linked by data. Each operator has its certain typed inputs, outputs, settings, and implementation described by a lightweight ontology using predefined concepts like "Operator", "Input", "Output", "Setting", "Worker", etc., and paradigmal relations "is_a", "a_part_of", "has", and "is_instance". This allows defining the analytical capabilities in a knowledge base, and thereby easily extending the module's palette of operators without manual changes of its source code.

The idea of generalized visualization of mental map representations was already discussed in [18]. In that work, maps were collected in the traditional paper form, and the visualization of the generalized map was built manually. To do this, the researcher looked at maps, selected the most frequently drawn settlements, calculated the dispersion and median values, and drew these data in the form of a diagram (an example of a diagram from [18] is shown in Figure 1). However, with the advent of digital technology, it became clear that the process of calculating the generalized map can be automated. Moreover, more information can be extracted from digital maps. Therefore, we decided to develop an analytical module in the Creative Maps Studio, in which it would be possible, among other things, to visualize generalized map.

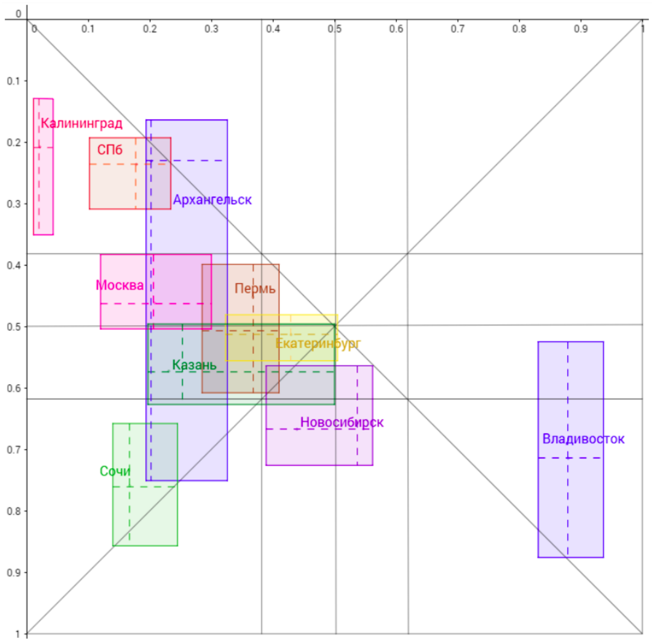

Fig. 1. Generalized map visualization diagram from [18]

5. Theoretical Issues of Digital Mental Map Representations Analysis

5.1. Mapping of Real Objects to Digital Mental Map Representation

People's ideas about space are very vague, so the first issue that a researcher may face is to understand what tools to use for the most complete and accurate reflection of the mental map. The usage of DMMR makes it possible to create some ready-made generalized images of objects that informants may want to draw. Appleyard [13] proposed a classification of the types of mental map representations on paper. Looking at these types, it can be figured out what kind of graphical primitives the informants may need. Our study proposes three types of objects that an informant can place on a map: a contour object, a point object, and a filled closed curve. In this case, the digital graphics editor offers the informant a set of specific objects of each of these three types, representing some generalized images of real objects.

When informants draw maps, they usually use more or less primitive labels and colorings for their objects. This can be seen by looking at examples of maps studied by various researchers [1, 2, 4, 8, 13, 14].

Accordingly, the interpretation of such objects is usually carried out mainly due to the presence of explanatory labels near the objects. The DMMR allows us to improve images of objects themselves to make them more specific. Of course, it may turn out that the desired object does not exist, then the informant can use something more abstract to represent the object.

The specific set of objects depends on what kind of space the informants draw. In our study, the informants draw a map of Russia; accordingly, the set of objects represents the main objects, which can be marked on national maps. The set of objects can be viewed here (the panel at the top of the application page): https://creativemaps.studio/. Note that for maps of a different scale, it may be necessary not only to use other generalized images of objects, but also, possibly, fundamentally new types of such images. For example, to depict roads or rivers on maps of urban space, it may be convenient to use a closed polyline or curve (which can be filled with specified color).

When informants draw maps, they may represent the same object in different ways. Accordingly, the object will be represented on different maps in different forms and with different names. These differences can be divided into several groups.

The first group includes differences in the graphical representation of the object. Informants can choose different default objects from those available for the image of the same real object, or, if the object is large, its shape can be very diverse for different informants. For example, for the image of the city, the object "Town", the object "City" or the contour denoting the bounds of the city can be used (an example is in Figure 2). Therefore, when automatically processing the DMMR, it should be kept in mind that diverse default objects can be used to display the same real object.

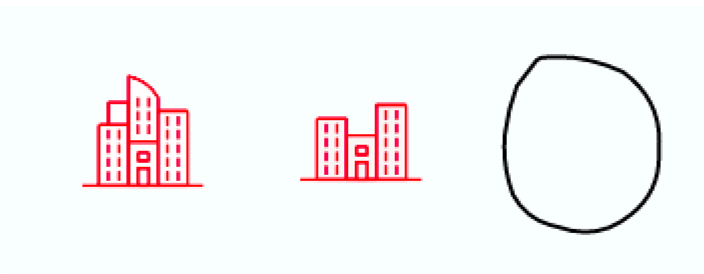

Fig. 2. An example of default objects set that can be used to depict a city

The second group of differences is varying names for the same object. The informant may not know the correct spelling of the name, or may use an abbreviation or an informal but familiar name. For example: the "Екатеринбург" (Yekaterinburg) city can be called

“Екатиринбург” (accidental spelling error) or “Екб” (common unofficial abbreviation). In this case, it may be useful to prepare a dictionary in advance, which will record which real objects with which names can be found on maps. In this study, such a dictionary is compiled manually. Automation of this dictionary composing is a non-trivial task that requires advanced artificial intelligence. This may be a subject of future works.

The third group of differences is the possible ambiguity in the definition of an object by its name. This case can be divided into two parts. Firstly, there are objects, which have the same name (or an option of the name), while being in different places. For example, small settlements, such as villages, often have typical names and can occur dozens of times in different regions of the country. Secondly, objects can be different in nature but have the same name. For example, there are a lot of cities, which share their names with rivers. The first case is difficult to process automatically, so our study uses manual processing for that. The second case can be automatically handled by dividing all objects by type. That is, objects of the “river” type cannot be checked when searching for a specific city, and vice versa.

The fourth group of differences is represented by unknown objects. These are objects, which were not named by the informant. And looking at those objects, it is impossible to unequivocally conclude whether they are reflections of any real objects or not. For example, a city is marked on the map, but it is not described in any way. Such an object can be interpreted in different ways. Maybe this is a specific city that the informant noted but did not name. But also, it may be that the informant meant that there is probably a city in this place, but he did not know which one.

Based on this, it is obvious that fully automatic processing of DMMR is not yet possible. In some cases, expert participation in map processing is required. However, the achieved level of automatization still removes a lot of routine work from the researcher.

5.2. Composing the Generalized Object from Objects Set of Digital Mental Map Representations

Each DMMR contains a set of objects as imagined by the informant. Each generalized object of a generalized map can be assembled from the corresponding objects of each of the DMMR in different ways, as described below.

Firstly, it is possible to assemble a generalized object using the most frequent parameter values that are found on specific DMMRs. This will give us an approximation of the “typical” map drawn by the “average” informant. On the one hand, this is convenient from the point of view of identifying a typical DMMR. But on the other hand, this approach does not consider the less frequent values of the object parameters, so the information on the generalized map may be incomplete.

Secondly, generalized objects can be assembled using the weighted averages of the parameters. This approach is better than the first one because it considers all parameter values, but at the same time it gives a slightly different result. The generalized map will show the average values and they may not look like the most popular ones. This approach, like the previous one, reflects well the values for those parameters, which are represented by single numbers. For example, the size of a point object. However, this approach works worse for those parameters, which are represented by vectors, for example, for coordinates or color (decomposed into channels). This is due to the fact that in weighted averaging, the parameters are considered separately. And the resulting joined value may not actually appear on the source maps at all.

A value that is not found on the DMMRs can also be obtained for a parameter represented by a single number. This situation can arise if the distribution of the parameter value has more than one local frequency maximum. However, the occurrence of several distribution peaks in different places rather indicates that the informants are incorrectly grouped and there is no meaningful generalized map for them. Perhaps the group is too large and it should be further divided according to some attribute. Therefore, this shortcoming was rated as having little effect.

For some parameters, the best way to generalize them is to display all possible values simultaneously (in a form of a grid or a diagram), but this can negatively affect the cognitive clarity of the generalized map cluttering up its visual representation.

5.3. Representation of Generalized map

The visual representation of the generalized DMMR is an issue that deserves attention. In many ways, this issue is related to the previous one, since the main difficulty of visualization is that, on the one hand, it is necessary to display as much information as possible, and on the other hand, the clarity of image can sink due to excessive information. Therefore, it is necessary to find the best option for each visualization element.

It makes sense to visualize the parameters of the DMMR objects in different ways, since they represent fundamentally different properties of the objects.

If two-dimensional space is used to create a visualization, then for coordinates, it is convenient to visualize not only a generalized value, but also the entire range.

If we consider the color of objects, then it is advisable to schematically represent the object itself and its label, coloring them in a generalized color. Regarding the object type, different informants can choose different pictures of the same real geographical object, so it is relevant to choose something neutral to depict a generalized object (for example, use just a circle to represent a settlement, and not an icon, as Creative Maps Studio allows using different icons for settlements, see Figure 2). As for the color, it can be generalized by averaging the RGB components. It may be not the best solution, as RGB space is non-linear by its nature, but accruing to our experiments the averaging gives satisfactory results. Improving the color generalization may be a matter of further studies.

Differences in size are also conveniently reflected in the sizes of generic objects. However, the sketchiness of the generic object also affects the size of the generalized object. Since, for example, it is difficult to draw a generalized curve, we can simply bound the area, where the curves are usually found, with a rectangle.

Informants who participated in this study rarely used the transparency parameter for objects, so transparency for generalized objects can be used to visualize another parameter. It is quite intuitive to reflect the importance of the object by its transparency. Therefore, it is convenient to use transparency to reflect the frequency of the presence of an object on the DMMR (the more often an object is present, the less transparent it is).

Informants draw objects at different times. One possible way to show sequence on a generalized map is to place objects on different planes (using so-called z-order). This is a logical solution, but it has a drawback: the z-order of arbitrary objects is difficult to compare if they do not intersect on a two-dimensional projection. Therefore, the sequence of drawing objects is better reflected by numbers indicating the minute from the beginning of the map drawing, in which the object was drawn on average (assuming the drawing process is sampled at the minute scale).

Summarizing the assumptions above, we can conclude that the various parameters of objects have their own peculiarities and the right approach should be found to visualize each of them.

6. Data Format

Since the DMMR is based on vector graphics, its internal format is textual. Listing 1 shows a format for the DMMR. It has two parts: the final state and the history of actions. The action history is used to load the map into the application and to analyze the map drawing sequence. The final state is cached for analytical purposes to avoid excessive calculations related to traversing the history and dynamically inferring the final state. An example of a loaded map is shown in Figure 3.

Listing 1. Suggested format of the DMMR

```
{
    "figures":{
        "c0405a2b-584b-4af8-b0f4-fb12fee2b2da":{"x": 234, "y": 83, …, "path": "M 61,76 Q 37,78 237,0 Q 300.5,61 214,178 Q 0,206 50,190 Q 43.5,186 39,190 L 61,76", …},
        …
    },
    "actionHistory":[
        {"type":"addPolygon", "x":131, "y":93, "points":"M 61,76 Q 37,78 237,0 Q 300.5,61 214,178 Q 0,206 50,190 Q 43.5,186 39,190 L 61,76", "time":11635, …},
        {"uuid":"c0405a2b-584b-4af8-b0f4-fb12fee2b2da", "type":"moveFigure", "time":27660, "x":234, "y":83},
        …
    ],
    "mapName":"Нижняя каменка",
    …
}
```

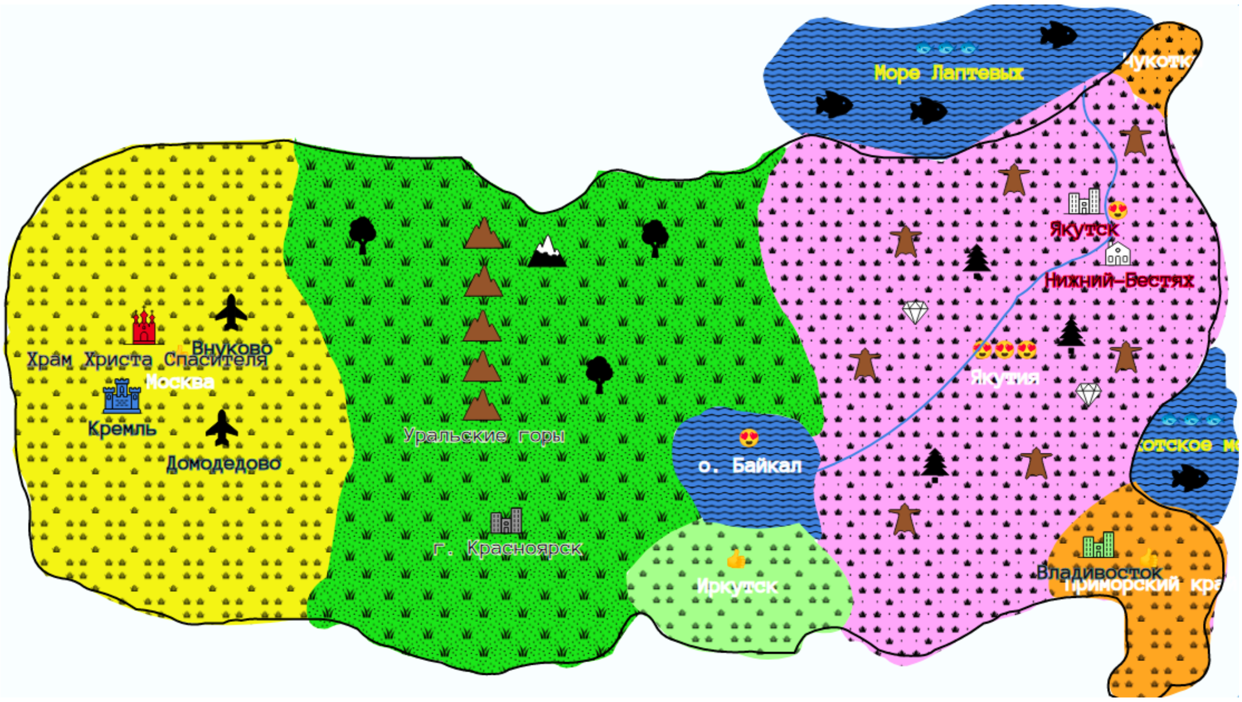

Fig. 3. An example of DMMR loaded in Creative Maps Studio

To build a generalized map, an analytical module is used, described in the next section. A generalized map format is shown in Listing 2. In fact, the generalized map contains a list of corresponding map objects split by category. Each object stores the frequency of its presence on the maps and a list of corresponding parameters. Each parameter contains a frequency distribution of its values.

Listing 2. Suggested format of a generalized map

```
{
    "Mountains": {
        "Ural mountains": {
            "frequency": 0.44,
            "params_distribution": {
                "colorB": {
                    "0": 1,
                    "40": 2,
                    "60": 1,
                    …
                },
                …
            },
            …
        },
    },
    …
}
```

7. Analytical Module of Creative Maps Studio

At the moment, an analytical module is being implemented in Creative Maps Studio, based on the visual data flow programming concept. Generally speaking, this analytical module contains not only the visualization algorithm presented below, but also other algorithms, however they are not considered here laying beyond the scope of the present work.

The point of creating a visual programming system directly in the Creative Maps Studio is that it allows you not to send large input data over the network to other software (for example, to the SciVi platform [19]), and also makes it possible to use algorithms and software operators, which are implemented using the React framework. React is a frontend framework that uses so-called components, which, unlike regular JavaScript, allow easy incorporating of HTML elements and provide state management routines to simplify the building of graphical user interfaces.

Figure 4 shows a data flow diagram that describes a step-by-step transformation of a set of source maps into a generalized map and a visualization of this generalized map. Each operator performs some data transformation algorithm. The inputs and outputs indicate the types of data, which must be submitted to the input, and which will be returned as a result of the algorithm. The “Data Source” operator has no inputs and is designed to download data from a server or local computer. As can be seen in the diagram, the processing is as follows. First, the list of maps is loaded (the data format `List[m]` denotes a list of maps) parallel to the loading of the objects’ names dictionary (the data format `mpng-usn` denotes a mapping of the users’ names of objects to the official ones). After that, the data is loaded and processed by the “Map Generalizer” operator. The operator removes all unnecessary data, combines all the necessary information into one data structure and returns it in the gm format (Generalized Map, see Listing 2). After that, data are passed to the "Generalized Map Visualizer" that renders a visualization result.

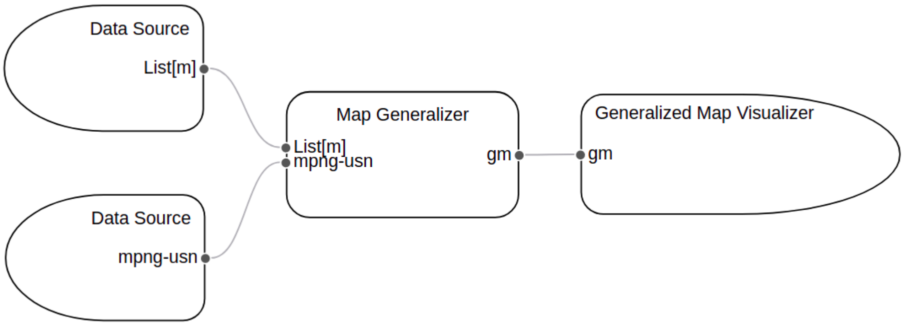

Fig. 4. Data flow diagram for generalized map visualization

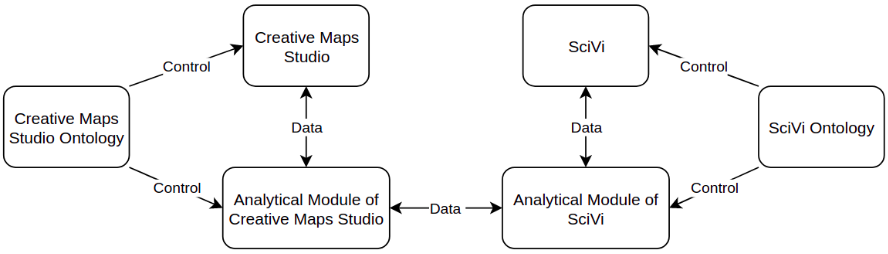

Fig. 5. Scheme of the proposed interaction, based on the API of the Creative Maps Studio and SciVi

As future work, we plan to set up the interaction of the SciVi and Creative Maps Studio systems in terms of data exchange via API (remote procedure call). This will allow using the data processing and visualization algorithms of both systems together without duplicating the code (see the diagram in Figure 5). The generalized map visualization algorithm is implemented as one of the software operators inside the analytical module and is executed on the Creative Maps Studio client.

8. Generalized Map Visualization

An example of a generalized map is shown in Figure 6. The generalized map displays the average values of various parameters of objects that were found on the maps this generalized map was built upon. The circles represent the settlements. The little squares represent the mountains and mountain-like objects (such as volcanoes). The big rectangular areas represent the seas, lakes, islands, and other big objects. The size of each figure reflects the weighted average size of the corresponding object on the maps. The color of each figure (except for the alpha channel) reflects the weighted average color of the corresponding object. The color and the size of the label near each figure reflects the weighted average of the corresponding properties of the corresponding map labels. The number after the label in parenthesis shows the time in which the corresponding object is drawn on the map. That is, for example, in the illustration below, the informants draw the settlement “Мурманск” (Murmansk) on average earlier than the sea “Море Лаптевых” (Laptev Sea), but later than the peninsula “Камчатка” (Kamchatka). The alpha channel reflects the frequency of occurrence of the corresponding object on the maps (in addition, the quantitative value of the frequency is indicated as a percentage placed in or near the corresponding figure). The greater the transparency, the rarer the object occurs, and vice versa (at a minimum frequency, transparency takes on a value of 20%). The frequency of the opaquest object at the moment is displayed in the upper right corner (in Figure 6 it is 48%).

It is also possible to display only one object category. Example is shown in Figure 7 (settlements only are shown). There is a possibility to display coordinate spreads for figures. However, it is more convenient to do this when there are few figures on the generalized map visualization. Figure 8 shows an example of manual filtering of objects on the map with display of coordinate spreads (the “Show dispersion of coordinates” option is set). It can be noticed that the maximum frequency among the displayed objects is 52%, while the most frequent object displayed is “Якутск” (Yakutsk). And it can be seen how precisely the informants represent the positions of the objects (the most precise result here is for the settlement “Калининград” (Kaliningrad), because it has the smallest spread).

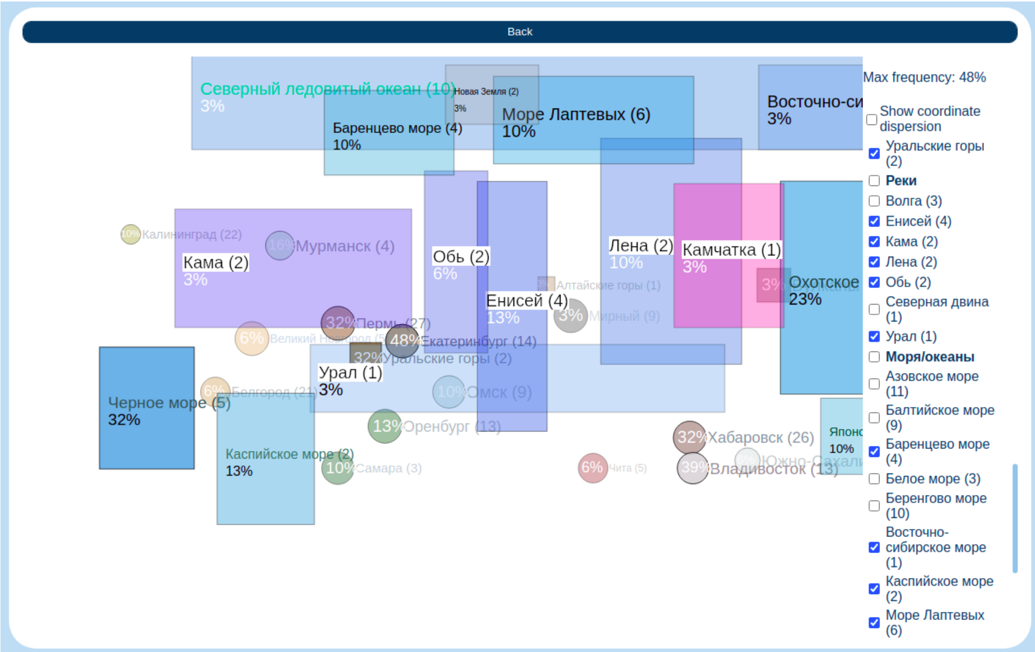

Fig. 6. Example of a generalized map visualization

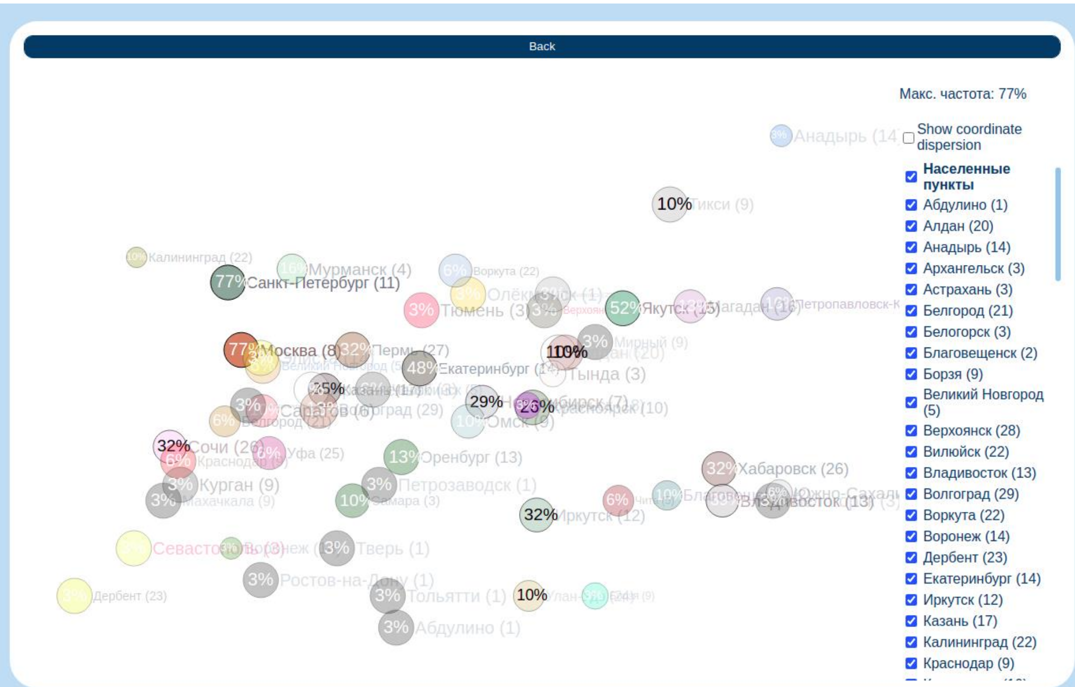

Fig. 7. Example of particular visualization of a generalized map (settlements only are shown)

Fig. 8. Example of particular visualization of a generalized map (manual filtering is applied and “Show coordinate dispersion” option is switched on)

9. Results Interpretation

The visualization of the generalized map makes it possible to obtain some aggregated information about the informants’ collective ideas about the object of study. In particular, firstly, looking at the map, we can find out which objects are in the center of attention of the informants and how they approximately appear (although the visualization of the generalized map provides much more scarce information regarding the image of the object (color, size, etc.) than if the text layer of the maps were analyzed). Secondly, we can compare the frequency of drawing an arbitrary group of objects on the maps (marking them in the column on the right of the graphical user interface shown in Figures 6–8). Thirdly, it is possible to obtain information about the positioning of objects: how uniform is the opinion of informants about the location of a certain object. Fourthly, information about the approximate order in which objects are drawn on maps can be obtained.

Also, in some cases, it is possible to determine the region of residence of the majority of informants from the sample. This is possible due to the fact that informants more often mark the capital and other objects from their own region, than from the foreign regions. The exceptions are the cities of “Москва” (Moscow) and “Санкт-Петербург” (St. Petersburg) and some other popular objects, such as lake “Байкал” (Baikal), which are often marked on the map, regardless of the region of residence of the informants, since they are very famous in Russia. However, according to our experience, this exception does not significantly affect the definition of the informant’ region of residence.

10. Conclusion

In conclusion, it can be said that automating the processing of map data (in this case, generalized map rendering) has some advantages. First, graphical display of a generalized map can help to generate or test hypotheses faster than having only a set of maps, which can be viewed separately from each other, or some textual data, which describe this generalized map. Secondly, it allows us not to waste time on some routine operations with maps. For example, some quantitative calculations and comparisons of maps can be done automatically, since maps have a well-defined digital format.

Of course, the proposed approach also has its drawbacks. First, expert input is needed in the early stages of preparing maps. The researcher needs to determine how to recognize whether an object is a populated area or not. To do this, it is necessary to compile a dictionary of objects' names, including in it, in addition to the official names of objects, also informal names, which informants may use to designate these objects. Of course, the more maps are processed, the less such participation is required in the future (new maps will contain less and less new objects' names), since for any object the set of its possible names is quite limited. Secondly, as mentioned earlier, there is an ambiguity problem for many rivers and small settlements, such as villages, and a few large ones, for example, the cities of "Ростов" (Rostov) and "Ростов-на-Дону" (Rostov-on-Don) (both can be called "Ростов"), "Великий Новгород" (Veliky Novgorod) and "Нижний Новгород" (Nizhny Novgorod) (both can be called "Новгород"), etc. Nevertheless, the visualization of the generalized map seems to be appropriate and quite informative.

11. Future Work

There are several directions for further research development. First, we plan to compare the visualized map with the real geographic objects (in different projections) to get information about the accuracy of the positioning of the objects relative to their real position. It is likely that for many objects there will be a regular shift. Saarinen mentioned this phenomenon in [14]. Moreover, there are quite a lot of works in the field of comparing representations of mental maps with GIS (for example, Curtis et al. composed a review of similar works in [5]).

Secondly, it is possible to improve the color representation of objects. The weighted average of the color can be replaced with a pie chart because it can give more relevant information about the colors used by informants.

Perhaps generalized map visualization can be useful not only for the analysis of mental map representations. Despite the fact that it is not yet known whether there are data of a similar format in other scientific fields, it is considered appropriate to organize API interaction with the SciVi visualization system so that, if necessary, it would be possible to reuse the created visualization operator in other application domains.

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