ViSiElse: An innovative visualization R package to ensure behavioral raw data reliability and transparency

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Background. In recent years, the scientific community encouraged the use of raw data graphs to improve the reliability and transparency of the results presented in papers. However, methods to visualize raw data are limited to one variable per graph and/or only small sample representation. In behavioral science as in many other fields, multiple variables need to be plotted together to allow insights of a behavior and/or process observations. In this paper, we present ViSiElse, a R-package that offers a new approach in raw data visualization.

Methods. This visualization tool was developed as a package of the open-source software R to provide a solution to both the lack of tools allowing visual insights of a whole dataset and the lack of innovative tools for raw data transparency.

Results. ViSiElse grants a global overview of a process by combining the visualization of multiple actions timestamps and all participants in a single graph. Individuals and/or group behavior can easily be assessed and supplementary features allow users to further inspect their data by adding statistical indicators and/or time constraints. ViSiElse allows a global visualization of actions, acquired from timestamps in any quantifiable observations.

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Abstract

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Introduction

Behavioral science focuses on the development of behavioral knowledge through experimental observations from diverse fields including psychology, cognitive science, social neuroscience, etc. where behavior can be regarded as any action of an organism that changes its relationship to its environment (Gramma & Paladi, 2011). Behavior can be defined as a series of actions realized by individuals and is thus person dependent. Methods allowing both a global visualization and an individual perspective of the process aim to maximize its initial comprehension.

In healthcare, many studies have shown the importance of individual and group behavior training to improve the quality of medical care (Becker, 2009; Marshall & Manus, 2007; McCulloch et al., 2009; Rosenstein & O'Daniel, 2008). Behavioral training mediated by simulation in healthcare is becoming an essential part of the medical education to avoid errors and give optimal care to the patients without any associated risk due to the learning process (Brewin et al., 2015; Kalaniti & Campbell, 2015; Ziv, Wolpe, Small, & Glick, 2006).

However, it is first necessary to explore behavioral data in order to comprehend and learn what the right behavior is and grant an adequate behavioral training. The right behavior is the series of actions leading to the achievement of a goal like the successful completion of a defined process. Raw behavioral data stored in large raw tables are difficult to interpret as the amount of data covers the useful overall information. In addition, the direct interpretation from raw data tables requires efforts and mental gymnastics. Graphic representations are, on the contrary, effortless, instantaneous and easy to understand. Plotting data should be a routine in the analyzing process and is mandatory in research but tools to visualize raw data are limited.

Scientific community recently pointed out the value of raw data presentation in publications (Fosang & Colbran, 2015; Prager et al., 2018; Rousselet, Foxe, & Bolam, 2016) and demonstrated how graphic methods that summarize data can be misleading and even suggest different conclusions from the reality of the data distribution (Weissgerber, Milic, Winham, & Garovic, 2015).

With the growing idea of open science, investigators are now encouraged to transparency, and plotting raw data not only increases clarity but also makes results more understandable and more reliable. Recommendations include choosing the relevant plot according to the data and favoring graphics that present all of the data as well as their structure like scatter plots, violin plot, beeswarm or pirate plot over graphics that only present a summary such as bar plots or line plots (Hertel, 2018; Larson-Hall, 2017; Pastore, Lionetti, & Altoè, 2017). Allen et al. (Allen, Poggiali, Whitaker, Marshall, & Kievit, 2018) introduced raincloud plots, an easy to use multi-platform tool that combines visual representations to provide complete overview of the data and make robust and transparent plots. Other researchers turned to interactive visualization (Ellis & Merdian, 2015; Goedhart, 2018; Weissgerber et al., 2017), letting readers explore the dataset with customizable graphs and additional features for statistical indicators and plotting options. All of those solutions successfully answered the need for reliability and transparency in publications but the visualization of raw data is limited to one variable per graph and/or small samples. To our knowledge, none proposed an innovative raw data visualization tool that could integrate an overview of an entire process including multiple variables while representing all individuals in a single graph.

To answer the limitation of visualization tools, we propose ViSiElse (Garnier, Fouret, & Descoins, 2018). ViSiElse is a package developed with the statistical programming language R (R Core Team, 2018) and is available at https://github.com/CEPOI/ViSiElse. ViSiElse is a graphical tool created to visualize and to provide a global insight of individuals and/or group actions defining behavior. ViSiElse allows visualization of raw data extracted from any experimental observations involving action timestamps regardless of the research filed (behavioral sciences, neuroscience, psychology…). For example, behavior can be analyzed during the realization of a procedure like a medical algorithm. Options for the package include complementary graphical information as statistical indicators (mean, standard deviation, quartiles or statistical tests) but also, for each action, green or black zones providing visual information about the accuracy of the realized actions. ViSiElse offers a new solution for data reliability and transparency with the visualization of a complete raw dataset in a single graph.

In this paper, we provide a step-by-step presentation of ViSiElse main features. We describe how to set up data in order to create a ViSiElse plot, how to custom this plot to get a clear view of the individuals' actions, and how to add time limits or statistical indicators. At each step, the orotracheal intubation technique used in the neonatal resuscitation algorithm serves as an illustrative example. The online supplementary material contains complete data, and R code to reproduce the following presented results (https://github.com/CEPOI/ViSiElse/tree/master/Example).

Methods

Before exploring all ViSiElse's features, the first step in the package's routine is to define the process of the observed behavior, build the dataset and then create an R object, the ViSibook.

Defining the process of actions: the dataset and ViSibook objects

To build the dataset correctly, researchers have to a priori defined or translate a procedure like a healthcare algorithm, into a linear process of actions. To define the process three elements must be defined: first the list of actions, then their type, and finally, their order. The fundamental question to answer is: “What are the elementary actions composing the procedure?”. Elementary action is an action that cannot be divided into shorter actions regarding of the time scale. Our explanatory model is endotracheal intubation (EI) which is the process of inserting a tube through the mouth and then into the airway. By restoring airway patency, EI is a lifesaving procedure and it has to be readily available to all patients whose ventilation is compromised in emergency or anesthesia context.

Endotracheal intubation consists of six elementary actions:

1- Decide to intubate the patient
2- Stop a mask ventilation
3- Insert the laryngoscope blade in the patient’s mouth
4- Insert the endotracheal tube
5- Remove the laryngoscope blade out of the patient’s mouth
6- Restart to ventilate the patient through the tube.

Once the list of elementary action is established, they should be classified as punctual or long. A punctual action is an action with no duration, or not lasting long enough to be measured, or not lasting long enough compared to the time scale of the studied behavior. A long action is an action having duration defined by two punctual actions, one for its beginning, and one for its ending. In the intubation example, the six elementary actions are punctual (actions 1 to 6). Additionally, two long actions can be defined:

7- The duration of the laryngoscope use delimited by the insertion and removal of the laryngoscope blade
8- The total duration of the intubation process delimited by the stop and restart of the ventilation of the patient.

Finally, to have a linear process of actions plotted, they should be chronologically sorted and numbered. If two actions are supposed to happen simultaneously, we suggest taking an arbitrary choice for their order. Not attributing a rank in the process order is only allowed—and useful—when the interest of a punctual action is purely to define a long one.

From raw data to datasets. Raw data correspond to the completion times of all the actions for each individual or group of individuals. The dataset is the organized raw data. The first column of the dataset identifies individuals. Other columns represent actions. Lines contain individuals' raw data (without any calculation). The intubation dataset (ViSiElse_intubation_data.csv) is available online at https://github.com/CEPOI/ViSiElse/tree/master/Example as an example of how data should be structured to run the visielse function. This dataset is a subset of the data collected from the SIMULRUN 1 project (POE FEDER number RE0001879) investigating the neonatal resuscitation training of midwifes using high-fidelity simulation. All participants gave written informed consent to participate in the study. The study was performed according to the guidelines of the Declaration of Helsinki.

Building the ViSibook. While the dataset contains the raw data of the studied behavior, the ViSibook contains the structure of the behavioral process. Mainly, it is a table consisting of the definition of every action. The minimum structure for a ViSibook must give for each action its name, its label, its type (punctual or long), its order in the behavioral process, and for long actions only, the name of the two punctual actions that define the beginning and the end of the long one. In addition, the ViSibook can include time constraints (green and/or black zones) which provide visual information about the accuracy of the realized actions. To create a ViSibook, users can define or import a table as long as they carefully keep the names and the order of the ViSibook's columns (see ViSiElse CRAN documentation). The ViSibook is an optional argument of the main function "visielse". "visielse" function generates a ViSiElse graph of the studied behavior, according to the dataset and the ViSibook. When it is not manually specified, "visielse" computes a default ViSibook from the dataset assuming the process order is given by the dataset column names. At any time, the ViSibook can be extracted from an execution of the "visielse" function, allowing modifications of all information saved in the table in order to adjust the plotted process. For example, ViSiElse uses the labels of the actions in the ViSibook as the y-axis title on the graph. By default, labels in ViSibook are the variable names defined by the dataset column names. Usually, variable names are a single short word lacking precision to describe an action, therefore it is often preferred to use a more explicit description as labels in an output. Through the ViSibook, users can change the action labels to improve clarity in the graph.

Visualize Time Raw Data With ViSiElse

ViSiElse gives, in a one-page single graph, an overview of the distribution of the timestamps of the actions sequence of all the individuals of the study. This innovative visualization facilitates the comprehension of individuals and/or groups behavior based on the profile of the data distribution. A major asset of ViSiElse is the ease of the identification of outliers or abnormal behaviors, i.e. a behavior not complying with good practice recommendations.

Creating the first plot. Simply running the "visielse" function with a dataset and an optional ViSibook as arguments will create and plot the ViSiElse graph. Fig 1 shows the EI process performed by 37 individuals during neonatal resuscitation training. Actions are organized on the graphic one under the other and their executions are distributed along the time axis. For punctual actions, a drawn rectangle means that at least one individual has done the action in an interval of time. The color's intensity of the plot rectangles is proportional to the number of individuals who realized the action during the time interval. For long actions, individuals are represented by lines which sizes are proportional to the duration of the action. Lines are chronologically sorted by the action start time.

To access and adjust the formatting options for the graph, the ViSiElse object should be plotted using the R basic "plot" function. Formatting options include many properties like changing the label's size and color, adding a title or modifying the time interval size and unit—set to 10 seconds by default. Modifying the time interval size through the plot function, "scal.unit.tps" parameter, will only change the divisions of the time axis and not the size of the time interval used to calculate the color's intensity of the punctual actions. Every formatting option is accessible through the "plot" function while the entire package features (group comparison, time constrains, statistical indicators) must be defined in the "visielse" function.

Adjusting the time interval with the pixel parameter. For punctual actions, the "pixel" parameter represents the time precision i.e. the time limit to which one subject is moved from a time interval to another. The default pixel size corresponds to 20 seconds but the value can be adapted to match the time variation of the observed data with a minimum value of 1 pixel. If users run the "plot" function on a ViSiElse object, they should verify that the time interval used in the formatting option ("scal.unit.tps" parameter) of the plot is the same—or at least inferior—as the time interval defined with the pixel parameter in the ViSiElse object. Indeed, the "plot" function changes the formatting option of the ViSiElse graph so the two parameters should be coherent. As data are aggregated into the time intervals, if the parameter pixel is too small, the plotted information will not be enough aggregated to allow interpretation as in Fig 2.A where most subjects are in different intervals. If the parameter pixel is too large, the plotted information will be too much aggregated to allow interpretation; all the subjects will be compressed in one unique pixel as in Fig 2.B where subjects are compressed in four intervals.

Apprehend Behavioral Raw Time Data With ViSiElse

ViSiElse offers many features to analyze behavioral raw time data. For example, users may define groups, time constraints or statistical indicators to complete their graph. ViSiElse provides both raw data inspection and interpretation condensed in a single graph.

Compare group behavior. ViSiElse enables the differentiation of two subsets of individuals through color distinction. Distinguishing experimental groups of participants is useful to identify different patterns of behavior. In the intubation process, the two groups represent two different intubation learning sequences. To define groups, users simply have to define the “group” and the “method” arguments of the “visielse” function. The first one is a vector containing the group distribution for each individual and the second one, the name of the chosen visualization method. ViSiElse provides three methods to plot groups:

- The “cut” method where each group is represented one under the other with different colors (see Fig 3.A). This representation is useful to compare groups as data are completely dissociated.
- The “join” method where groups are spatially mixed but are differentiated by distinct colors (see Fig 3.B). With this method, users can analyze the group distribution among the data.
- The “within” method where all data are plotted together with a unique color and, under it, a subgroup of the global data is plotted with another color (see Fig 3.C). This visualization allows users to examine a specific group behavior against the global

population. As the ViSiElse package only allows two colors distinction, the "within" method is the most suitable option for data containing more than two groups. Users can confront each group, one after the other, to the global population and identify their differences.

Set time constraints. In case of behavior constrained by guidelines to work smoothly, like in many healthcare processes where actions taken by individuals must often respect an order and a timing. Usually, punctual actions should either be achieved during a specific period or not be executed before or after a specific time point. Likewise, long actions should not exceed a specific duration or continue after a specific time point. ViSiElse uses green and black zones to help visualize time boundaries. Green zones represent time obligation i.e. when actions should be achieved. Black zones set time interdiction i.e. when actions should not occur. Setting visual time constraints shows whether or not the individuals' behavior is accurate. For each punctual action, users can define one green zone and two black zones (one before and one after the expected execution times). To create those zones, users only have to define their delimitations: two-time points—one for the beginning and one for the ending of each zone. The time points of the green and black zones must be defined in the ViSibook object as columns and they will automatically be plotted when running the "visielse" function. ViSiElse also allows the repetition of green zones when a punctual action should be realized multiple times. For this option, users define the delimitation time points of the green zone, and then, the time interval between each green zone in a new column of the ViSibook. For long action, ViSiElse only offers time interdiction—black zones. As long actions are in fact duration, there are two ways of restricting them: a deadline not to cross or duration not to exceed. To define the time constraints of a long action, users must choose the appropriate restriction method and define the time limits in the

ViSibook. For example, in the neonatal resuscitation process, the insertion of the laryngoscope blade in the newborn's mouth for intubation should be done between 120 and 210 seconds after the beginning of the resuscitation. In Fig 1, for the punctual action "Blade in", green and black zones has been set to visualize if the subjects respect those time constraints. In addition, the intubation process should not last more than 30 seconds. As a result, a time restriction limits the long action "Intubation". Black zones defining duration not to exceed—as in our example—are represented by the darker end of the individual's line while black zones defining a deadline not to cross are represented like the punctual action black zones.

Analyze with statistical indicators. To complete the ViSiElse's graph and analyze the behavioral data tendency, statistical indicators can be added. Users can choose between plotting the mean and standard deviation (see Fig 3) or the median with the first and third quartiles (see Fig 1). Moreover, if the data contains groups, and statistical indicators are defined, ViSiElse computes a statistical test to compare the time data between the two groups (see Fig 3.A-B). If the statistical indicator is set to mean and standard deviation, ViSiElse runs a Wilcoxon test; if the statistical indicator is set to median and quartiles, ViSiElse runs a Mood's two-sample test. An asterisk appears in the right side of the graph if the statistical test is significant with a 0.01 alpha risk (default value). The alpha risk could be manually set. For example, in Fig 3.A-B, it was set to 0.3 resulting in a significant test for two punctual actions. Statistical indicators are arguments of the "visielse" function. By default, ViSiElse plots the mean and standard deviation and computes the statistical test if groups are defined.

Discussion

We presented ViSiElse, a graphical tool conceived to visualize raw data from experimental observations of individuals and/or groups' behavior. ViSiElse is a package of the open-source software R that can be applied to visualize any behavioral interactions between an organism and a process.

Range of possible uses

The package includes many features to provide a global overview of the data and can be used in different ways:

- Inspection of raw data
- Verification of the time adequacy to a procedure
- Global visualization to understand a behavior
- Apprehend learning processes or learning changes by using ViSiElse on repeated measures or sessions.
- Compare groups' behavior

ViSiElse was developed as a solution to the lack of visualization tools for behavioral raw data, but the users-friendly package can be used for all time data collected from a linearized process regardless of the research field. For example, cognitive ergonomics, including development of training programs or human-machine interaction, are study fields where ViSiElse can be an asset. The package can ease the visualization of processes like web search and software applications, allowing the comprehension of users' behavior. Another promising area where ViSiElse's features can widen raw data analysis is assembly line where processes are easily linearized and where timing is crucial. For example, ViSiElse could improve the time efficiency in an assembly line by easily identifying which work station is out of timing and needs changes.

In the case of data automatically extracted, ViSiElse could also be used as a visual feedback. For example, in healthcare simulation where a lot of software for automated data extraction exists, the simulation session often ends with a debriefing between the examiners and the subject. With ViSiElse, the debriefing could be upgraded with an instantaneous visualization of the subject's performance.

Limitations

Currently, ViSiElse is limited to the visualization of raw data solely from procedures that can be linearized. Many complex procedures can be divided in short ones that can be linearized but visualizing multitasking or teamwork could be a great asset to understand human behavior. Another limitation concerns ViSiElse's features which only offer a descriptive support of raw data. To provide complete data analysis, it should be integrated with complementary tools. Extracting patterns from the graph, running complete statistical analysis or examining the quality of the actions execution are many additional investigations that can be done. As ViSiElse uses raw time data, it can be associated with software that manages data extraction from video recorded sessions or software that directly provide time data like serious games.

In addition, based on a 21.5-inch screen with a resolution of 1920x1080 pixels and a pixel pitch of 0.248, a maximum of 60 punctual actions can be plotted per graph, without any limitation of the number of individuals. For long actions, ViSiElse's visualization on screen is limited by the pixel pitch and the maximum discrimination capacity is limited to 725 individuals with the previous screen characteristics.

Finally, ViSiElse only handles processes with time variations that are on the same scale. As the plotted result have a unique time axis with no time gap allowed, users can't observe time variation both in seconds and hours, for example. If a procedure involves actions that must be achieved within the seconds and others within the hour, we suggest splitting the process in two according to the time scale.

Future Work

To improve the package, future work will focus on expanding ViSiElse's features. Increasing the number of groups or plotting nonlinear processes would help visualize more complex procedures that involves executing parallel actions or interdisciplinary teams. Another improvement may be to add a method to visualize not only quantitative data but also qualitative data like the goodness of the actions realization to determine if the action was correctly done. Finally, the restriction on the number of individuals that can be plotted in a single graph for long actions could be solved by adding a gradient of color just like for the punctual actions.

In addition to the improvement of ViSiElse's features, future work will also aim at expanding the range of the allowed data type in ViSiElse by creating an option to change the x-axis unit. Users could visualize not only timestamps but also any quantitative variable. For example, concentrations or intensity could be visualized in different conditions. This improvement could enlarge potential uses of ViSiElse. Similarly, developing an online interactive version of ViSiElse could facilitate its use and make it handy for any beginner in data analyses.

Conclusion

ViSiElse is a package from R, the open-source software for statistical computing and data analysis. ViSiElse transforms a raw time data matrix into a comprehensible graph for an instantaneous insights of individuals and/or groups' behavior. In a single one page graph, users check their raw data, visualize the time accuracy, compare groups and analyze the data distribution through statistical indicators and tests. ViSiElse's options are accessible through the ViSibook for all the actions characteristics (names, labels, types, order, delimitations and green and black zones), through the arguments of the "visielse" function for all the analysis features (time scale, groups, statistical indicators and tests) and through the arguments of the "plot" function for all the formatting options (labels size and color, adding a title, time interval size and unit). This graphical tool suits every process involving actions that can be linearized. It has been developed to be applied in the medical field but can be used more widely in all fields using time data to analyze behavior. With ViSiElse, data reliability and transparency can be assessed for an entire dataset in a single graph.

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Figure 1

ViSiElse graph of the orotracheal intubation process during simulated neonatal resuscitation.

This figure shows ViSiElse's representation of the orotracheal intubation process (8 actions) during a simulated neonatal resuscitation realized by 37 participants. Statistical indicators for punctual actions are interquartile range (line and dots) and for long actions median of the duration (line). Time constraints are set on the insertion of the laryngoscope blade in the newborn's mouth with one green zone for adequate period and two black zones for inadequate time. An additional time constraint is set on the duration of the intubation process shown by darker blue color when the process last more than 30 seconds ("Not in time").

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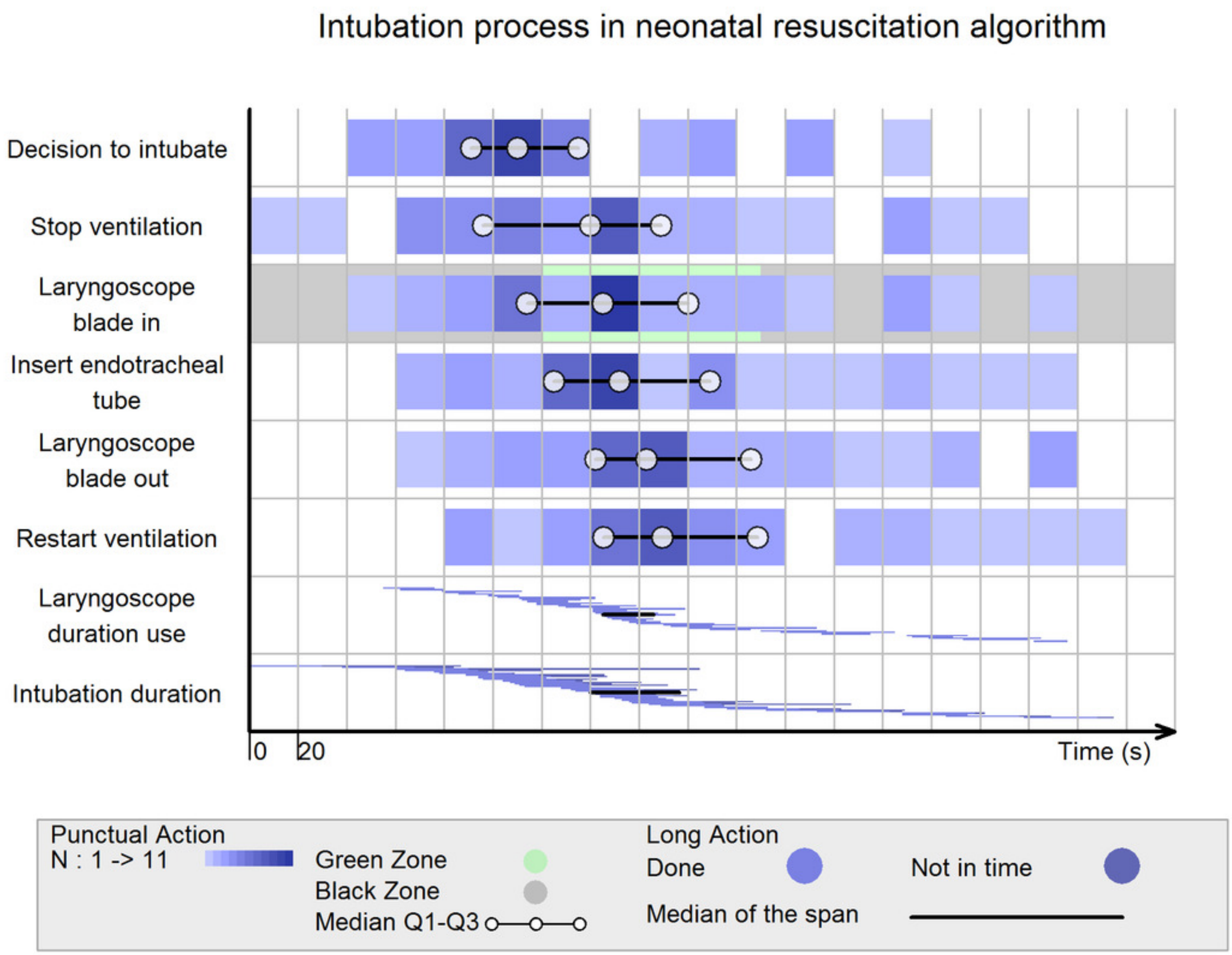
Intubation process in neonatal resuscitation algorithm
Decision to intubate
Stop ventilation
Laryngoscope blade in
Insert endotracheal tube
Laryngoscope blade out
Restart ventilation
Laryngoscope duration use
Intubation duration
0
20
Time (s)
Punctual Action
N : 1 -> 11
Green Zone
Black Zone
Median Q1-Q3
Long Action
Done
Not in time
Median of the span

Figure 2

Graphical consequences of the pixel modification parameter.

VisiElse pixel is a key parameter linked to the behavior observed duration. It should be carefully set. In panel *(A) ViSiElse graph with pixels = 2s.* The too short pixel duration made participants data not enough aggregated to allow a clear visualization*. (B) ViSiElse graph with pixels = 100s* participants were too much aggregated resulting in a loss of information about the statistical distribution of the participants over the actions.

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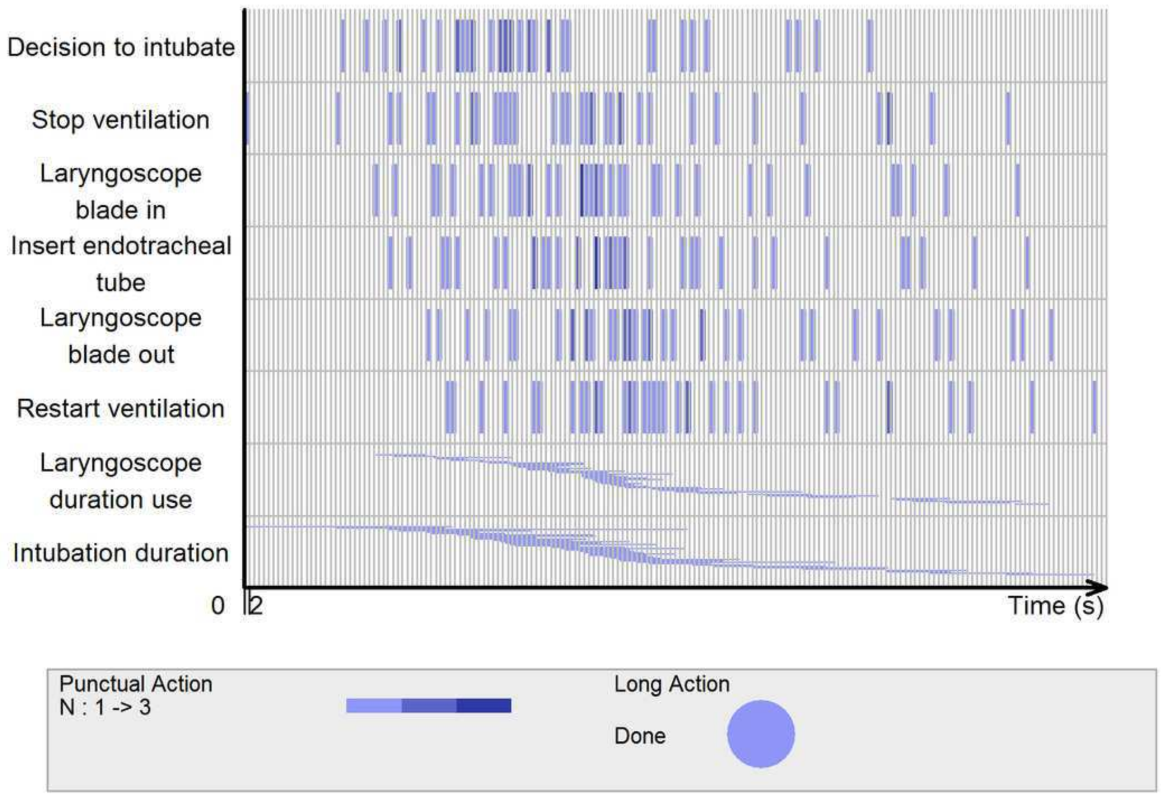
(A) pixel = 2s



(B) pixel = 100s

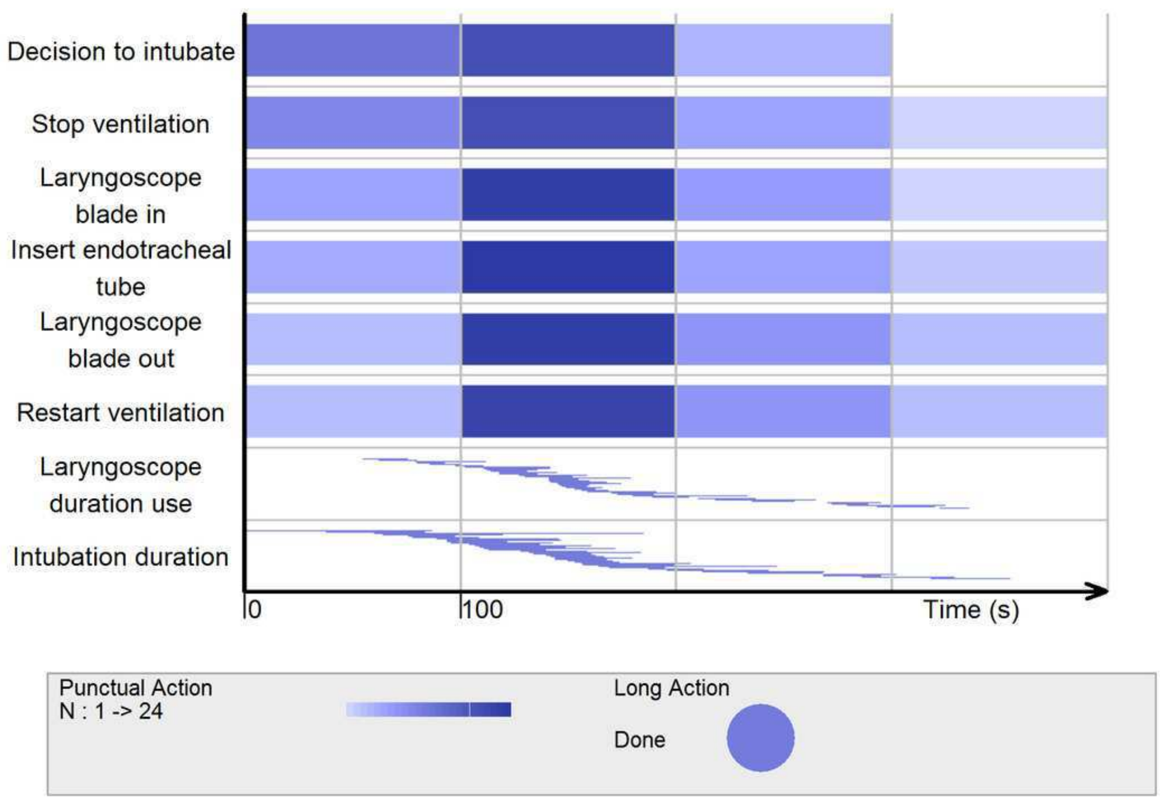
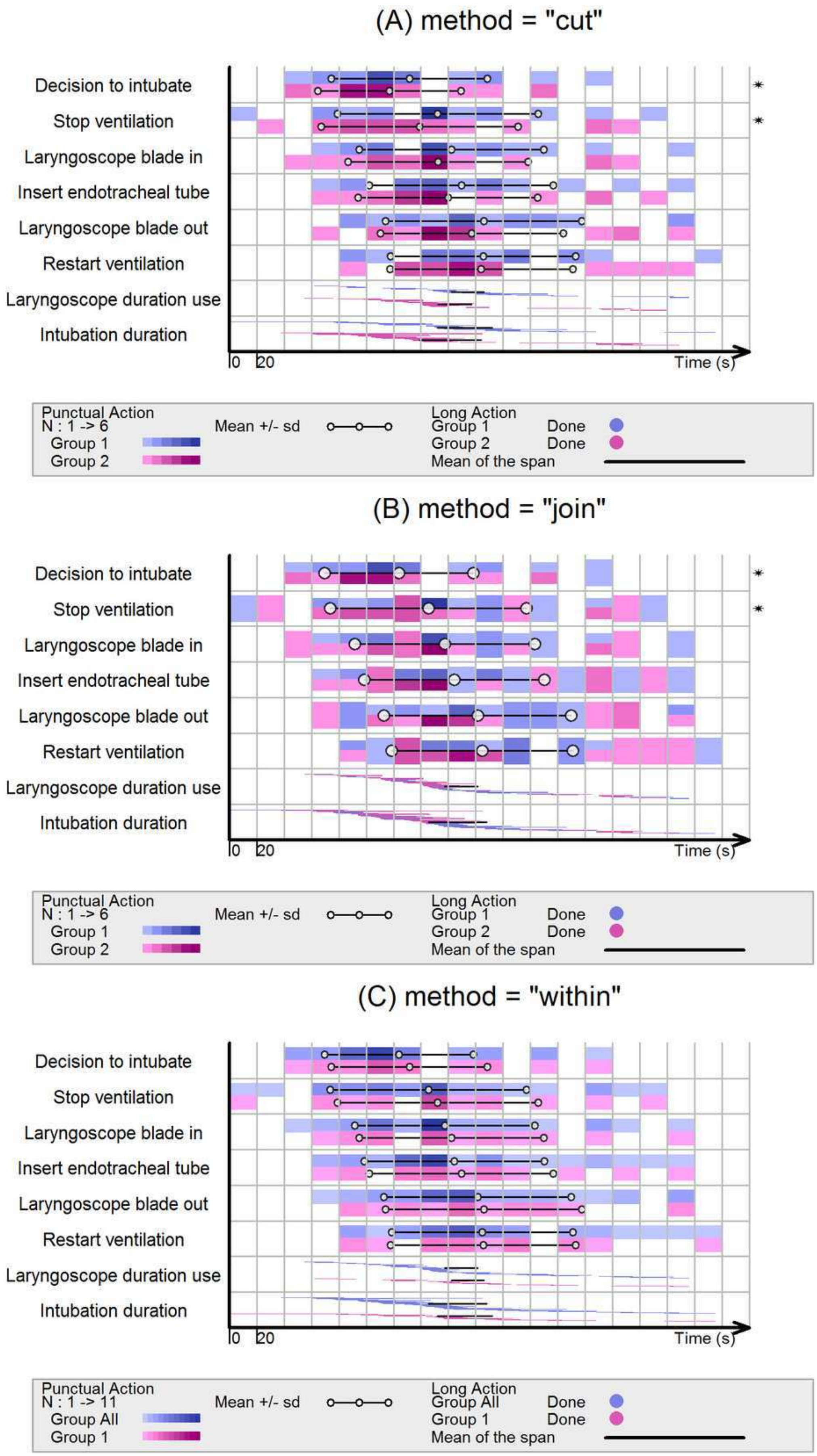


Figure 3

ViSiElse graph with three different methods to plot groups.

The three graphs show the intubation process for two groups and for each action, mean and standard deviation are presented. (A) The "cut" method is used: groups1 and 2 are one under the other. Each group has its own statistical indicators (B) The "join" method is used: groups are mixed together but differentiable by colors. Statistical indicators are calculated for all the individuals and not per group (C) The "within" method is used: groups are plotted together in blue and group1 is plotted again in pink. The first statistical indicator is for the global data and the second is for the repeated group.



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