Экспериментальная психология
2021. Т. 14. № 2. С. 101—112
DOI: https://doi.org/10.17759/exppsy.2021140207
ISSN: 2072-7593
ISSN: 2311-7036 (online)

Experimental Psychology (Russia)
2021, vol. 14, no. 2, pp. 101—112
DOI: https://doi.org/10.17759/exppsy.2021140207
ISSN: 2072-7593
ISSN: 2311-7036 (online)

DYNAMICS OF KEY FACIAL POINTS AS AN INDICATOR OF THE CREDIBILITY OF REPORTED INFORMATION

VLADIMIR A. BARABANSCHIKOV
Moscow State University of Psychology & Education, Moscow, Russia
ORCID: https://orcid.org/0000-0002-5084-0513,
e-mail: vladimir.barabanschikov@gmail.com

ALEXANDER V. ZHEGALLO
Moscow State University of Psychology & Education, Moscow, Russia
ORCID: https://orcid.org/0000-0002-5307-0083,
e-mail: zhegs@mail.ru

This research describes a method for studying the authenticity/unauthenticity of the information reported by people in video images. It is based on automatic tracking of coordinates of key points of a speaker's face using OpenFace software. When processing the data, the multiple linear regression procedure is used. It was found that the dynamics of neighboring key points in the obtained models has a multidirectional character, indicating the presence of a superposition of several dynamic structures, corresponding to the characteristic complex changes in the face position and facial expressions of the sitter. Their isolation is realized by means of the principal component analysis. It is shown, that the first 11 principal components describe 99.7% of the variability of the initial data. The correlation analysis between the number of credibility/confidence statements on the set of time intervals and the principal component loadings, allows to differentiate the dynamic structures of the face, connected with the assessments of credibility of the reported information. Automated analysis of face dynamics optimizes the process of collecting empirical data on the sitter's appearance and their semantic structuring, as well as expands the range of predictors of the assessments of the truthfulness of the messages received.

Keywords: video images of the communicant, predictors of the reliability of the reported information, key points of the face, dynamic structures associated with assessments of the truthfulness of the information.

Funding. The reported study was funded by Russian Science Foundation (RSF) project No. 18-18-00350-P.

For citation: Barabanschikov V.A., Zhegallo A.V. Dynamics of Key Facial Points as an Indicator of the Credibility of Reported Information. *Eksperimental'naya psikhologiya = Experimental Psychology (Russia)*, 2021. Vol. 14, no. 2, pp. 101—112. DOI: https://doi.org/10.17759/exppsy.2021140207 (In Russ.).

ДИНАМИКА КЛЮЧЕВЫХ ТОЧЕК ЛИЦА КАК ИНДИКАТОР ДОСТОВЕРНОСТИ СООБЩАЕМОЙ ИНФОРМАЦИИ

БАРАБАНЩИКОВ В.А.
Московский государственный психолого-педагогический университет (ФГБОУ ВО МГППУ), г. Москва, Российская Федерация
ORCID: https://orcid.org/0000-0002-5084-0513, e-mail: vladimir.barabanschikov@gmail.com

ЖЕГАЛЛО А.В.
Московский государственный психолого-педагогический университет (ФГБОУ ВО МГППУ), г. Москва, Российская Федерация
ORCID: https://orcid.org/0000-0002-5307-0083, e-mail: zhegs@mail.ru

Описывается метод изучения достоверности/недостоверности сообщаемой информации людьми на видеоизображениях. В его основе лежит автоматическое отслеживание координат ключевых точек лица говорящего с помощью ПО OpenFace. При обработке данных используется процедура множественной линейной регрессии. Обнаружено, что динамика соседних ключевых точек в полученных моделях имеет разнонаправленный характер, указывающий на наличие суперпозиции нескольких динамических структур, отвечающих характерным комплексным изменениям положения лица и мимики натурщика. Их выделение реализуется посредством анализа главных компонент. Показано, что первые 11 главных компонент описывают 99,7% вариативности исходных данных. Корреляционный анализ между количеством оценок достоверности/недостоверности высказываний на множестве временных интервалов и нагрузками главных компонент позволяет дифференцировать динамические структуры лица, связанные с оценками достоверности сообщаемой информации. Автоматизированный анализ динамики ключевых точек лица оптимизирует процесс сбора эмпирических данных по внешности натурщика и их семантическое структурирование, а также расширяет спектр предикторов оценок истинности получаемых сообщений.

Ключевые слова: видеоизображения коммуниканта, предикторы достоверности сообщаемой информации, ключевые точки лица, динамические структуры, связанные с оценками истинности информации.

Финансирование. Работа выполнена при поддержке Российского научного фонда (РНФ) проект № 18-18-00350-П.

Для цитаты: *Барабанщиков В.А., Жегалло А.В.* Динамика ключевых точек лица как индикатор достоверности сообщаемой информации // Экспериментальная психология. 2021. Том 14. № 2. С. 101—112. DOI: https://doi.org/10.17759/exppsy.2021140207

Introduction

When analyzing the assessments of the reliability / unreliability of the information, reported by the communicant, general and local changes in facial expressions, gaze direction, head position, various gestures, hand movements and other non-verbal acts are used as markers [2]. This requires from the researcher a preliminary specification of the allocated acts and their step-by-step marking. Manual step-by-step coding and decoding of dynamic features, seems to be very laborious, and the objectivity of the experimental data obtained in this way needs additional justification. Automatic facial landmark detection tools provide a more effective solution to this problem. This paper discusses the prospects for the use of technologies for automatic facial landmark detection when performing assessments of the reliability / unreliability of the reported information.

OpenFace software [5] performs automatic facial landmark detection in the photo and video images. 68 facial landmarks and additional 55 points in eyes area (in 2D and 3D coordinate) detected. Also gaze direction, head orientation and 17 Action Units (AU1, AU2, AU4, AU5, AU6, AU7, AU9, AU10, AU14, AU15, AU17, AU20, AU23, AU25, AU26, AU45) detected. Farther, software record parameters of Point Distribution Model (PDM), used to localize facial landmarks. These parameters represent loadings of 34 principal components, corresponding to the patterns of changes in the structure of the face. This PDM was previously built on the material of the training sample.

As you can see from the above description, the resulting markup contains groups of data, refer to different levels of facial expression description. As pilot experiments have shown, the joint use of several groups of indicators complicates further meaningful interpretation of the results. In this work, we used only 3D facial landmarks. The work is methodological in nature, aimed at development of techniques of analysis and subsequent visualization of the results, as well as assessing the prospects of using the OpenFace markup as initial data about the expression of a person's face.

The work is based on the experimental materials, obtained in previous study. Eye movements of participants in this study described in [1], linear regression model, based on the manual expert data markup described in [2].

Methods

Procedure. The stimuli were video records of simulated and natural communication situations. In simulated situations participant had to tell the experimenter either knowingly reliable or knowingly false information. The natural communicative situation was a fragment of a structured autobiographical conversation based on the identification of risk factors and bad habits [3]. A total of 15 video clips were used (5 — a "true" situation, 5 — a "lie" situation, 5 — an "interview"). The duration of each fragment was 60 s, the frequency was 25 frames / sec, and the duration of one frame was 40 ms. The subject's task was to determine, by the person's facial expression, the fragments of the conversation when the latter looks sincere and inspires confidence in the observer — he is telling the truth (the answer is "right arrow", "true" on the PC keyboard), or not inspires confidence, lies (the answer is "left arrow", "lie").

Participants. Thirty five participants (23 female) aged between 18 and 49 ears (mean = 24.7) participated. Participants reported normal or corrected-to-normal visual acuity. All the subjects had no experience in assessing the reliability of the information provided by non-verbal signs.

Data Anaysis

The video clips, used in the experiment, were processed with OpenFace 2.0 software. 3D coordinates of facial landmarks (face contour, eyes, mouth, nose) obtained. Facial landmarks coordinates and information about the number of assessments "believe" / "do not believe" averaged on the time intervals of 1000 ms (25 sequential frames). Linear regression performed in R statistical environment [7] using the lm function (stats package). The construction of models, explaining the estimates of observers through coordinates of facial landmarks at the current or previous time intervals, performed. The selection of the best models was carried out according to the maximum value of the corrected coefficient of determination R adj. For further analysis, models were selected that correspond to the coordinates of key points in the time interval, preceding the observers' estimates by 3 sec. Data set include 750 data intervals (50 consecutive intervals for each 60-second video clip; 10 initial intervals were excluded). Insignificant variables were excluded step by step, based on Akaike information criterion (AIC), (package stats, step function). At the next step, the variable that provides the maximum decrease in the criterion value was excluded from the model. The procedure was stopped when the exclusion of any of the remaining variables did not decrease the criterion value [6].

The final regression model for the estimates "true" had a value of $R^2adj = 0.31$, for estimates "false" $R^2adj = 0.27$. Direct interpretation of the models is difficult by their significant size (99 variables for estimates of "true", 100 variables for estimates of "false"). For ease of interpretation, we have applied the following technique. Since the discussed variables represent the coordinates of the facial landmarks, the corresponding model weights should be considered as the directions and values of the displacement of the corresponding facial landmarks, corresponding to the estimates "true" and "false". The reference face coordinates were calculated as average coordinates over the original dataset. The weights were rendered as vectors outgoing from facial landmarks points. The final coordinate of each vector was determined by the values of the corresponding weighting factors. The results are shown in Fig. 1.

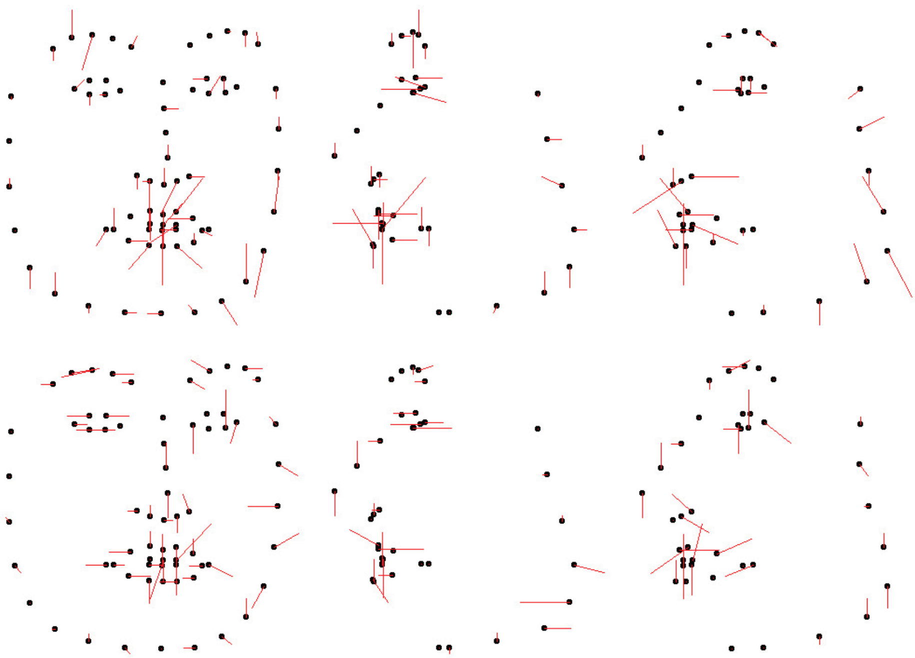

Fig. 1. Visualization of linear regression models, corresponding to estimates "true" (upper row) and "false" (bottom row). Face projections: frontal view, left (relative to the observer) profile, right profile

For the "true" estimates the image is characterized by vertical dynamics of the left (relative to the observer) eyebrow and a downward displacement of the lower part of the mouth. For the "false" estimates the image is characterized by horizontal displacements in the area of the eyebrows, the left eye, and partly the mouth. There are also multidirectional horizontal displacements in the middle right part of the face contour.

As seen in Fig. 1, the dynamics of neighboring facial landmarks is often multidirectional and contradictory. Interpreting this result, we conclude that the constructed linear regression models actually reflect not a single complex of features, associated with estimates of the reliability, or not the reliability of the reported information, but a superposition of several different changes in the structure of the face, associated with these estimates.

In this case, the selection of the actual features, that the observers are guided by, can be carried out by solving a problem similar to that performed by the Open Face developers via Point Distribution Model. The distribution kit of the program contains an example of the source code that performs the selection of the main components of the model on the training set.

Based on this example, we performed principal component analysis on the evaluated videos. OpenFace frame-by-frame facial landmarks markup performed. Each video record of 60 seconds duration at 25 frames / sec corresponded to 1500 marked frames. The total size for 15 video fragments was 22500 frames, 204 variables for each frame (X-, Y-, Z- coordinates of 68 facial landmarks). Principal component analysis performed in R with stats package (function prcomp, scale=TRUE). The results of the analysis show that the existing variability of the facial expression is well explained by the first main components. Thus, the first 11 components explain 99.7% of the variability in the coordinates of facial landmarks (Fig. 2).

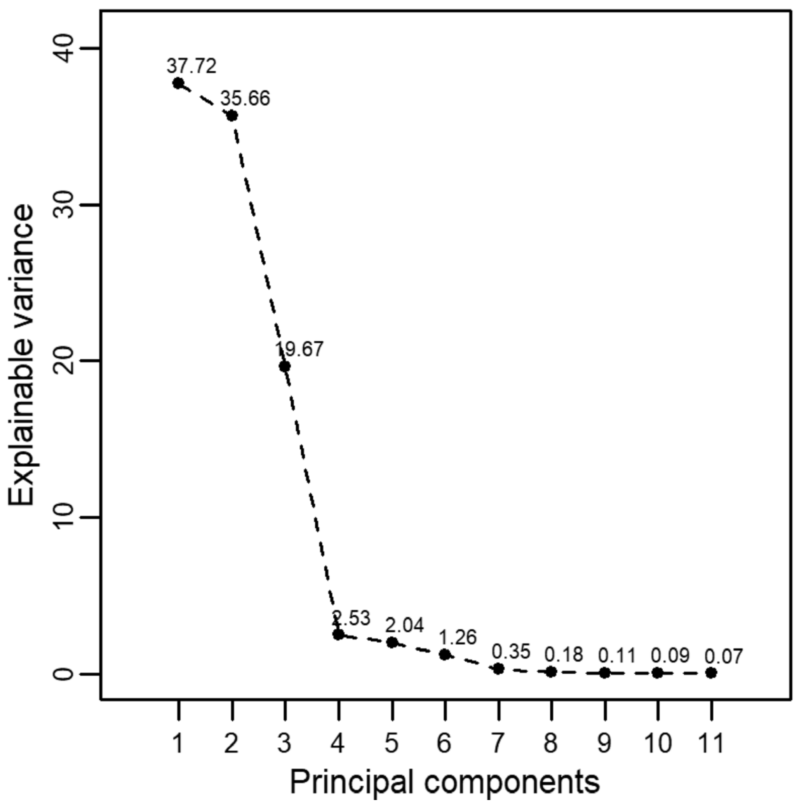

Fig. 2. Variation in facial expressions attributed by the first principal components

Let us describe in detail the content of the first principal components.

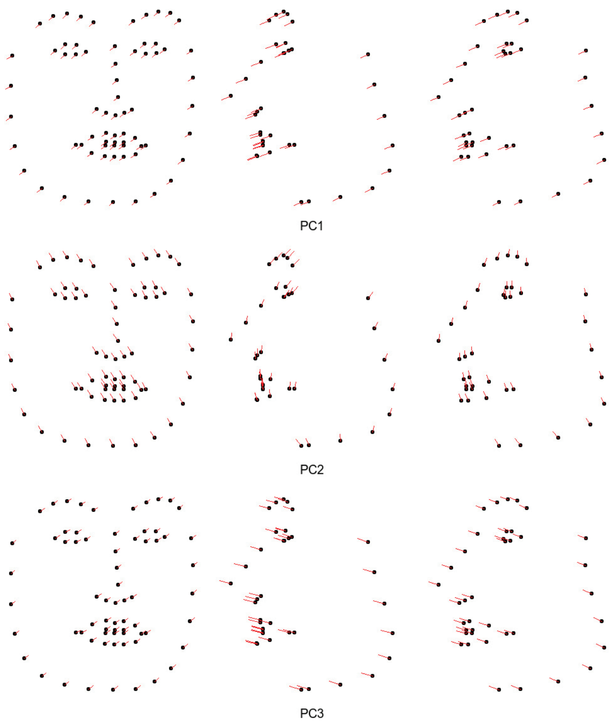

Fig. 3. Visualization of principal components PC1 — PC3. Face projections: frontal view, left (relative to the observer) profile, right profile

The PC1 component represents the displacement of the face to the left — down — forward (relative to the observer). Component PC2 — consistent left — up offset; the left half of the face turns back, the right half forward. Component PC3 — consistent shift to the right — up — forward; see Fig. 3.

Component PC4 represents shift to the right, the left half of the face turns back, the right half — forward. Component PC5 — counterclockwise rotational movement relative to the tip of the nose; the left half of the face turns forward, the right half of the face turns back. Component PC6 — tilt, upper part moves forward, lower part back; see Fig. 4.

Component PC7 represents "depth reduction" of the face; the contour of the face is displaced forward, the contours of the mouth and nose are displaced backward. Component PC8 — "increase in depth" in the left half of the face and "decrease in depth" in the right. Component PC9 — displacement of the mouth forward and chin — backward; see Fig. 5.

Component PC10 represents nose moves backward, corners of the mouth forward. Component PC11 — compression of the mouth, the corners of the mouth are displaced forward, the contour of the face is partially back; the eyes and eyebrows are raised; see Fig. 6.

Are the identified principal components related to the estimations of reliability / unreliability of the reported information? For the verification, the matrix (204x22500 values) of the loads, obtained as a result of the analysis of the principal components, was used. The data was aggregated for intervals of 12 frames (480 ms). For each interval, the total number of estimates of

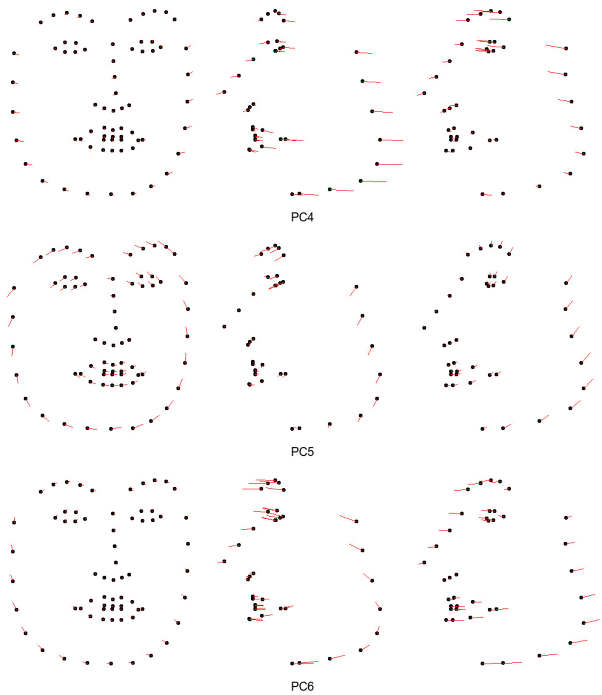

Fig. 4. Visualization of principal components PC4 — PC6

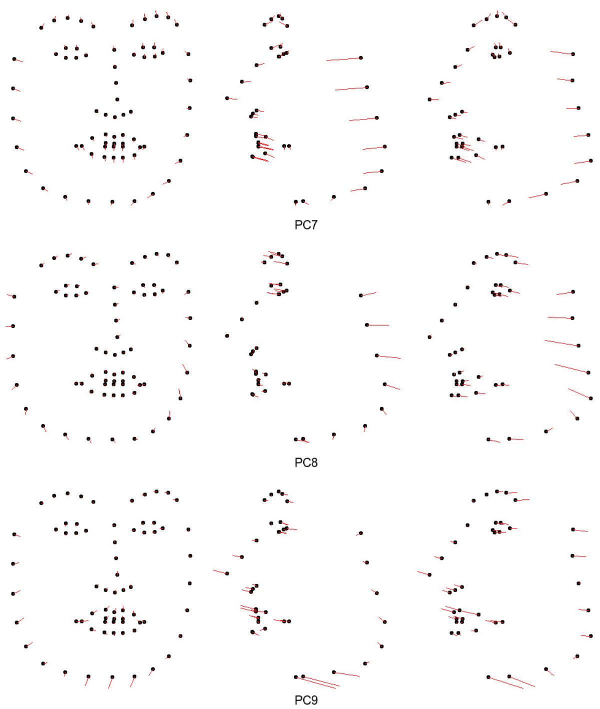

Fig. 5. Visualization of principal components PC7 — PC9

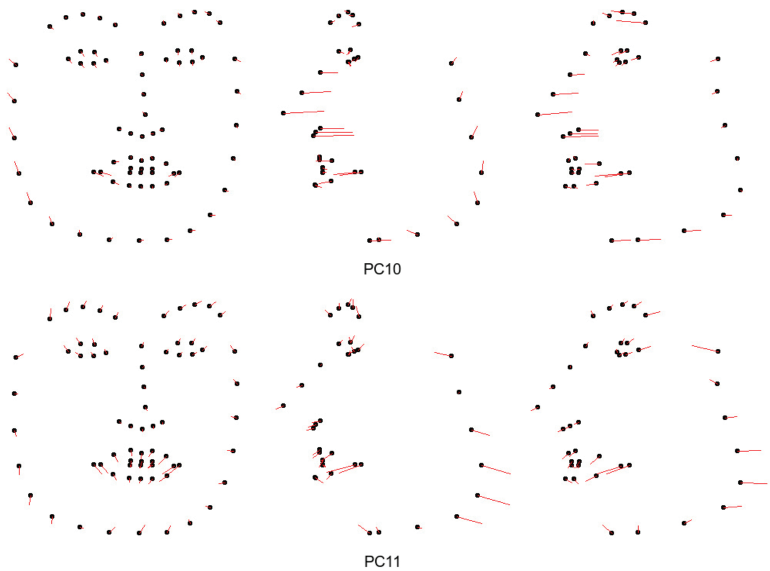

Fig. 6. Visualization of principal components PC10 — PC11

"true" / "false" given by observers was calculated. These estimates compared the loads of the principal components for the time interval in which the estimates were given and the previous time intervals. The depth of analysis was 40 intervals. For each assessment and loads of the principal component, the Pearson correlation coefficient was calculated. In total, 204 (number of principal components) x 40 (number of time intervals) = 8160 combinations were tested. The initial selection of data was carried out at a significance level of $p < 10^{-4}$.

For assessments of the reliability of the information reported, 71 significant correlations were obtained based on the results of the initial selection. A total of 46 significant correlations correspond to the four most frequent principal components. 69 significant correlations were obtained for assessing the uncertainty of the reported information based on the results of the initial selection. A total of 39 significant correlations correspond to the four most frequent principal components.

The results of the correlation analysis for the four most frequent principal components that determine the assessment of the reliability of the reported information are presented in Fig. 7.

The presented results show that the individual principal components contribute to the "true" estimates at different time intervals. The PC2 component operates in the time interval from -1.5 sec to -7 sec and in the interval from -17 to -19 sec. Component PC7 — in the range from -7 to -14 sec. Component PC9 — in the interval up to -8 sec. The PC5 component reduces the number of validity assessments in an interval of up to -2 sec.

The results of the correlation analysis for the four most frequent principal components that determine the assessment of the unreliability of the reported information are presented in Fig. 8.

The PC4 component causes a decrease in the "false" estimates in the range from -7 sec to -11 sec. The PC7 component causes a decrease in the "false" estimates in the range from -0.5 sec to -2 sec. The PC10 component causes an increase in the "false" estimates in the range from -12 sec to -17 sec. The PC11 component causes a decrease in the "false" estimates in the interval up to -8 sec.

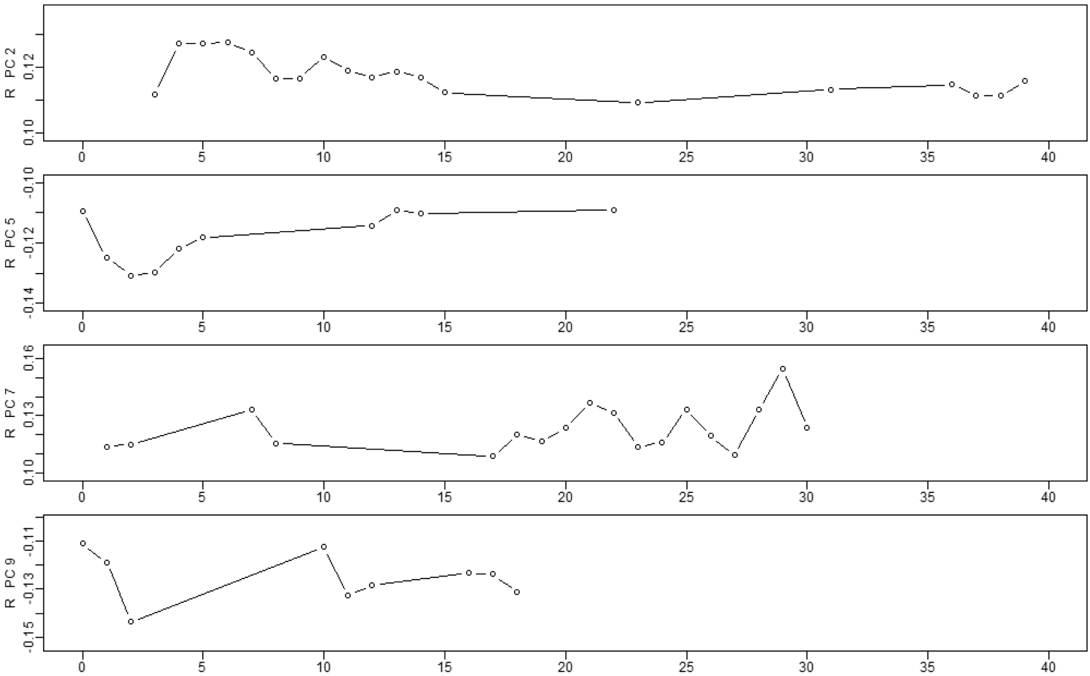

Fig. 7. Correlations of the estimates of the reliability of the reported information with the loads of the principal components at separate intervals of the analysis

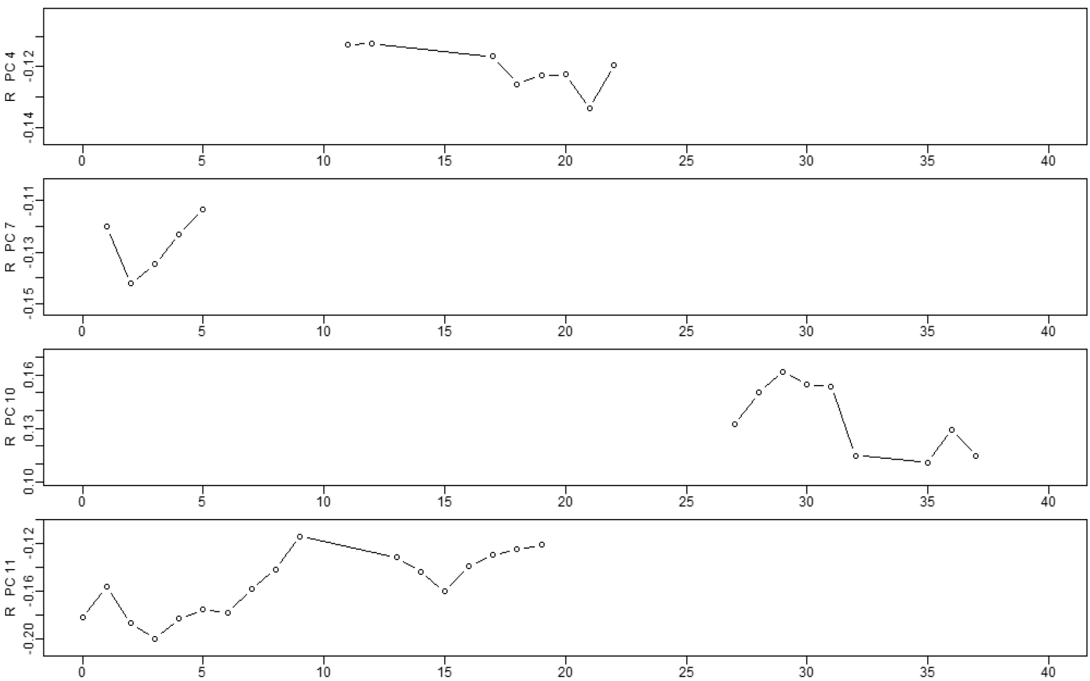

Fig. 8. Correlations of the estimates of the unreliability of the reported information with the loads of the principal components at separate intervals of the analysis

Discussion

Assuming a maximum analysis volume of 11 principal components and an analysis time range of 40 intervals, we obtain a total analysis volume of 440 correlations. In this case, the initial level of significance $p < 10^{-4}$ after conservative correction for multiple comparisons corresponds to $p < 0.05$. Thus, it can be argued that the revealed patterns are indeed statistically significant. Beyond the scope of the analysis remains the contribution of low-frequency principal components, characterized by correlations on a small number of time intervals (from 1 to 4 correlations per component). Indeed, rare facial expressions can potentially be markers of the reliability / unreliability of the information being reported, however, obtaining statistically reliable results in this case requires a significant increase in the volume of the analyzed video sequence.

Clarification of the features of the contribution of individual principal components can be carried out by visualizing the unsmoothed temporal dynamics of the analyzed component with the application of time stamps corresponding to the estimates given by observers. An additional factor mediating the contribution of the dynamics of facial expressions may be the direction of the observer's gaze at the time of the appearance of potentially important changes in the dynamics of the face.

The results of the correlation analysis show that individual dynamic structures are characterized by different sensitive time ranges. Various changes in the dynamic structure of the face can affect the assessments given by observers both relatively quickly and with a significant delay. The depth of analysis we used, of 20 seconds, does not fully cover the actual range of relationships between changes in the dynamic structure of the face and the estimates given by observers. When planning future experiments, instead of a large number of short videos, you should use a smaller number of longer videos, which will make it possible to increase the depth of analysis without drastically increasing the total duration of the experiment.

Further application of multiple linear regression does not seem promising due to high correlations between the loads of the analyzed principal components at adjacent time intervals. As a result, linear regression can give opposite signs of regression coefficients for the same principal component for adjacent time intervals, which contradicts the data of correlation analysis.

The analyzed three-dimensional markup is produced by the OpenFace program based on the analysis of a two-dimensional video sequence. At the same time, we did not analyze the algorithm for the transition to 3D data. Separate data on the identified main components (PC7, PC8) raise questions regarding the actual dynamics of the face, corresponding to changes in its depth. The solution to this problem requires additional analysis, which implies the selection of video sections with high values of the corresponding components. In the future, the optimal way to obtain markup is to switch to the use of equipment that allows hardware to determine the image depth, for example, Intel RealSense D435.

Conclusion

The results obtained demonstrate the fundamental possibility of using the marking of facial landmarks as a source of information about facial dynamics. Further, the identified characteristics of the dynamics of the face can be associated with the studied features of the perception of the facial expression of the communicant.

The allocated principal components are complex coordinated dynamic changes in the structure of the face, reflecting the characteristic changes in the position of the head and facial expressions. The features of the analysis make it possible to determine characteristic dynamic patterns that cover the main range of dynamic changes.

Obviously, the proposed method does not cancel, but supplements the previously described procedures for manual encoding / decoding of dynamic information about the communicant's appearance. Automated analysis of the dynamics of key points of the face not only optimizes the process of collecting empirical data and their semantic structuring, but also expands the range of predictors of estimates of the truth of received messages.

References

1. *Barabanschikov V.A., Zhegallo A.V.* Okulomotor activity at the perception of dynamic and static expressions of the face. Eksperimental'naâ psihologiâ = Experimental Psychology (Russia), 2018. Vol. 11, no. 1, pp. 5—34. DOI:10.17759/exppsy.2018110101. (In Russ., abstr. in Engl.).
2. *Barabanschikov V.A., Zhegallo A.V., Khoze E.G., Solomonova A.V.* Nonverbal predictors in the estimates of truthful and deceptive statements. Eksperimental'naâ psihologiâ = Experimental Psychology (Russia), 2018. Vol. 11, no. 4, pp. 94—106. DOI:10.17759/exppsy.2018110408. (In Russ., abstr. in Engl.).
3. *Barabanschikov V. A., Nosulenko V. N., Samoilenko E. S., Khoze E. G.* Polipozitsionnoe nablyudenie za povedeniem lyudei v protsesse tselenapravlennoi strukturirovannoi besedy = Polypositional observation of human behavior in the process of purposeful structured conversation // Psychology and Pedagogy of the XXI century: theory, practice and prospects / N.B. Karabushchenko, N.P. Sungurova. Moscow. RUDN, 2015. P. 109-131. (In Russ.).
4. *Baltrušaitis T.* Automatic facial expression analysis // Submitted on March, 2014 for the Degree of Doctor of Philosophy. Fitzwilliam College. University of Cambridge.
5. *Baltrušaitis T., Zadeh A., Lim Y.C., Morency Y-P.* OpenFace 2.0: Facial Behavior Analysis Toolkit // Proc. IEEE International Conference on Automatic Face and Gesture Recognition. 15—19 May 2018. Xi'an, China, 2018. (FG '18). Piscataway, NJ: Institute of Electrical and Electronics Engineers (IEEE), 2018. P. 59—66. DOI: 10.1109/FG.2018.00019
6. *Hastie T.J., Pregibon D.* Chapter 6. Generalized linear models // Statistical Models in S / eds Chambers J.M., Hastie T.J. London: Chapman & Hall, 1992. P. 195—248.
7. R Core Team. R: A language and environment for statistical computing [Электронный ресурс] // R Foundation for Statistical Computing. Vienna, Austria, 2020. URL: https://www.R-project.org/ (Accessed: 07.06.2021).

Литература

1. *Барабанщиков В.А., Жегалло А.В.* Окуломоторная активность при восприятии динамических и статических выражений лица // Экспериментальная психология. 2018. Том 11. № 1. С. 5—34. DOI:10.17759/exppsy.2018110101
2. *Барабанщиков В.А., Жегалло А.В., Хозе Е.Г., Соломонова А.В.* Невербальные предикторы оценок достоверности/недостоверности сообщаемой информации // Экспериментальная психология. 2018. Том 11. № 4. С. 94—106. DOI:10.17759/exppsy.2018110408
3. *Барабанщиков В.А., Носуленко В.Н., Самойленко Е.С., Хозе Е.Г.* Полипозиционное наблюдение за поведением людей в процессе целенаправленной структурированной беседы // Психология и педагогика XXI века: теория, практика и перспективы / Н.Б. Карабущенко, Н.П. Сунгурова. М.: РУДН, 2015. С. 109—131.
4. *Baltrušaitis T.* Automatic facial expression analysis // Submitted on March, 2014 for the Degree of Doctor of Philosophy. Fitzwilliam College. University of Cambridge.
5. *Baltrušaitis T., Zadeh A., Lim Y.C., Morency Y-P.* OpenFace 2.0: Facial Behavior Analysis Toolkit // Proc. IEEE International Conference on Automatic Face and Gesture Recognition. 15—19 May 2018. Xi'an, China, 2018. (FG '18). Piscataway, NJ: Institute of Electrical and Electronics Engineers (IEEE), 2018. P. 59—66. DOI: 10.1109/FG.2018.00019

6. *Hastie T.J., Pregibon D.* Chapter 6. Generalized linear models // Statistical Models in S / eds Chambers J.M., Hastie T.J. London: Chapman & Hall, 1992. P. 195—248.
7. R Core Team. R: A language and environment for statistical computing [Электронный ресурс] // R Foundation for Statistical Computing. Vienna, Austria, 2020. URL: https://www.R-project.org/ (дата обращения: 07.06.2021).

Information about the authors

Vladimir A. Barabanschikov, Doctor of Psychology, Professor, Corresponding Member of the Russian Academy of Education, Director of the Institute of Experimental Psychology, Moscow State University of Psychology & Education, Moscow, Russia, ORCID: https://orcid.org/0000-0002-5084-0513, e-mail: vladimir.barabanschikov@gmail.com

Alexander V. Zhegallo, Ph.D. in Psychology, Senior Researcher, Institute of Experimental Psychology, Moscow State University of Psychology & Education, Moscow, Russia, ORCID: https://orcid.org/0000-0002-5307-0083, e-mail: zhegs@mail.ru

Информация об авторах

Барабанщиков Владимир Александрович, доктор психологических наук, профессор, член-корреспондент РАО, директор Института экспериментальной психологии, Московский государственный психолого-педагогический университет (ФГБОУ ВО МГППУ), г. Москва, Российская Федерация, ORCID: https://orcid.org/0000-0002-5084-0513, e-mail: vladimir.barabanschikov@gmail.com

Жегалло Александр Владимирович, кандидат психологических наук, старший научный сотрудник, Институт экспериментальной психологии, Московский государственный психолого-педагогический университет (ФГБОУ ВО МГППУ), г. Москва, Российская Федерация, ORCID: https://orcid.org/0000-0002-5307-0083, e-mail: zhegs@mail.ru

Получена 14.04.2021
Принята в печать 01.06.2021

Received 14.04.2021
Accepted 01.06.2021