This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Bee Swarm Detection Based on Comparison of Estimated Distributions Samples of Sound

Grzegorz Krzywoszyja, Ryszard Rybski, *Member, IEEE*, and Grzegorz Andrzejewski

***Abstract*— This paper describes a new measuring method of digital signal processing for detecting bee swarm phenomenon. The new method uses a comparison of the similarity between the estimated distribution of unknown sound samples with some estimated pattern distributions of known sound samples. The value of similarity of distributions was determined using statistical tools. The new method was tested in MATLAB and its results were compared with the results of a well-known classification method in the diagnostic space state. All calculations were made on recorded, real bee sounds. After testing in MATLAB, the method was successfully implemented in a prototype embedded system as an automated diagnostic system. The use of the method makes it possible to automatically detect the phenomenon of swarming. The authors see the possibility of using the developed method in other technical fields.**

***Index Terms*— Bee sounds, density comparisons, embedded system, kernel density estimation (KDE), measurement system.**

I. Introduction

SINCE 2006, the disappearance of the bee species has been observed. Scientists have not unambiguously established the reasons behind the unfavorable phenomenon [1]. Up until now, no way has reversed the unfavorable trend. The problem of disappearing species is serious because it yields a significant reduction in profit from insect-pollinated plants. Deficiency of bees causes large losses in agriculture [1].

Another reason for the loss of large numbers of bees in families destined for pollinating crops is their spontaneous reproduction (it is called a swarm). The moment of occurrence of the phenomenon of swarming is difficult to determine because it depends on biological factors, environmental conditions, and the way a beekeeper works.

The sounds and bee vibrations have long been of great interest to biologists trying to establish their association with the swarm [2]. Some of the scientific discoveries have been honored with the Nobel Prize [3]. Many known bees' sounds and vibrations are associated with their behavior [2]–[9]. Bees produce sounds and vibrations for mutual communication. They inform each other about the direction and distance of the source of food [6]–[9] or threat of pest presence [4].

Manuscript received March 20, 2018; revised September 27, 2018; accepted October 15, 2018. This work was supported in part by the Research Fund for the Doctoral at the University of Zielona Góra. The Associate Editor coordinating the review process was Dr. Chao Tan. *(Corresponding author: Grzegorz Krzywoszyja.)*

G. Krzywoszyja and R. Rybski are with the Institute of Metrology, Electronics, and Computer Science, University of Zielona Góra, 65-516 Zielona Góra, Poland (e-mail: krzywoszyja@gmail.com; r.rybski@imei.uz.zgora.pl).

G. Andrzejewski is with the Department of Technology, Jacob of Paradise University, 66-400 Gorzów Wielkopolski, Poland (e-mail: gandrzejewski@ajp.edu.pl).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TIM.2018.2878594

Scientific studies confirm the relationship between observed bee behavior and their sounds or vibrations. There are many known bee sounds produced during various behaviors. The knowledge acquired by the biologists was not practically used. Electronic systems built so far are only for collecting sound data [2] and are not capable of interpreting the measurement results automatically [10]. The results obtained from these systems are presented in the form of graphs or sets of numbers without an unequivocal interpretation. Beekeepers expect support in the form of a verbal communication, the content of which would inform him or her of the event in the hive. In order to meet the expectations of beekeepers, measuring systems should now be equipped with methods of automatic interpretation of measurement results (described in Section II). The development of microelectronics enables the practical use of the acquired knowledge of the sounds and vibrations produced by bees. Digital signal processing techniques and their mathematical modeling techniques [11]–[13] make it possible to perform calculations which replace the difficult ones when using analog hardware devices.

An automated diagnostic system (ADS) is required to develop analytical data processing methods and develop algorithms that can be implemented in a microprocessor-based measurement system [14]. This work describes a new measuring method for automatic detection of bee behavior, theoretically developed, analytically tested, and implemented in a prototype embedded system.

The sounds produced by a bee family are similar to color noise [15]. The nature of bee sounds determines the use of nonparametric methods for their analysis [16]–[21], [22]. From the audio fragments recorded at the time of the swarm, a set of pattern distributions for comparisons was made. From a limited number of sound pattern samples, the distributions were estimated with the use of a kernel estimation method [16]. The obtained set of pattern distributions was optimized by removing the distributions contributing a small share in the recognition of the swarm phenomenon. The pattern distributions were compared with the distributions generated from the recordings that were made during the bee swarm. Estimated pattern distributions and distributions obtained from test sounds were statistically evaluated for similarity using the Kolmogorov–Smirnov test [23]. A number of results describing the similarity of distributions were used for the detection of the bee swarm phenomenon [19].

Currently, the diagnostic work of beekeepers is based on the observation of the work of bees outside the beehive or control of the bee family within the hive. In the apiary with a large number of beehives conducting traditional diagnostics is ineffective. The use of smoke during a hive review produces

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

defense bee reactions and interferes with their work for many hours. It may have a negative impact on the behavior of the bees in the apiary. Beekeeping work supported by ADS may be less invasive. Bees do not react to a small microphone placed in the hive and its work does not affect their behavior. Automatic identification of the swarm phenomenon will reduce the number of uncontrolled bee escapes. The ADS helping the beekeepers in his work will allow them to manage the beekeeping more effectively.

II. Proposed Method for Detecting Bee Swarm

A. Preliminary Study on the Properties of Bee Sounds

Our investigations confirm the hypothesis that bee sounds are sufficiently diverse to be detected and classified [24]. Bee sounds were recorded in an apiary located in western Poland. All recordings of bee sounds were made by means of a digital voice recorder. The recorder sampled sound at 44.1 kHz and with 16-bit amplitude resolution. An external electret microphone was connected to the recorder. Recordings of bee sounds were made in different behavioral situations (during bee swarm), during their normal work (during nectar collection) and in isolated conditions (closed sick bees in a soundproof box). Bee sounds characteristic of their behavior were examined in detail. Spectral power distributions and composition of the spectra of different bee behaviors were analyzed. The highest power spectral density was observed near the base vibration frequency of bee wings (about 250 Hz). Graphs of the spectral density of sounds vary and depend on the type of the bees' activity. It was found that 99% of the sound power is contained in the band to about 7 kHz. It follows that the initial part of the sound spectrum is most suited to look for differences due to changes in bee behavior. Sound spectra of the selected phenomena recorded at short intervals show amplitude changes but the position of the extremes is almost constant. For a selected phenomenon, observed in different bee families, the spectra of sounds exhibit similarity.

Preliminary studies have examined the classification of bee sounds in relation to their various behaviors (nectar collection, smoke stress, bee swarm, orphan, disease, and other behaviors). Samples from small fragments of records (about 9 ms) were subjected to asynchronous averaging [12]. Then, the average values of the sound samples were treated as diagnostic vectors and placed in a multidimensional diagnostic state space. Asynchronous averaging leads to the loss of some information but improves the concentration of points belonging to a given class in the diagnostic state space. For several states, a diagnostic matrix was built and then subjected to dimensionality reduction. The transformation matrix obtained in the reduction process was used to test new data. The study of new data consisted of observing the location of points in the diagnostic space of states and their classification. Data dimensionality reduction was performed with the use of the following transformations: linear discriminant analysis, principal component analysis (PCA), neighborhood preserving embedding, kernel PCA, and stochastic neighbor embedding [13]. The obtained results indicated the possibility of classifying bee sounds [24]. Observations in diagnostic state space have also shown an unfavorable tendency to evolve points representing the phenomena studied. States observed in the diagnostic observation states space often underwent evolution to space occupied by other states. Numerous classification errors limit the applicability of the method in the ADS. Classification in diagnostic state space effectively confirms the differentiation of bee sounds and paves a way to find a more reliable method.

The project was made with the LPC1768 Mini-DK2 (an evaluation board based on the Cortex-M3 microcontroller) with an additional amplifier and a filter made on the LM324 chip. The program for the microcontroller was written using programing environment CooCox in C language. The analysis of the microcontroller's program results was performed on a PC (64-bit Windows system, 2-GHz clock, and 16-GB RAM).

B. Stationarity of Sounds of Bees

On the basis of the presented method, it is assumed that during the bee swarm the wings are stimulated to vibrate in a specific way, which affects the distribution of the values of the recorded sound samples. Time-varying noise characteristics produced by bees and the detection of information contained therein demands the use of statistical methods [16]–[21]. An important difficulty is determining the necessary number of sound samples to be used to construct a meaningful distribution of their values. Too small sample sizes result in a low-resolution distribution, which makes statistical comparisons difficult. An excessive number of samples make the empirical distribution fail to converge to the population distribution, which also makes statistical comparisons difficult. It was established that the number of samples needed to create a value distribution should be lower than that for which the series becomes quasi-stationary [18]. For that purpose, summary statistics (here mean and variance) were checked for changes over time. Specifically, each summary statistic was computed over an incrementally longer time window until no substantial changes in its value were spotted. The convergence was considered to be the beginning of stationarity [25]. The averaging results so obtained for the various phenomena are shown in Fig. 1. From Fig. 1, it follows that for several phenomena, the summary statistics are convergent after collecting about 200 samples (for stress, orphan, and swarm). In all cases, the convergence is achieved after collecting about 400 samples. Fig. 2 shows changes in the sample variance for an increasing number of samples. For all studied phenomena, the sample variance is convergent for over 200 sound samples. From our considerations, it follows that the number of samples taken for further calculation should be less than 400 for the mean and less than 200 to 300 for the variance. Therefore, a fixed number of 250 sound samples were used to form empirical distributions. In order to provide the appropriate power of the statistical test to determine the similarity of pattern distributions with the current distributions, it was considered necessary to estimate the distributions from the random samples composed of 250 samples [20], [21].

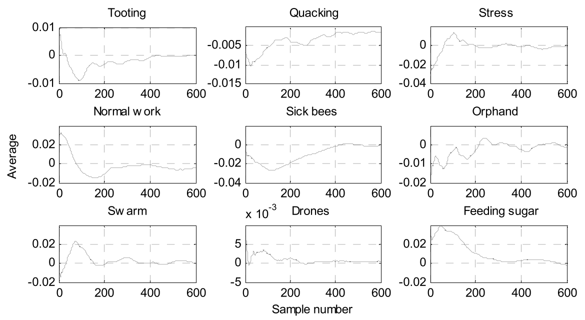

Fig. 1. Convergence of average value of sound samples.

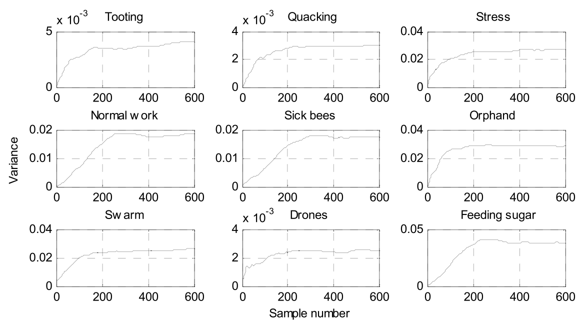

Fig. 2. Convergence of sample variance.

Prior to the estimation of distributions, the quality of recordings of bee behavior patterns was assessed. The homogeneity of the information in the fragments of the recordings intended for the generation of patterns representing the individual phenomena was checked. For this purpose, sequences of bee behavior patterns were extracted from recordings and approximate entropy (ApEn) was computed [26]. ApEn was calculated by the formula

$$\mathrm{ApEn}_{m=2,r=0.0388,N=250} = \Phi^{(m=2)}(r) - \Phi^{(m=3)}(r) \quad (1)$$

where N is the length of the time series, m is the number of sound samples in the patterns, r is the distance that is the criterion for patterns similarity, and Φ is the average of the logarithms of the number of similar patterns. For the computation of ApEn, patterns were composed of two ($m = 2$) and three ($m = 3$) sound samples. Value of comparison criterion (r) was set at 0.2 of the standard deviation for the whole series of samples representing the phenomenon ($r = 0.2\sigma = 0.0388$). Graphs of patterns of various phenomena are shown in Fig. 3. Patterns having a constant level of information were found to be reliable. Each point of the graph corresponds to the ApEn value of ApEn determined from (1) in the intervals of 250 samples of sound from the recording. The sampling intervals were constructed without overlapping. The level of ApEn in the studied phenomena does not change much. The exception is the recording of a bee pattern "Sick bees." For this phenomenon, the number of patterns will be variable and will depend on the moment of collecting sound samples which may make the new method difficult to use. The entropy analysis gives an opinion on the possibility of using the developed method.

C. Construction of Distribution

Values of independent measurement results occur around the expected value, and their average values tend toward a Gaussian distribution. The distributions of sound samples were estimated using the kernel density estimation (KDE) method with the Gaussian kernel function [16]. The KDE method places the kernel function at the actual values of the measurements, and then adds their values. By choosing the increment value of the distribution estimator argument x, the planned number of distribution intervals was obtained (2). The number of created intervals of distribution has an impact on the statistical power of the test determining similarity.

An audio sample chosen by the expert for creating master charts is not ideal. The part hidden in the data pattern does not represent the behavior of the bee. We cannot prioritize the degree of representativeness of the phenomenon for the estimated distribution patterns. In order to determine their representativeness, one-second pattern recording of the phenomenon was divided into 176 segments of 250 samples, and then all distributions were made using KDE ($176 \cdot 250$ samples $=$ 44 000 samples, about 1 s at 44.1 kHz sampling frequency). The distribution was estimated using

$$\hat{f}(x) = \frac{1}{mh^n} \sum_{i=1}^{m} K\left(\frac{x - x_i}{h}\right) \quad (2)$$

where m is the number of summed components, h is the smoothing parameter, and $K(\cdot)$ is a generalized kernel function dependent on the value of the estimation point and the value of the sound sample. The distribution was estimated from 250 sound samples ($m = 250$). The smoothing parameter h was not optimized ($n = 1$). Estimated values at x are calculated by summing the values of the Gaussian kernel function (3) for all consecutive values of sound samples $\{x_1, x_2, \ldots, x_m\}$

$$\hat{f}(x) = \frac{1}{mh} \sum_{i=1}^{m} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{x - x_i}{h}\right)^2\right). \quad (3)$$

The value of the smoothing constant h was determined in separate calculations [16]. The accuracy of the distribution depends on the increment of x and can be arbitrary. For practical reasons, "tails" of the estimated distributions were cutoff and only values from -0.5 to 0.5 were accepted, which reduces computational complexity at the expense of a small estimation error. Estimated distributions consisted of 1000 values. Fig. 4 shows the shape of 10 successive estimated distributions for all studied phenomena. On the y-axis, there are consecutive numbers of estimated distributions. On the x-axis, sample values are less than the absolute value of 0.5. The mean values of errors caused by the tailing of the estimated tails did not exceed 0.5% for all the phenomena studied. The set of model distributions consisted of 10 groups (10 studied phenomena) with 176 estimated distributions (for each study), which gives 1760 distributions altogether.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

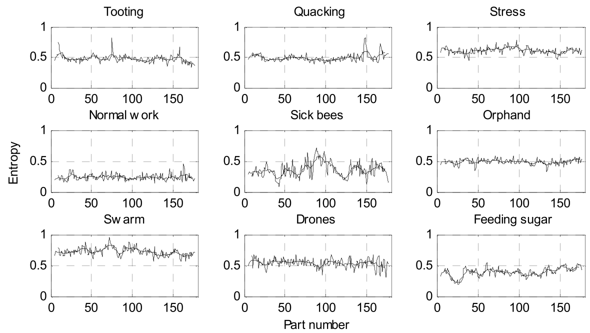

Fig. 3. ApEn changes in the patterns of sounds.

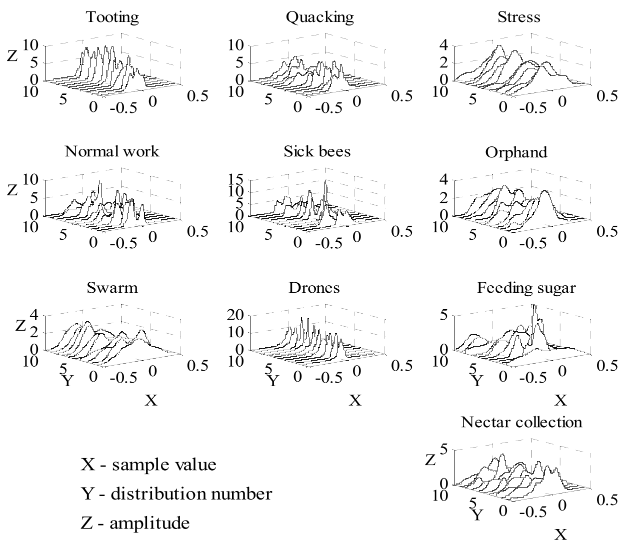

Fig. 4. Estimated distribution for various bee behavior.

D. Experimental Validation of Distribution

Detailed results were obtained from the estimation of a sound pattern distribution for bee swarm. Estimated pattern distributions of the swarm phenomenon were validated. In order to assess the representativeness of the pattern distributions, the frequency of these distributions in the record containing the full course of the bee swarm was analyzed. Every 28 s, a fragment containing 250 sound samples was taken from the recording and then a distribution was calculated for comparison with the pattern distributions. Each newly created distribution estimator was subjected to the Kolmogorov–Smirnov test [23] for two distributions with the assumed significance level $\alpha = 0.05$. Fig. 5 shows schematically a way to obtain pattern estimators with the highest efficiency (those that really take part in the bee swarming process). The Kolmogorov–Smirnov test confirms or rejects the null hypothesis H_0 (existence of the similarity of distributions) and returns the minimal p-value at which the null hypothesis H_0 can still be accepted. The probability values (p-value) for the i-th estimator of the time series tested and the j-th estimate of the distribution pattern are stored in the i-th row and j-th column of a matrix. For such organized measurement data, it is possible to calculate the probabilities in columns or rows. Column accumulation determines the total probability for each pattern distribution. Line accumulation

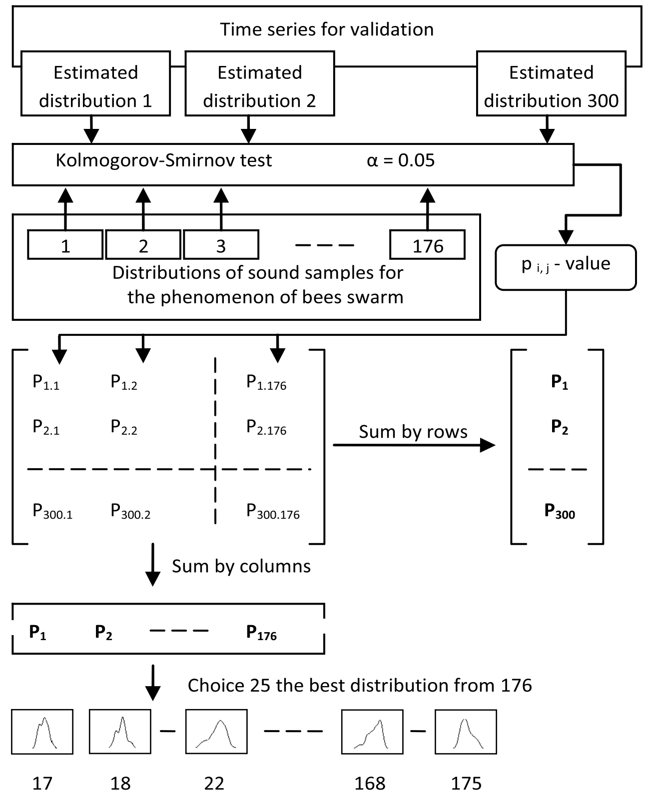

Fig. 5. Process of creating a set of effective distribution estimators.

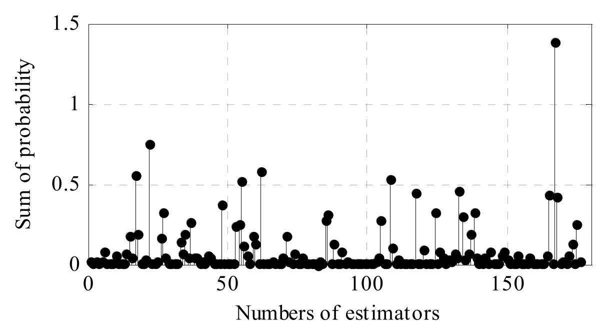

Fig. 6. Participation of pattern distributions in recognition of bee swarm.

determines the total probability for the currently examined fragment of the time series used for validation. Fig. 6 shows the sum of probabilities obtained for the distribution patterns when testing a whole time series containing the swarm phenomenon (column accumulation). Values of summed probabilities inform us about the utility of a given pattern estimator. Estimators with a sum of probabilities equal or close to zero had little impact on the detection of the phenomenon (the probability of similar distributions in the studied series was small). Since the significance of such distributive estimators in the process of detecting the phenomenon was negligible, it is justified to remove them from the group of estimators of pattern distributions for the phenomenon of swarm. Estimators with large sums of probabilities can potentially be a part of an effective set of distributions of the studied phenomenon. Fig. 6 shows the values of probability sums computed for all

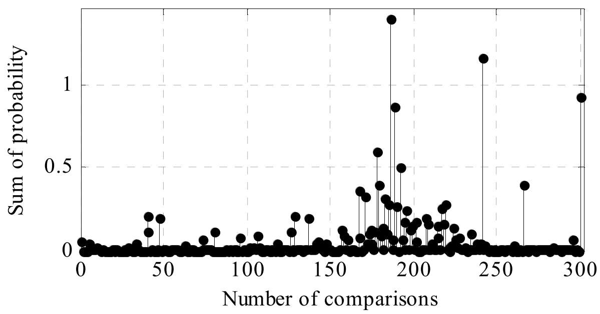

Fig. 7. Studying bee swarm with effective pattern distributions.

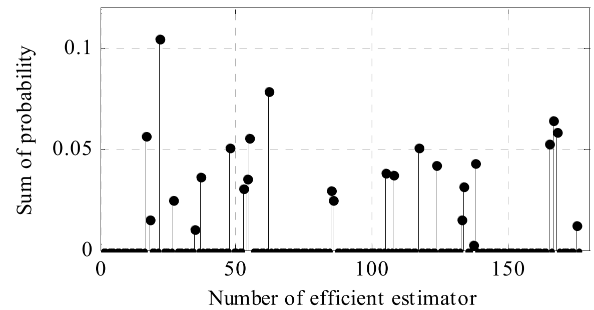

Fig. 8. Effective pattern distributions.

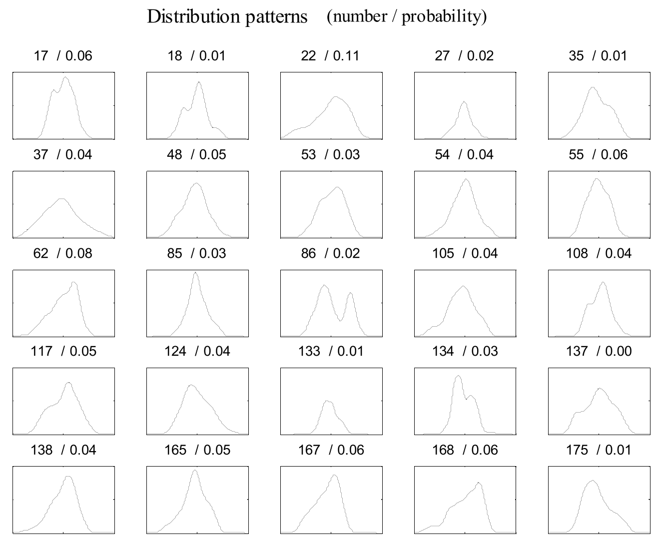

Fig. 9. Estimated distribution patterns of bee swarms.

estimators of distribution patterns. The results were obtained from a similarity comparison with the Kolmogorov–Smirnov test for the two distributions of all the pattern distributions with successive estimators formed from the time series tested (row accumulation). The distribution of the values of probability sums presented in Fig. 7 assumes a shape indicating the existence of a hidden phenomenon in the examined time series. After 180 tests comparing the distributions, the increase in the sum of probabilities is visible. Exactly at the time when bees were recorded, a large group of bees left their hives (bees were swarming). Out of the culmination of the swarm phenomenon, sporadically large sums of probability appear, which is difficult to interpret (this could be the beginning of a phenomenon or an accidental similarity of distributions). From Fig. 7 and from the observation of the phenomenon, it appears that the detected swarm is between 150 and 250 comparisons of the distribution patterns with the test distributions. Pattern distributions having a sufficiently high cumulative probability in this interval are more representative and others are less significant. In Fig. 6, we can see that some of the estimated pattern distributions, irrespective of the place of their comparison with the time series of the studied series, have small values of the probability sum. Only passive distributive estimators within the area of the detected phenomenon (from 150 to 250 of the investigated distribution estimator) can be removed from the set of pattern distributions without affecting the detection efficiency of the phenomena significantly (including the test series as well as the other containing the swarm phenomenon). In the first reduction step, the probability values for the pattern distributions estimators in the area of the detected phenomenon were calculated (from 150 to 250 of the distribution estimator formed for the time series tested). Then, the value of the discriminatory level needed to remove the distributions with low probabilities was selected. Because there are no premises for determining the critical value of the probability sum, a permissible error of recovery of the pattern distributions of the phenomenon is assumed at the level of 5%. Discrimination is done by summing the probability values of the pattern distributions starting with the largest ones and ending with the sum of probabilities reaching 95% of their total probability. Estimators of the pattern that were not part of the sum were removed. The reduction result is shown in Fig. 8. After reducing the number of distribution patterns there were only the 25 most significant ones. Fig. 9 shows the shapes of the selected distributions representing the swarm phenomenon. There is a number from the set and the normalized probability of occurrence above each distribution pattern. Several of estimators' distributions make the greatest contribution to the recognition of the phenomenon (22, 62, and 167), their total share in the recognition of the phenomenon is about 24%. The reduction of the estimated pattern distributions is significant and is approximately 86% (25 out of 176 distributions) with a 5% set reproduction inaccuracy. Significant reduction in the number of distributions for comparison has the effect of reducing the computational complexity of the proposed method. The obtained set of distributions creates a mathematical model of the bee swarm phenomenon. The obtained model was used to study other recordings of bee swarm phenomenon.

E. Results of the Detection Test

Detection was performed using a nonparametric one-sample t-test [19]. The null hypothesis says that it cannot be excluded that the test detected an attempt to represent the phenomenon of swarming, and the alternative hypothesis says that the test sample does not represent the phenomenon. Samples intended for detection are the results of the comparison of Kolmogorov–Smirnov's 25 selected estimated distribution patterns with the estimated distributions from the sample sounds of the tested time series. One estimated distribution was made of

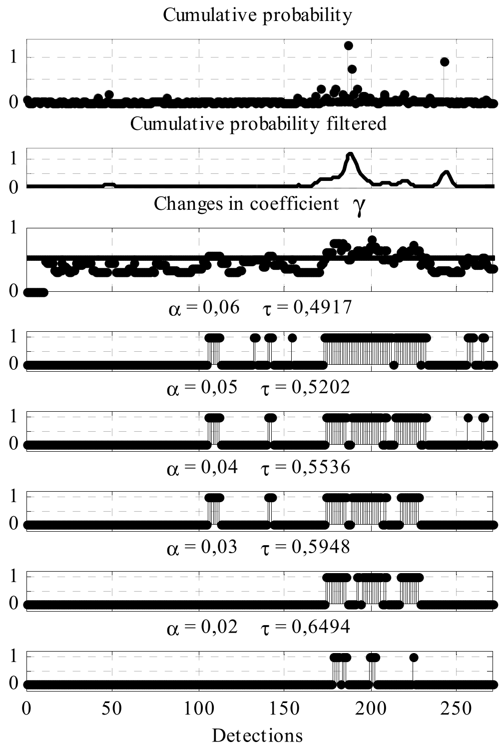

Fig. 10. Detection of bee swarm phenomenon.

250 samples of the test sound (sample time was about 6 ms at 44.1 kHz sampling frequency). The new distribution was compared with 25 distribution patterns. Comparisons with Kolmogorov–Smirnov test returned p-values whose totals were treated as a measure of similarity to the pattern distributions. Detection was performed from 10 consecutive results of the comparison of distribution with pattern distributions. The total time of one measurement performed by the microcontroller, the export of calculation results to the PC, and their presentation is 28.34 s. Hence, the system after startup has no detection for about 5 min (28.34 s/measurement, 10 measurements, 4.7 min). After this time, the detections are performed at regular intervals of approximately 28 s. Ten probability values are subjected to the t-test as described by (4), where γ is the decision threshold and τ is the hypothetical probability value (read from the cumulative distribution function of the normal distribution for the determined significance level α)

$$\hat{\delta}_n(Y) = \begin{cases} 1 & > \\ \gamma & \text{if } \dfrac{\bar{y}}{\left(\sigma^2\right)^{\frac{1}{2}}} = \tau \\ 0 & < . \end{cases} \tag{4}$$

The test compares the statistics from the density distribution with changing characteristics with the hypothetical value of statistics from a well-defined distribution. The changing value of the decision threshold γ (each successive series of measurements has a different mean and standard deviation) makes the t-test asymptotically become nonparametric at a fixed, constant value of τ. Fig. 10 shows the results of the detection of the phenomenon of swarming for a few selected values of the level of significance of the test. The null hypothesis was accepted for points where the decision threshold is above the hypothetical probability value τ. All the test decisions assuming the null hypothesis do not give the possibility of rejecting the claim that precisely at these moments detected phenomenon occurred. As the level of significance of the test decreases, the number of accepted null hypotheses is reduced. For $\alpha = 0.02$ and $\tau = 0.6494$, the detection occurs only at the culmination of the phenomenon.

The efficiency of the system was assessed practically. The system was tested by providing an input of the actual sound of bees containing the swarming noise from many bee families along with natural disturbances. Then, the sounds recorded during various behaviors of bees that did not contain the noise of the swarming were given to the system input. The duration of each recording was about 1.5 h. The obtained result for the described method (before a definitive t-test) is positive predictive value (PPV) = 0.955, Sensitivity (TPR) = 0.340 and Accuracy (ACC) = 0.662.

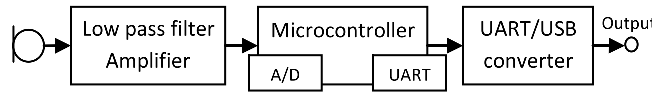

Fig. 11. Block diagram of embedded system.

III. Application in Embedded System

In order to verify the possibility of implementing the developed method in the embedded system, an electronic system was designed, made, and programed, its block diagram illustrated in Fig. 11. The low-pass, antialiasing filter was built with the Butterworth characteristic on an operational amplifier included in the LM324 chip. The bandwidth of the filter is limited to 20 kHz. A 12-bit analog-to-digital converter (ADC) located on the LPC1768 microcontroller chip was used to sample sound of bees. The composite signal (ac and dc) from the amplifier was fed to the ADC through the capacitor, thus removing the dc component. The ADC converter input was polarized with a constant voltage equal to half of the reference voltage (0.5×3.3 V $= 1.65$ V). In the microcontroller program, 2048 is subtracted from the value obtained from the ADC, the result is negative or positive depending on the value of the measured signal. The LPC1768 core clock can be set up to 100 MHz. The applied evaluation board contains an Ethernet interface, USB device interface, UART interfaces, SPI interface, and a 16-bit parallel LCD interface. The LPC1768 microcontroller features a high level of integration and low power consumption at high frequencies. Features include up to 512 kB of flash memory, up to 64 kB of data memory, general purpose timers, up to 70 general purpose input–output pins, and other peripherals. Almost all available interfaces were used in the project. The microcontroller was powered from the personal computer's USB port and received a 165 mA current (at 100 MHz core clock).

The calculated results (statistics values) from the embedded system were transferred via the USB port to the interface on the personal computer. The user interface enabled the analysis

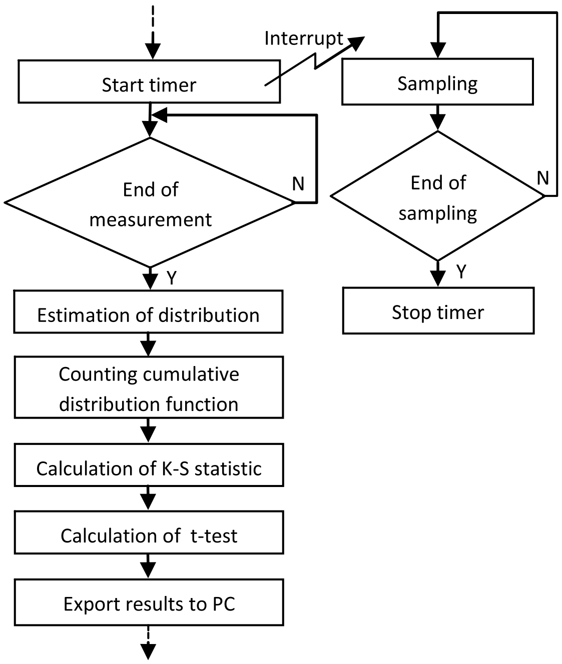

Fig. 12. Fragment of algorithm of microcontroller program.

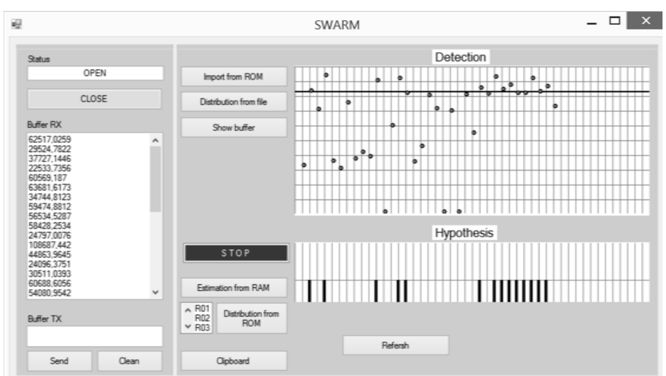

Fig. 13. Appearance of the user interface.

of each statistic calculated in the embedded system. Pattern of distribution was placed in ROM, in the protected area of program memory included in the microcontroller. It is impossible to place the distribution patterns in the RAM of the microcontroller because their size is too large and unreasonable because of their constant values. A fragment of the algorithm that performs the measurements and calculations is shown in Fig. 12. Method implementation consumes 18% of the memory resources of the microcontroller program and 33% of RAM (assuming a simplified detection process with constant discrimination threshold). One full cycle of measurement in the embedded system takes about 23 s. The program execution time was measured using a microcontroller system clock (Sys Tick) with a programed resolution of 1 ms. One measurement consists of sampling bee sounds, estimating the distribution of sound samples, calculating Kolmogorov–Smirnov's statistics with distribution patterns, detecting and sending results to an interface on a personal computer. The arrays of 25 pattern distributions stored in the program memory take up 52 kB. The microcontroller program uses

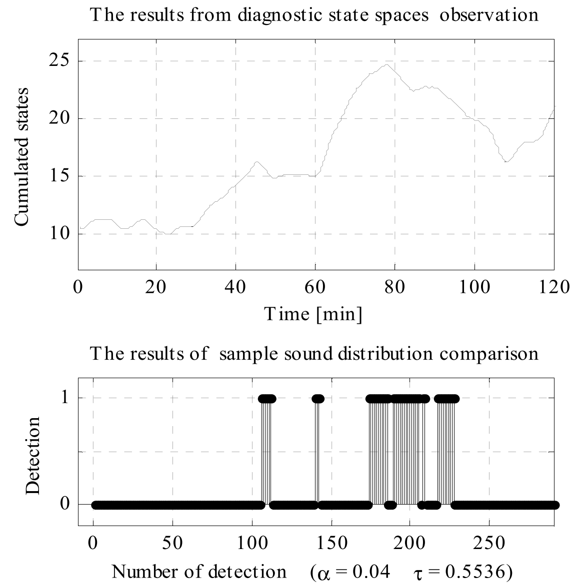

Fig. 14. Comparison of the results of both methods.

39.9 kB. The microcontroller ROM memory contains a total of 91.9 kB of data (pattern distribution and microcontroller program together) of the available 512 kB. The main load of the RAM of the microcontroller is a table intended for values estimated from the distribution samples and variable declarations, it takes up 11 kB of the 64 kB of the available RAM.

Fig. 13 shows the user interface during the measurements performed on the embedded system. Positive detections are presented on the interface form as bar charts.

IV. Discussion

The operation of the new method was compared with the method of classification based on diagnostic state space. Comparisons were made on exactly the same recording of bee sounds containing the sounds of the swarm. The diagnosis results from the classification method in diagnostic states space were effectively filtered to show the trend. Fig. 14 shows synchronous results obtained by both methods. This example shows the consistency of the results of both methods with the observation of the phenomenon (in the 80th min of observation, the bees had a swarm). The proposed new method is capable of detecting a swarm after about 23 s of microcontroller calculations. To avoid false alarms, several consecutive detection results are tested with a nonparametric t-test. The classification method in diagnostic space states requires a lot of calculation and averaging of the result which often cannot be accepted. The superiority of the proposed method is significant. The new method requires four times less computing time and 17 times less memory (the time complexity of both methods was compared using the MATLAB program, the results obtained are about 450 and 104 ms). Resource savings are particularly desirable when implemented on embedded systems, which typically have fewer resources than a personal computer. The analysis of time and memory resources was carried out on a PC in the MATLAB application.

TABLE I
COMPARISON OF TIME RESOURCES

The name of the method			
Classifications in the diagnostic state space		Comparison of the distribution	
The name of the resource	Size [kB]	The name of the resource	Size [kB]
Matrix for 10 fragments of 1 second recording 10x44100x2	882.0	10 vectors with 250 sound samples 10x250x2	0.5
Matrix of pseudo diagnostic vectors 100x8x2	1.6	1 vector for the estimated distribution 1x1000x2	2.0
The matrix of learned diagnostic vectors 100x8x2	1.6	25 patterns of distributions for comparisons 25x1000x2	50.0
Vector for the classification results 1x100x2	0.2	Variable for accumulated probability 1x2	0.002
		Vector for accumulated probability 1x10x2	0.02
Sum	885.4	Sum	52.5

TABLE II
COMPARISON OF MEMORY RESOURCES

The name of the method			
Classifications in the diagnostic state space		Comparison of the distribution	
Activity name	Average time [ms] (for 1000 calculations)	Activity name	Average time [ms] (for 1000 calculations)
Download 1 s of recording (44100 samples)	Not added	Download (250x10 =2500 samples)	Not added
Building diagnostic matrix from sound file with rows normalization	13.302	Estimation of 10 distributions from 250 sound samples	14.982
10 - fold creation of a diagnostic matrix (averaging, standardization, matrix centering, transformation PCA, dimensional reduction)	408.031	10 comparisons of distributions with 25 distribution patterns	88.931
10-fold classification by the KNN method, filtering results	28.532	1 detection, presentation of results	0.090
Sum	449.865	Sum	104.003

The results of the comparison for both methods are shown in Tables I and II.

Noteworthy is the detection of bee swarm in recording after over 100 attempts of detection (Fig. 14). Positive detections appear before the culmination of the swarm phenomenon and may be important for the prediction of the phenomenon. Calculations show that the delay time required to perform the first measurements necessary for the detection, the phenomenon of swarming bees, the system will detect ahead of time about 33 min (for α not less than 0.04). Early notification obtained from the system allows beekeepers to control the phenomenon of bee swarm. The appearance of detection long before the culmination of the phenomenon can also be seen as a small local extreme appearing on the chart diagnostic classification in the state space.

There are many species of bees on the planet, differing in body structure (wing muscles and their shape). It should be assumed that the created pattern consisting of 25 distributions will have to be rebuilt for other species of bees. Significant support for a new, nonparametric method to detect the phenomenon of swarming may be the sporadic appearance of sounds young queen bees make during the preparation for swarming colony. The detection of bee moths (also developed by the authors) can be considered as an indirect method of detecting bee swarm preparation. The ability to detect events occurring in the bee family and their registration in the system makes it possible to move from detailed research to general studies on the bee family. Automated identification of bee family events opens the way to building a sound model of bee family development.

V. Conclusion

There is a well-known problem with a drastic reduction in bee populations. It is necessary to support the work of the beekeeper by monitoring the behavior of bees. This paper presents a new measuring method for detecting the bee swarm phenomenon. The method is based on the assumption that the sound samples have different distributions, for the different behaviors of bees family. The new method uses a comparison of the similarity between the estimated distribution of unknown sound samples with some estimated pattern distributions. The proposed measurement method replaces the need for continuous observation of distributions. It does not require the ability to make your own conclusions from observation. This method gives the observer ready information. The new method was tested in MATLAB and then was successfully implemented in a prototype embedded system. All calculations were made on recorded, real bee sounds.

Obtained results allow believing that the method can be used in other technical fields. Currently, the authors investigate the possibility of detecting other sound phenomena occurring in the bee family.

References

[1] K. Hackett, “Colony collapse disorder 2012 annual progress report,” U.S. Dept. Agriculture, Washington, DC, USA, Tech. Rep., Jun. 2012. [Online]. Available: www.ars.usda.gov/is/br/ccd/ccdprogressreport2012.pdf

[2] D. A. Mezquida and J. L. Martnez, “Short communication. Platform for bee-hives monitoring based on sound analysis. A perpetual warehouse for swarm’s daily activity,” *Spanish J. Agricult. Res.*, vol. 7, no. 4, pp. 824–828, Apr. 2009.

[3] K. Frisch, “Decoding the language of the bee,” *Science*, vol. 185, no. 4152, pp. 663–668, Aug. 1974.

[4] A. Papachristoforoul, J. Sueur, A. Rortais, S. Angelopoulos, A. Thrasyvoulou, and G. Arnold, “High frequency sounds produced by cyprian honeybees apis mellifera cypria when confronting their predator, the oriental hornet vespa orientalis,” *Apidologie*, vol. 39, no. 4, pp. 468–474, Jul./Aug. 2008.

[5] G. Kastberger, T. Weihmann, and T. Hoetzl, “Social waves in giant honeybees *(Apis dorsata)* elicit nest vibrations,” *Naturwissenschaften*, vol. 100, no. 7, pp. 595–609, Jul. 2013.

[6] S. S. Schneider and L. A. Lewis, “The vibration signal, modulatory communication and the organization of labor in honey bees, apis mellifera,” *Apidologie*, vol. 35, no. 2, pp. 117–131, Mar./Apr. 2004.

[7] W. H. Kirchner, “Acoustical communication in honeybees,” *Apidologie*, vol. 24, no. 3, pp. 297–307, Jan. 1993.

[8] F. C. Dyer, “The biology of the dance language,” *Annu. Rev. Entomol.*, vol. 47, pp. 917–949, Jan. 2002.

[9] T. Seeley and P. Visscher, “Group decision making in nest-site selection by honey bees,” *Apidologie*, vol. 35, no. 2, pp. 101–116, Mar./Apr. 2004.

[10] A. Qandour, I. Ahmad, D. Habibi, and M. Leppard, “Remote beehive monitoring using acoustic signals,” *Acoust. Australia*, vol. 42, no. 3, pp. 204–209, Dec. 2014.

[11] S. W. Smith, “Statistics, probability and noise,” in *The Scientist and Engineer’s Guide to Digital Signal Processing*, 1st ed. San Diego, CA, USA: California Technical Publishing, 1997, ch. 2, pp. 11–34.

[12] R. G. Lyons, “Signal averaging,” in *Understanding Digital Signal Processing*, 3rd ed. Redford, MI, USA: Pearson Education, 2011, ch. 11, pp. 589–617.

[13] L. Maaten. (Oct. 18, 2016). MATLAB toolbox for dimensionality reduction. Delft University of Technology. [Online]. Available: http://cseweb.ucsd.edu/~lvdmaaten/dr/download.php

[14] W. Nawrocki, *Measurement Systems and Sensors*. Norwood, MA, USA: Artech House, 2005.

[15] S. Drosopoulos and M. F. Claridge, “Vibratory and airborne-sound signals in bee communication,” in *Insect Sounds and Communication: Physiology, Behaviour, Ecology, and Evolution*. Boca Raton, FL, USA: CRC Press, 2005, ch. 32, pp. 421–436.

[16] L. Wasserman, “Density estimation,” in *All of Nonparametric Statistics*. New York, NY, USA: Springer, 2006, ch. 6, pp. 125–142.

[17] S. Brandt, “Random variables: Distributions,” in *Data Analysis—Statistical and Computational Methods for Scientists and Engineers*. Cham, Switzerland: Springer, 2014, ch. 3, pp. 15–40.

[18] S. Bisgaard and M. Kulahci, “Stationary models,” in *Time Series Analysis and Forecasting by Example*, 1st ed. Hoboken, NJ, USA: Wiley, 2011, ch. 3, pp. 47–73.

[19] J. P. M. de Sá, “Non-parametric test of hypotheses,” in *Applied Statistics*, 2nd ed. Berlin, Germany: Springer-Verlag, 2007, ch. 5, pp. 171–217.

[20] P. Sprent and N. C. Smeeton, “Other single-sample inferences,” in *Applied Nonparametric Statistical Methods*, 3rd ed. Washington, DC, USA: Chapman & Hall, 2001, ch. 3, pp. 99–112.

[21] M. H. Hayes, “Discrete-time random processes,” in *Statistical Digital Signal Processing and Modeling*, 1st ed. New York, NY, USA: Wiley, 1996, ch. 3, pp. 57–128.

[22] P. Carbone, J. Schoukens, I. Kollár, and A. Moschitta, “Measuring the noise cumulative distribution function using quantized data,” *IEEE Trans. Instrum. Meas.*, vol. 65, no. 7, pp. 1540–1546, Jul. 2016.

[23] J. Durbin, *Distribution Theory for Tests Based on the Sample Distribution Function*, 5th ed. Philadelphia, PA, USA: SIAM, 2004.

[24] G. Krzywoszyja and G. Andrzejewski, “A support system for diagnosing bee colonies,” Düsseldorf, Germany, VDI Verlag GmbH, Tech. Rep. 10/836, 2014, pp. 1–13, vol. 836.

[25] K. Barbé, L. G. Fuentes, L. Barford, and L. Lauwers, “A guaranteed blind and automatic probability density estimation of raw measurements,” *IEEE Trans. Instrum. Meas.*, vol. 63, no. 9, pp. 2120–2128, Sep. 2014.

[26] S. M. Pincus, “Approximate entropy as a measure of system complexity,” *Proc. Nat. Acad. Sci. USA*, vol. 88, pp. 2297–2301, Mar. 1991.

Grzegorz Krzywoszyja was born in 1956. He received the M.Sc. degree from the Faculty of Physics and Astronomy, Pedagogical College, University of Zielona Góra, Zielona Góra, Poland, in 1980, the M.Sc. degree from the College of Professional Studies, Gorzów, Poland, in 2010, and the Ph.D. degree in computer science from the University of Zielona Góra, in 2017.

He is currently a Teacher of physics and computer science at the Jacob of Paradies University, Gorzów.

Ryszard Rybski (M’13) received the M.Sc. degree in electrical engineering from the University of Zielona Góra, Zielona Góra, Poland, in 1979, the Ph.D. degree from the Wrocław University of Technology, Wrocław, Poland, in 1989, and the Habilitate Doctorate (D.Sc.) degree from the University of Zielona Góra in 2008.

Since 1979, he has been with the Institute of Metrology, Electronics and Computer Science, Faculty of Computer, Electrical, and Control Engineering, University of Zielona Góra, where he became a Director of the Institute in 2008 and the University Professor in 2010. His current research interests include with high-accuracy measurements of electrical quantities, in particular with precision impedance measurements.

Grzegorz Andrzejewski was born in 1970. He received the M.Sc. degree from the Poznan University of Technology, Poznań, Poland, in 1995, and the Ph.D. degree in computer science from the Szczecin University of Technology, Szczecin, Poland, in 2002.

His current research interests include modeling and synthesis of digital control systems.