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Computerized Motion Analysis of Videotaped Neonatal Seizures of Epileptic Origin

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Summary: *Purpose:* The main objective of this research is the development of automated video processing and analysis procedures aimed at the recognition and characterization of the types of neonatal seizures. The long-term goal of this research is the integration of these computational procedures into the development of a stand-alone automated system that could be used as a supplement in the neonatal intensive care unit (NICU) to provide 24-h per day noninvasive monitoring of infants at risk for seizures.

Methods: We developed and evaluated a variety of computational tools and procedures that may be used to carry out the three essential tasks involved in the development of a seizure recognition and characterization system: the extraction of quantitative motion information from video recordings of neonatal seizures in the form of motion-strength and motor-activity signals, the selection of quantitative features that convey some unique behavioral characteristics of neonatal seizures, and the training of artificial neural networks to distinguish neonatal seizures from random infant behaviors and to differentiate between myoclonic and focal clonic seizures.

Results: The methods were tested on a set of 240 video recordings of 43 patients exhibiting myoclonic seizures (80 cases), focal clonic seizures (80 cases), and random infant movements (80 cases). The outcome of the experiments verified that optical-flow methods are promising computational tools for quantifying neonatal seizures from video recordings in the form of motion-strength signals. The experimental results also verified that the robust motion trackers developed in this study outperformed considerably the motion trackers based on predictive block matching in terms of both reliability and accuracy. The quantitative features selected from motion-strength and motor-activity signals constitute a satisfactory representation of neonatal seizures and random infant movements and seem to be complementary. Such features lead to trained neural networks that exhibit performance levels exceeding the initial goals of this study, the sensitivity goal being $\geq$80% and the specificity goal being $\geq$90%.

Conclusions: The outcome of this experimental study provides strong evidence that it is feasible to develop an automated system for the recognition and characterization of the types of neonatal seizures based on video recordings. This will be accomplished by enhancing the accuracy and improving the reliability of the computational tools and methods developed during the course of the study outlined here. **Key Words:** Motion segmentation—Motion tracking—Motion-strength signal—Motor-activity signal—Neonatal seizure—Seizure-type characterization—Seizure-type recognition—Video recording.

Seizures occur in two to five per 1,000 live births, depending on studied populations and methods (1–8). Seizure occurrence represents one of the most frequent clinical signs of central nervous system dysfunction in the newborn (9–11) and has been associated with significant long-term adverse sequelae such as neurologic impairment, developmental delay, and postnatal epilepsy (2–4,10,12–17). Identification of seizures in the newborn initiates a prompt evaluation for a wide range of etiologies and, whenever possible, treatment of the underlying pathologic processes. In some situations, antiepileptic medication is provided to diminish the likelihood of recurrent seizures and to limit any systemic or physiologic instability that may occur during seizures. Prompt recognition of clinical seizures by those who care for neonates is the critical first step in the diagnosis and management of underlying neurologic problems.

Despite the importance of seizure recognition, a number of limitations exist in rapid and accurate clinical identification. Seizures in the neonate have clinical characteristics that are distinct from those of older children; various seizure types may be based on different pathophysiologic mechanisms; and not all clinical seizures are associated with electroencephalographic seizure activity. Most importantly, neonatal seizures may be fleeting—short in duration and unpredictable in occurrence and frequency. This requires continuous surveillance for effective recognition.

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Neonates cared for in intensive care units are at greatest risk for seizure occurrence. Although this setting may provide the greatest opportunity for continuous seizure surveillance, the clinical demands of caring for sick neonates limit continuous 24-h/day observation. In addition, significant variability is found among nursery caregivers in the level of skill and experience in recognition of clinical seizures. Finally, even when clinical seizures are recognized, there is typically no permanent visual record of these events that can be reviewed and used for diagnostic confirmation. These factors illustrate the clear need for improved seizure surveillance methods that supplement direct observation by nurses and physicians and that are practical and economically feasible.

Early attempts to characterize neonatal seizures involved primarily bedside observation and relatively brief EEG recordings. The development of portable EEG/video/polygraphic monitoring techniques has allowed investigators to assess and characterize neonatal seizures at the bedside and has permitted retrospective review (18–21). Investigations using these techniques have confirmed that clinical neonatal seizures are either electroclinical (electrographic and clinical features that are temporally linked) or clinical only (clinical features with no consistent electrographic correlate) in character (22). Electrical-only seizures are not associated with clinical events. The overwhelming majority of neonatal seizures have a clinical component (electroclinical or clinical only) (22).

Most research involving neonatal seizures has focused on analysis of EEG features, and few investigations have used quantitative techniques to characterize clinical features (19). However, significant progress has been made in automated video processing and analysis that, until recently, has not been applied to clinical seizures. Automated video processing and analysis may supplement and extend human analysis of clinical seizure behaviors and provide new information leading to more useful classification schemes.

The results of our ongoing project, "Video Technologies for Neonatal Seizures," provided evidence suggesting that the analysis of motion in video can facilitate the recognition and characterization of the types of neonatal seizures (23–30) and revealed the potential of computerized video as a relatively inexpensive and noninvasive health-monitoring tool. Computerized video processing and analysis of video recordings of neonatal seizures can generate novel methods for extracting quantitative information that is relevant only to the seizure. This information can be used to develop automated mechanisms capable of detecting the onset of clinical seizures, refine the characterization of repetitive motor behaviors, and facilitate the differentiation of certain clinical seizures from other abnormal paroxysmal behaviors not associated with seizures.

The main objective of the research outlined here is the development of automated video analysis procedures aimed at the recognition and characterization of the types of neonatal seizures. The long-term goal of this research is the integration of the proposed computational procedures into the development of a stand-alone automated system that could be used as a supplement in the neonatal intensive care unit (NICU) to provide 24-h/day noninvasive monitoring of infants at risk for seizures. Such a system would be capable of detecting neonatal seizures, processing video recordings of neonatal seizures, and facilitating the analysis and characterization of the types of videotaped neonatal seizures by physicians during retrospective review.

METHODS

Data collection and preprocessing

This study relied on video recordings selected from a database developed by the Clinical Research Centers for Neonatal Seizures (CRCNS) in Houston, Texas, U.S.A., established by the National Institute of Neurological Disorders and Stroke (31). The overall goal for this initiative was to develop a comprehensive understanding of the clinical and EEG features, predisposing risk factors, etiology, and outcome of seizures in the newborn. A comprehensive database includes detailed demographic information and maternal and infant risk factors, medical and neurologic problems, neurologic examinations, weekly tracking of subjects throughout hospitalization, and long-term follow-up at ages 6, 12, and 24 months. As part of this work, bedside video/EEG/polygraphic monitoring was performed (minimum of 2 h for initial study), followed by repeated 1-h studies 3–5 days after the initial seizure characterization, and at the time of discharge. Additional studies were performed whenever clinically indicated, particularly when new seizure behaviors occurred.

The CRCNS database contains several hundred individual clinical seizures, which have been characterized and classified by a team of clinical neurophysiologists and neonatal electroencephalographers in terms of their electrographic and behavioral features, and the associated physiological manifestations have been documented. In making these determinations, the team members studied each video recording together with simultaneously recorded EEG. Decisions on characterization of seizures were made during group reviews (face-to-face discussions) in a way that a consensus was reached for each seizure included in the CRCNS database. The analog video recordings contained in the CRCNS database were digitized with a temporal sampling rate of 30 frames/s, which is considered high enough to capture sudden and rapid motion. The digitized frames that contained an image of the infant together with EEG were of size

352 × 240 pixels. After the elimination of the EEG signals, the video recordings produced sequences of frames of size 203 × 240 pixels.

Extraction of quantitative motion information from video

The first specific aim of this project was to extract quantitative motion information from video recordings of neonatal seizures and other normal and abnormal clinical events not associated with seizures in the form of temporal motion-strength and motor-activity signals.

Extraction of motion-strength signals

In principle, motion-strength signals quantify motion by measuring the area of each frame occupied by moving body parts affected by seizures. As the seizure progresses in time, the area measurements A produce temporal motion-strength signals $A(t)$. The extraction of motion-strength signals requires an automated procedure capable of segmenting the infants' moving body part(s) at each frame of the sequence.

In this study, we attempted to improve the extraction of motion-strength signals by modifying the procedure developed in our preliminary study (23). This investigation resulted in a new procedure, which extracts motion-strength signals from video recordings by applying nonlinear filtering, clustering, and morphological filtering on the differences between adjacent frames (24). Our experiments indicated that the combination of the new clustering scheme with morphologic filtering improves considerably the robustness of the new extraction procedure to noise. However, this procedure underestimated motion in most of the cases and failed completely in some video recordings.

The extraction of quantitative motion information from videotaped neonatal seizures in the form of motion-strength signals also was attempted by relying on optical-flow computation methods (25). Optical flow is the term used to indicate the velocity field generated by the relative motion between an object and the camera in a sequence of frames (32). Optical flow provides important information for analyzing motion in video. Our work produced a methodology for the development of regularized optical-flow computation methods based on a continuous formulation that involved a broad variety of smoothness constraints (25). As an alternative, we also developed a discrete formulation of the optical-flow problem, which relied on the discrete approximation of a family of quadratic functionals (25). The optical-flow methods produced by the proposed formulations were used to extract quantitative information from video recordings of neonatal seizures in the form of motion-strength signals. Motion-strength signals were obtained after the computation of the velocity fields by measuring the area at each frame containing all pixels with velocities exceeding a certain threshold.

Extraction of motor-activity signals

In principle, motor-activity signals are obtained by projecting to the horizontal and vertical axes an anatomical site located on the body part affected by the seizure. As the seizure progresses in time, the projection X of the anatomical site of interest to the horizontal axis and its projection Y to the vertical axis produce temporal signals $X(t)$ and $Y(t)$ recording motor activity of the body parts of interest. The extraction of motor-activity signals requires an automated procedure capable of tracking an anatomical site of interest throughout the video frame sequence.

Temporal motor-activity signals were extracted in our preliminary study (23) by the KLT algorithm, which tracks selected anatomical sites throughout a video-frame sequence by relying on a pure translation block-motion model (33,34). The KLT algorithm was generally successful in extracting motor-activity signals from video recordings of neonatal seizures. However, in some cases, the algorithm lost anatomical sites that were located on moving body parts tracked throughout the video-frame sequence (23). The susceptibility of the KLT algorithm to "lost sites" motivated several approaches aimed at the development of more accurate and reliable motion trackers. Such approaches dealt with several aspects of motion tracking, including the use of more sophisticated block-motion models (34,35).

Motion tracking was performed in this study by using adaptive block matching to track a block of pixels located on a moving body part throughout a sequence of frames (26). Although adaptive block matching was generally successful, it was not always reliable, because it attempts to find the best match of the block of interest within a large search window in the next frame. Our investigation led to the development of predictive block matching, a method developed to track motion by exploiting the advantages of block-motion estimation and adaptive block matching (27).

Motion tracking also was performed in this study by trackers based on novel minimization approaches (28) and a variety of block-motion models (29). The motion trackers developed in this study overcome most of the problems associated with the application of existing motion trackers in video recording of neonatal seizures, with the most notable being the occasional failure to track throughout the sequence of video frames. However, such motion trackers were found to be susceptible to noise and other recording imperfections. We addressed this problem recently by developing robust motion trackers, which are specifically designed to suppress the effect of noise (29).

Motion tracking in video also requires an automated procedure capable of selecting anatomical sites on the moving body part, which also was developed in this study (30). This automated procedure was developed even further to perform tracking of multiple anatomical sites located on moving body parts. This is necessary because

neonatal seizures are frequently associated with motion of multiple extremities.

Selection of quantitative features from video

The second specific aim of this project was to select quantitative features that convey some unique behavioral characteristics of neonatal seizures and nonseizure infant behaviors from temporal signals extracted from video recordings. Quantitative features can be obtained based on a global view of the temporal signals to represent some of their key properties and also to reveal their relation with the underlying clinical event.

Quantitative features from motion-strength signals

The quantitative features obtained from motion-strength signals were the variance of time intervals, the energy ratio, the maximum spike duration, and the number of spikes. This article shows only the results obtained for the first three of the features, which were experimentally found to provide the most solid basis for separating the classes.

Variance of time intervals. This feature can be obtained from motion-strength signals by computing the variance of the time intervals between any two adjacent spikes. If a motion-strength signal contains one or two spikes, the variance can be assigned an arbitrary large value. This feature was introduced to measure the rhythmicity of the infants' movements based on the observation that rhythmic movements would produce variance values close to zero. The variance of time intervals can be useful for distinguishing myoclonic seizures from focal clonic seizures because it is expected to take small values for focal clonic seizures but considerably higher values for myoclonic seizures.

Energy ratio: The correlation sequence of any two signals provides a measure of how similar these signals are and for how long they remain similar when one of them is shifted with respect to the other. The autocorrelation sequence is the correlation sequence of a signal with itself and may be used to measure the rhythmicity of motion manifested as quasiperiodic spikes in motion-strength signals. For a motion-strength signal that is N samples long, the autocorrelation was computed by shifting the signal with respect to itself by up to $0.6 \times N$ samples. The energy ratio of the autocorrelation sequence, or simply the energy ratio, was calculated as the ratio of the energy contained by the last 75% of the samples of the autocorrelation sequence to the energy contained by the first 25% of samples of the autocorrelation sequence. If two signals are similar in shape, their correlation sequence decays very slowly, and the corresponding energy ratio is expected to take large values. This is expected to be the case for the energy ratio computed for motion-strength signals produced for focal clonic seizures due to the rhythmicity of motion that is their signature. In contrast, the energy ratio is expected to take small values for myoclonic seizures because their autocorrelation sequence decays very fast, whereas most of its energy is contained by a few samples near the origin.

Maximum spike duration: The maximal spike duration provides a quantitative measure of the speed of the infants' movements. The maximum spike duration is expected to take the smallest values for myoclonic seizures, which are typically associated with rapid movements of short duration. Such values can differentiate neonatal seizures from random infant movements, which are typically slower and produce spikes of longer duration.

Number of spikes: This feature can be obtained from motion-strength signals by counting the number of spikes per time unit. Such a feature can be obtained by shifting a window over the entire frame sequence and counting the number of spikes per window. By fixing the size of the window, this feature becomes independent of the length of the frame sequence. The selection of such a feature can be justified by the fact that myoclonic seizures are expected to produce a small number of spikes because they are typically associated with isolated and rapid movements. In contrast, focal clonic seizures are expected to produce a large number of spikes per time unit because they are typically associated with rhythmic movements of considerable duration.

Quantitative features from motor-activity signals

Our investigation indicated that the selection of quantitative features from motor-activity signals can be facilitated by computing the motion trajectories for each of the moving body parts. The motion trajectory signal $Z = Z(t)$ was computed to measure the fluctuations of the motor activity signals $X = X(t)$ and $Y = Y(t)$ from their means $\bar{X}$ and $\bar{Y}$, respectively. The quantitative features selected from the motion trajectory signals were the energy ratio, the maximum spike duration, the variance of the time intervals between the extrema, and the number of extrema. Once again, this article shows only the results obtained for the first three of them, which formed the most successful set.

Energy ratio: The procedure outlined for computing the energy ratio for motion-strength signals also can be used for computing the energy ratio from the autocorrelation sequence of motion trajectory signals. For "sawtooth-like" signals produced for focal clonic seizures, the energy of the autocorrelation sequence is distributed over all its samples, and the energy ratio is expected to take large values. In contrast, the energy ratio is expected to take relatively small values for myoclonic seizures. This can be attributed to the fact that most of the energy of their autocorrelation sequence is contained by a few samples near the origin.

Maximum spike duration: The maximum spike duration provides a quantitative measure of the speed of the infants' movements. The maximum spike duration is obtained from the gradient of the motion trajectory signals

$Z = Z(t)$. If a movement produces a step-like displacement in the motion trajectory signal, the gradient would produce a spike at the step location. The duration of the spike would provide a measure of the speed, with rapid movements producing sharp spikes of short duration. The maximum spike duration is expected to take the smallest values for myoclonic seizures, which are typically associated with rapid movements of short duration. Such values can differentiate myoclonic seizures from random infant movements, which are typically slower and smoother than those associated with myoclonic seizures.

Variance of time intervals: The rhythmicity of the infants' movements can be quantified by computing the variance of time intervals between the extrema of the motion trajectory signals. In case of signals containing a single extremum or two extrema, the variance of time intervals between the extrema can be set to a predefined high value. This measure was established based on the observation that rhythmic movements would produce small variance values. Motor-activity signals produced by random infant movements may contain a large number of extrema as well, but the duration of the intervals between those extrema may vary considerably. As a result, such random infant movements are expected to produce high values for the variance of the intervals between extrema.

Number of extrema: This feature can be obtained from motor-activity signals by counting the number of extrema per time unit. The selection of such a feature can be justified by the fact that focal clonic seizures are expected to produce the largest number of extrema. This is consistent with the rhythmicity of motion characterizing these clinical events. The number of extrema is expected to be significantly smaller in the motor-activity signals extracted from myoclonic seizures and random infant movements.

Recognition and characterization of neonatal seizures based on neural networks

The third specific aim of this project was to train artificial neural networks to recognize neonatal seizures of the focal clonic and myoclonic types and differentiate them from normal and abnormal infant behaviors not associated with seizures. The development of an automated seizure-recognition system is essentially the problem of classifying a set of temporal signals that describe neonatal seizures and clinical events not associated with seizures. Neural networks provide a solid basis for the development of a seizure-recognition system because of their versatility and flexibility. Neural networks are nonlinear computational models that can be trained by examples to implement classifiers with no a priori assumptions regarding the statistics of the data or the size of the available data set (36,37).

The development of an automated seizure-recognition system relied on traditional feed-forward neural networks (FFNNs) (36,37). The FFNNs trained to recognize and characterize neonatal seizures contained a single hidden layer with 20 units and three sigmoid output units that represented the classes myoclonic seizure, focal clonic seizure, and random infant movement. The number of hidden units was chosen in these experiments by trial and error. The specific procedure used for determining the number of hidden units aimed at selecting the minimal number of hidden units required by the FFNNs to implement the mapping defined by the training set without degrading the generalization ability of the trained models. The FFNNs were trained by a learning algorithm developed to accelerate the training of supervised neural network models by gradient descent (38). The training was terminated when the classification error computed on the testing set increased for five consecutive iterations.

RESULTS

The methods were tested on a set of 240 video recordings of 43 patients exhibiting myoclonic seizures (80 cases), focal clonic seizures (80 cases), and random infant movements (80 cases).

Extraction of quantitative motion information from video

Figures 1 to 3 show the motion-strength and motor-activity signals extracted by the procedures developed during this project from video recordings of myoclonic seizures, focal clonic seizures, and random infant movements. The locations of the moving body parts during the clinical event are shown in representative frames of each video recording. The frames of the video recordings shown in Figs. 1–3 can be used as a reference to verify the consistency of the temporal signals with the corresponding clinical events. The values of the signals corresponding to the frames shown at the top of each figure are indicated by dots, whereas the moving body part in each video recording is shown within a box.

Figure 1 shows the temporal motion-strength and motor-activity signals produced for a myoclonic seizure. In the myoclonic seizure shown in Fig. 1, the infant's right hand is moving rapidly toward the bottom of the frame between frames 112 and 122 and from frame 200 to frame 220. According to Fig. 1a, this motion was captured and quantified correctly by the optical-flow method, which also captured the slow motion between frames 108 and 110. The motion-segmentation method based on clustering and morphologic filtering underestimated the area of the frames occupied by the moving body part by almost an order of magnitude. Both methods used for extracting the motor-activity signals shown in Fig. 1b managed to track the anatomical site selected by the automated procedure on the infant's right hand.

Figure 2 shows the temporal motion-strength and motor-activity signals produced for a focal clonic seizure. The focal clonic seizure shown in Fig. 2 affected the

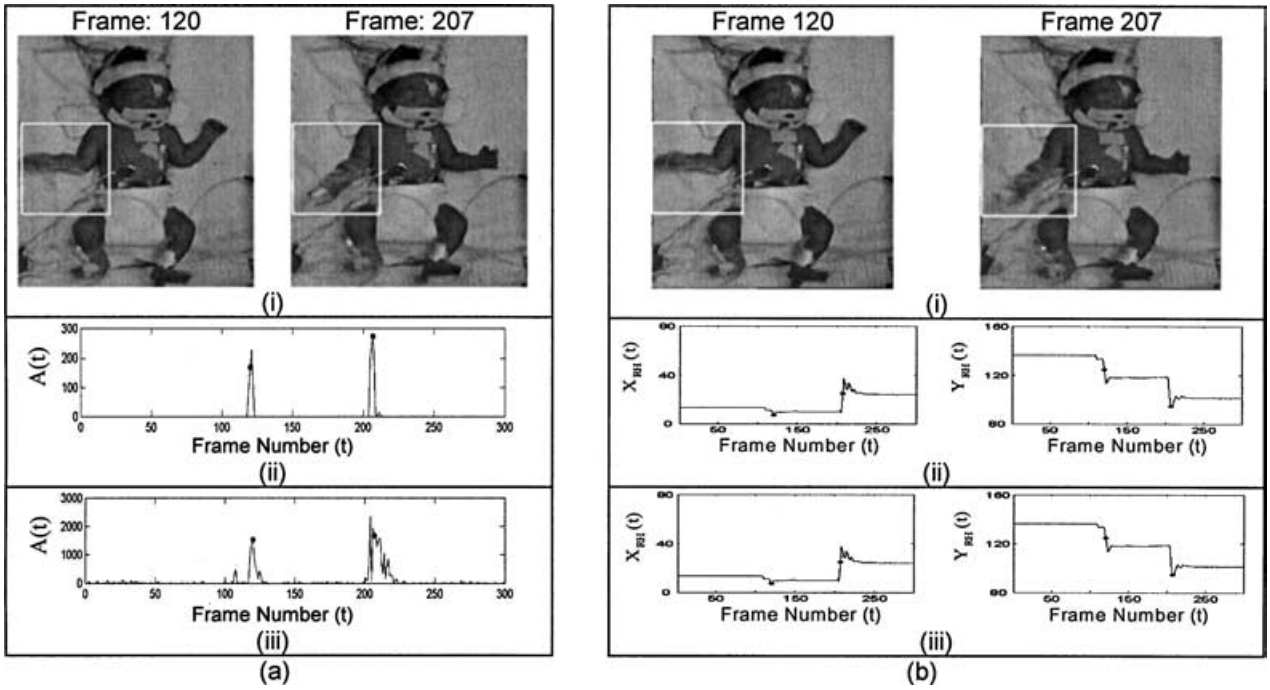

FIG. 1. **(i)** Selected frames of video recordings of a myoclonic seizure affecting an infant's right hand and quantitative motion information extracted in the form of **(a)** motion-strength signals produced by **(ii)** the motion-segmentation method based on clustering and morphological filtering and **(iii)** the optical-flow method, **(b)** motor-activity signals produced by **(ii)** the predictive block-matching method and **(iii)** the robust block motion-tracking method.

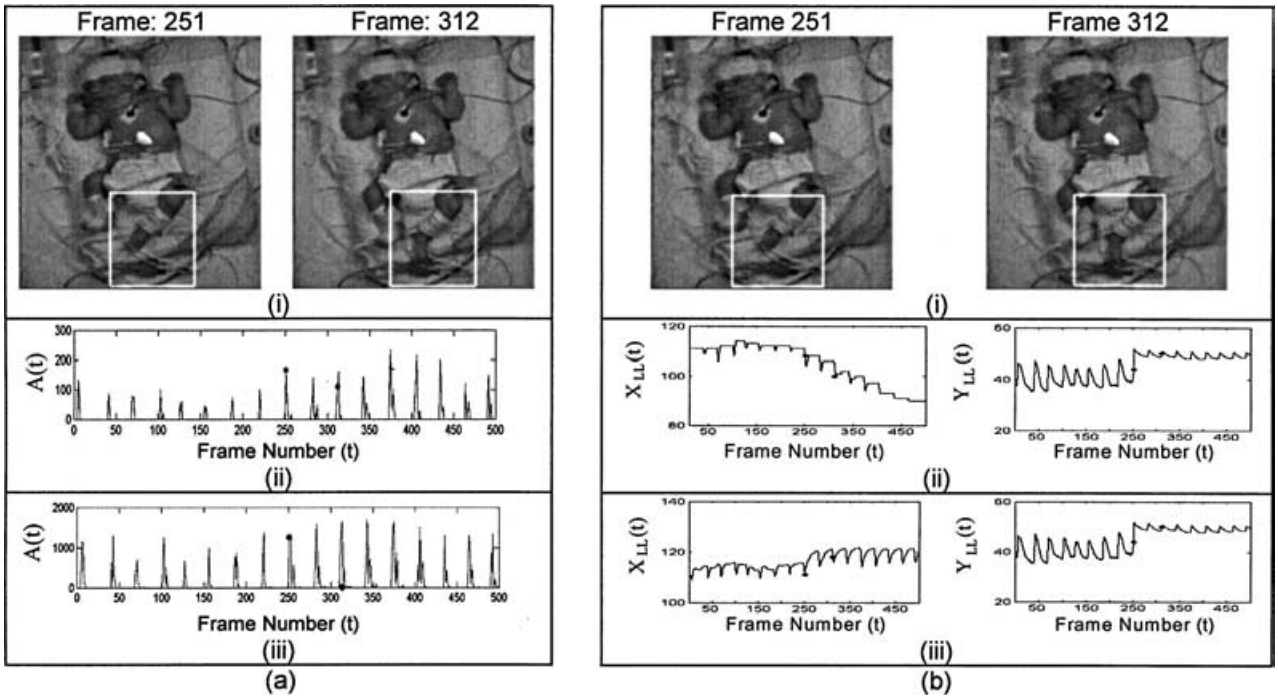

FIG. 2. **(i)** Selected frames of video recordings of a focal clonic seizure affecting an infant's left leg and quantitative motion information extracted in the form of **(a)** motion-strength signals produced by **(ii)** the motion-segmentation method based on clustering and morphological filtering and **(iii)** the optical-flow method, **(b)** motor-activity signals produced by **(ii)** the predictive block-matching method and **(iii)** the robust block motion-tracking method.

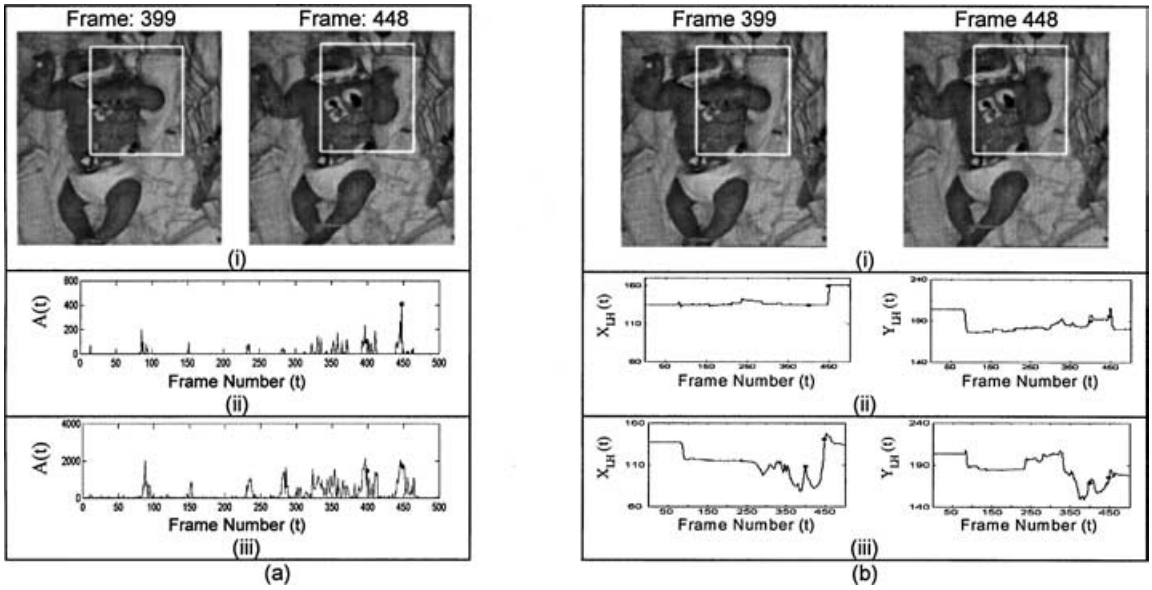

FIG. 3. **(i)** Selected frames of video recordings of a random movement of an infant's left hand and quantitative motion information extracted in the form of **(a)** motion-strength signals produced by **(ii)** the motion-segmentation method based on clustering and morphological filtering, and **(iii)** the optical-flow method, **(b)** motor-activity signals produced by **(ii)** the predictive block-matching method and **(iii)** the robust block motion-tracking method.

infant's left leg. The motion-strength signals produced by both methods captured the rhythmicity of the movements associated with this seizure. However, the motion-segmentation method based on clustering and morphological filtering underestimated the area of the frames occupied by the moving body part, as indicated by comparing the heights of the spikes present in the two motion-strength signals shown in Fig. 2a. According to Fig. 2b, both methods used for extracting motor-activity signals captured the rhythmicity of motion and produced very similar signals quantifying the motion along the vertical direction. However, only the signal $X_{LL}(t)$ produced by the robust block motion-tracking method is consistent with the motor activity of the infant's left leg along the horizontal direction.

Figure 3 shows the temporal motion-strength and motor-activity signals produced for a random infant movement. The two methods used in the experiments for extracting motion-strength signals captured the significant motion observed in the video recording during the random movement of the infant's left hand shown in Fig. 3a. The motion-segmentation method based on clustering and morphological filtering missed the movement of the infant's left hand between frames 300 and 310 that was captured by the optical-flow method. Figure 3b shows the motor-activity signals obtained for the random movement of the infant's left hand. The predictive block-matching method failed to track the anatomical site selected on the infant's left hand by the automated initialization procedure. The motion in this video recording was quantified accurately by the motor-activity signals produced by the robust block motion-tracking method.

Selection of quantitative features from video

Quantitative features from motion-strength signals

Figure 4 shows a collection of intermediate results obtained in the process of selecting quantitative features from motion-strength signals. According to Fig. 4c, the autocorrelation sequence obtained from the myoclonic seizure decays quickly to values close to zero and remains close to zero most of the time, except during a short interval prior to frame 100. In contrast, the autocorrelation sequence computed from the focal clonic seizure takes nonzero values most of the time, a fact that is consistent with the rhythmicity of motion associated with seizures of this type. The autocorrelation sequence obtained from the random infant movement is closer to that obtained from the focal clonic seizure. However, the proportion of the energy contained by its last 75% of samples is lower than that corresponding to the focal clonic seizure. The energy ratio for the random infant movement was 0.363, which can be compared with the energy ratio value of 0.561 corresponding to the focal clonic seizure. The rhythmicity of motion associated with the focal clonic seizure is also revealed by the time intervals between the spikes, many of which are of comparable length. This is the reason that the focal clonic seizure produced the lowest value of the variance of the time intervals. The highest variance value was obtained for the myoclonic seizure, whereas the random infant movement produced a variance value between the two extremes corresponding to the two types of seizures. The random infant movement produced the longest spikes, an outcome that is consistent with the fact that random infant movements are typically slower than the rapid and jerky movements

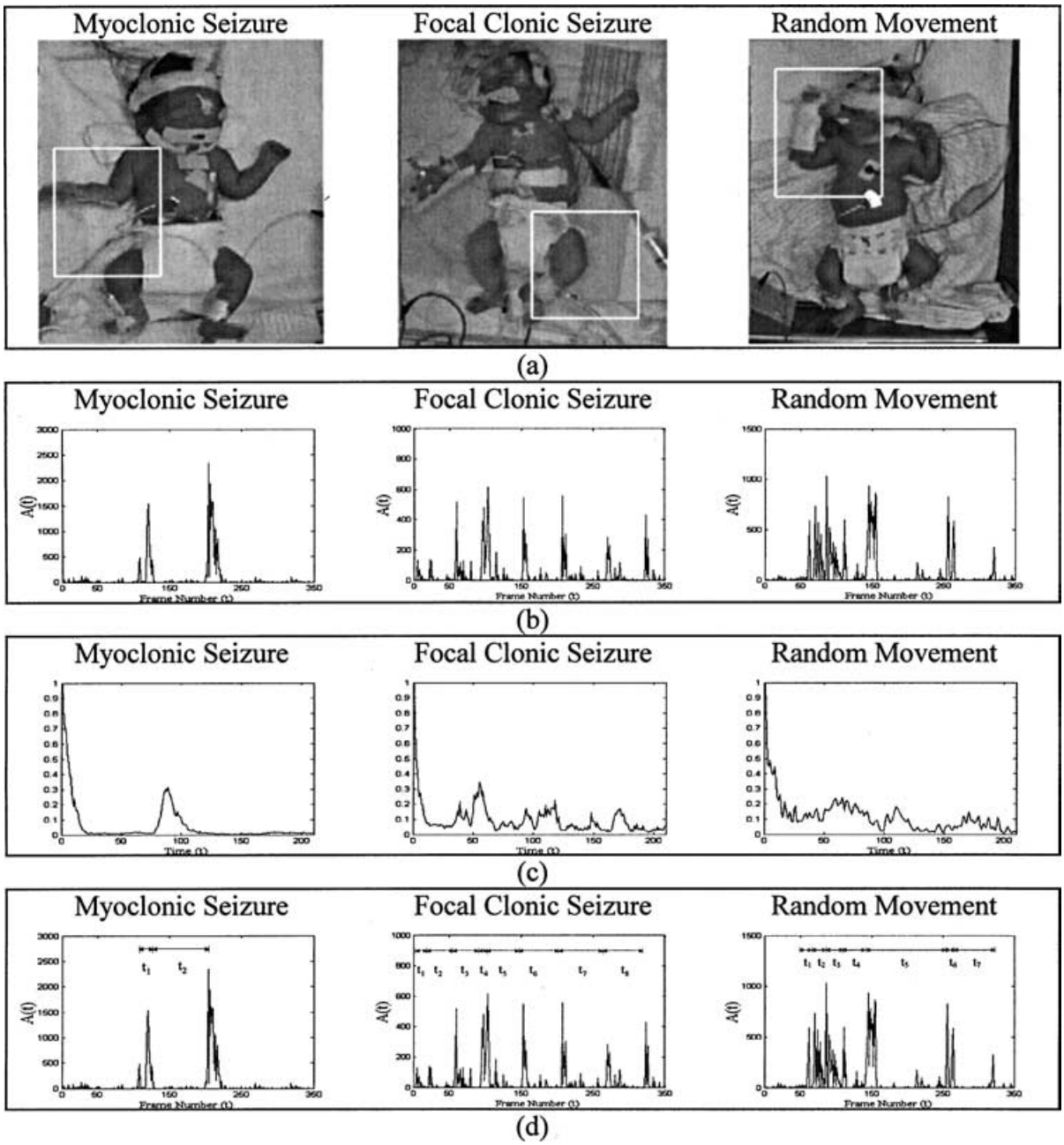

FIG. 4. (a) Selected frame from the video recordings of a myoclonic seizure (MCS), focal clonic seizure (FCS), and random infant movement (RIM); **(b)** the motion-strength signals $A(t)$ extracted from the video recordings by the optical-flow method; **(c)** the autocorrelation sequences computed from the motion-strength signals, and **(d)** the motion-strength signals together with the time intervals between the spikes. Variance of time intervals: 150 (MCS), 12.2 (FCS), 38.1 (RIM); energy ratio: 0.216 (MCS), 0.561 (FCS), 0.363 (RIM); maximal spike duration: 23 (MCS), 15 (FCS), 29 (RIM); and number of spikes per 50 frames: 0.6 (MCS), 1.5 (FCS), 1.1 (RIM)

associated with neonatal seizures. The focal clonic seizure produced the largest number of spikes, whereas the second largest number of spikes was obtained for the random infant movement. This is consistent with the fact that focal clonic seizures are events of considerable duration, whereas myoclonic seizures are manifested as an isolated movement or as a short sequence of movements.

Table 1 shows the Fisher ratio (FR) for the three features selected from motion-strength signals produced by the motion-segmentation method based on clustering and morphological filtering for the video recordings of 80 cases of myoclonic seizures, 80 cases of focal clonic seizures, and 80 cases of random infant movements. The FR is a statistical measure of class separability; increasing values of the FR computed for two classes reveal improving class separability (39). The FR was computed for three pairs of the classes myoclonic seizure, focal clonic seizure, and random infant movement. Table 1 also shows the

TABLE 1. *Fisher ratio and generalized Fisher ratio computed for three features selected from motion-strength signals*

Class separability measure	Classes	Variance of time intervals	Energy ratio	Maximal spike duration
Fisher ratio	Focal clonic seizure/myoclonic seizure	0.806	0.435	0.008
Fisher ratio	Myoclonic seizure/random movement	0.449	0.410	0.294
Fisher ratio	Focal clonic/random movement	0.029	0.008	0.183
Generalized Fisher ratio	All three classes	0.071	0.047	0.027

The motion-strength signals were extracted from video recordings of 80 myoclonic seizures, 80 focal clonic seizures, and 80 random infant movements by the motion segmentation method based on clustering and morphological filtering.

generalized Fisher ratio (GFR) for the same features, which was computed according to the formula suggested for multiple classes by Krishnan and Rao (39). The same measures are shown in Table 2 for the features selected from motion-strength signals produced by the optical-flow method. Comparison of Tables 1 and 2 reveals the superiority of the features selected from the motion-strength signals produced by the optical-flow method. According to Table 2, the features selected from motion-strength signals produced by the optical-flow method can be rated in terms of class separability as follows: variance of time intervals (highest GFR value), energy ratio, and maximum spike duration (lowest GFR value). Finally, Table 2 indicates that the most challenging problem is to distinguish random movements from either myoclonic or focal clonic seizures. These conclusions are consistent with Fig. 5, which shows a scatterplot of the energy ratio and the variance of time intervals obtained for motion-strength signals extracted by the two methods tested in the experiments from the video recordings of 40 cases of myoclonic seizures, 40 cases of focal clonic seizures, and 40 cases of random infant movements. According to Fig. 5a, the motion-segmentation method based on clustering and morphological filtering placed a relatively large number of random movements in the region occupied by myoclonic seizures. Even more cases of random movements were placed by this method in the region occupied by focal clonic seizures. According to Fig. 5b, most of the myoclonic seizures produced high values of the variance of time intervals. Figure 5b also explains why differentiating random infant movements from either myoclonic seizures or focal clonic seizures is by far a more challenging problem than distinguishing myoclonic from focal clonic seizures.

Quantitative features from motor-activity signals

Figure 6 shows a collection of intermediate results obtained in the process of selecting quantitative features from motion trajectory signals. According to Fig. 6c, the autocorrelation sequence computed for the myoclonic seizure decays very fast and takes values close to zero for large time intervals. This is consistent with the rapid and jerky movements that are the signature of myoclonic seizures. In contrast, the sustained rhythmic movements that characterize focal clonic seizures produce autocorrelation sequences that do not decay to zero, such as that shown for the focal clonic seizure in Fig. 6c. Random infant movements can produce a great variety of autocorrelation sequences that typically constitute a compromise between myoclonic and focal clonic seizures in terms of their decay patterns. The rapid movements associated with neonatal seizures produce spikes of short duration, as indicated by the gradient of the motion trajectory signals shown in Fig. 6d for the myoclonic and focal clonic seizures. Figure 6d also describes a situation in which the random infant movement produced a sequence of short spikes followed by spikes of longer duration. In this case, the maximum spike duration associated with the random infant movement was longer than those corresponding to the myoclonic and focal clonic seizures. The sustained rhythmic movements associated with focal clonic seizures correspond to time intervals between the extrema that are almost equal in length. This is the reason focal clonic seizures lead to small values of the interval variance compared with myoclonic seizures and random infant movements. Such clinical events produce relatively large values of the interval variance because they correspond to irregular time intervals between the extrema, as indicated by Fig. 6d. The number of

TABLE 2. *Fisher ratio and generalized Fisher ratio computed for three features selected from motion-strength signals*

Class separability measure	Classes	Variance of time intervals	Energy ratio	Maximal spike duration
Fisher ratio	Focal clonic seizure/myoclonic seizure	8.711	7.459	0.101
Fisher ratio	Myoclonic seizure/random movement	3.600	1.812	0.844
Fisher ratio	Focal clonic/random movement	0.139	1.521	0.012
Generalized Fisher ratio	All three classes	0.692	0.554	0.053

The motion-strength signals were extracted from video recordings of 80 myoclonic seizures, 80 focal clonic seizures, and 80 random infant movements by the optical-flow method.

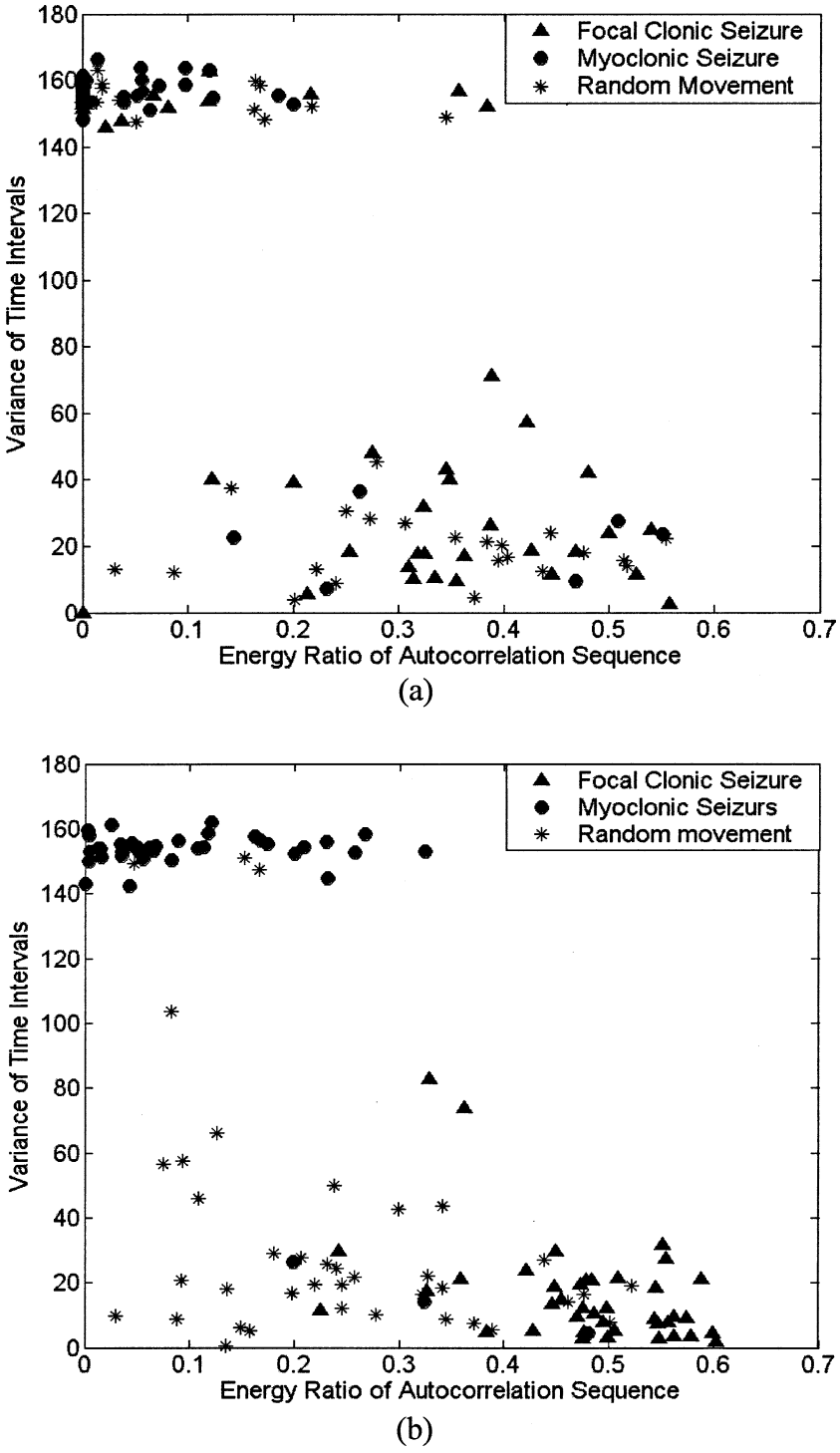

FIG. 5. Scatterplot of the energy ratio and the variance of time intervals obtained for motion-strength signals extracted from video recordings of myoclonic seizures, focal clonic seizures, and random infant movements by **(a)** the motion-segmentation method based on clustering and morphological filtering, and **(b)** the optical-flow method.

extrema was low for myoclonic seizures, which are typically associated with a few isolated movements, and random infant movements. Figure 6d shows a situation in which the random infant movement produced a higher number of extrema per time unit compared with both the myoclonic seizure and the focal clonic seizure. This is an indication that this particular quantitative feature may not always be reliable.

Tables 3 and 4 show the FR and the GFR for the three features selected from motor-activity signals produced by the predictive block-matching method and the robust block motion-tracking method, respectively, for the video recordings of 80 cases of myoclonic seizures, 80 cases of focal clonic seizures, and 80 cases of random infant movements. Tables 3 and 4 indicate that the robust block motion-tracking method produced features that provide

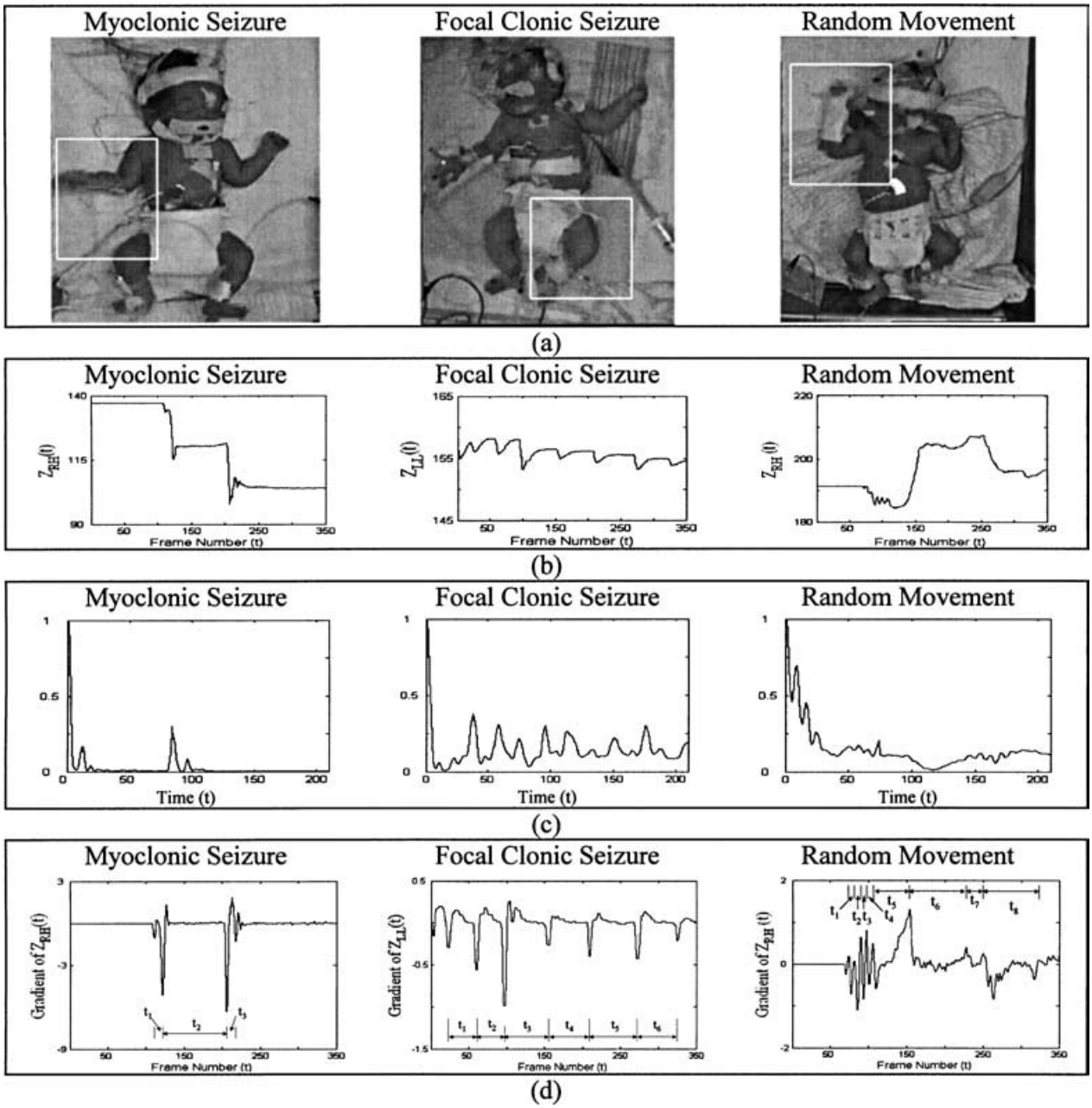

FIG. 6. (a) Selected frame from the video recordings of a myoclonic seizure (MCS), focal clonic seizure (FCS), and random infant movement (RIM). **(b)** The motion trajectory signals $Z(t)$ extracted from the video recordings by the robust block motion method. **(c)** The autocorrelation sequences computed from the motion trajectory signals. **(d)** The signals produced by computing the gradient of the motion trajectory signals. Energy ratio: 0.174 (MCS), 0.609 (FCS), 0.303 (RIM); maximal spike duration: 7 (MCS), 16 (FCS), 34 (RIM); variance of time intervals: 50.1 (MCS), 11.7 (FCS), 29.4 (RIM); number of extrema per 50 frames: 0.6 (MCS), 1.0 (FCS), 1.3 (RIM).

a more reliable basis for class separation. According to Table 4, the features selected from motor-activity signals produced by the robust block motion-tracking method can be rated in terms of class separability as follows: energy ratio (highest GFR value), maximum spike duration, and variance of time intervals (lowest GFR value). Just like the features extracted from motion-strength signals, the features selected from motor-activity signals indicate that distinguishing myoclonic and focal clonic seizures from random infant movements is a more challenging problem than that of distinguishing between focal clonic and myoclonic seizures. This evaluation can be verified by Fig. 7, which shows a scatterplot of the energy ratio and the maximum spike duration obtained for motor-activity signals extracted by the two methods tested in the experiments from the video recordings of 40 cases of myoclonic seizures, 40 cases of focal clonic seizures, and 40 cases of random infant movements. Figure 7a indicates that predictive block

TABLE 3. *Fisher ratio and generalized Fisher ratio computed for three features selected from motor-activity signals*

Class separability measure	Classes	Variance of time intervals	Energy ratio	Maximal spike duration
Fisher ratio	Focal clonic seizure/myoclonic seizure	7.282	2.904	2.473
Fisher ratio	Myoclonic seizure/random movement	2.128	2.033	0.832
Fisher ratio	Focal clonic/random movement	1.843	1.561	1.067
Generalized Fisher ratio	All three classes	0.625	0.361	0.243

The motor-activity signals were extracted from video recordings of 80 myoclonic seizures, 80 focal clonic seizures, and 80 random infant movements by the predictive block matching method.

matching placed a large proportion of focal clonic seizures in the regions of the 2-D feature space occupied by random infant movements or myoclonic seizures or both. This can be attributed to the fact that predictive block matching failed occasionally to capture and quantify the rhythmicity of motion associated with focal clonic seizures. According to Fig. 7b, myoclonic seizures produced the lowest values of the energy ratio when motor-activity signals were extracted by the robust block motion-tracking method. The values of the energy ratio can be used to distinguish myoclonic seizures from focal clonic seizures, which produced the highest values of the energy ratio. Figure 7b also indicates that random infant movements produced the largest values of the maximum spike duration. Such values are consistent with the fact that random infant movements are typically slower than those associated with neonatal seizures. According to Fig. 7b, the majority of myoclonic seizures produced low values of the maximum spike duration. This outcome is consistent with the rapid and "jerky" movements that are the signature of myoclonic seizures.

Recognition and characterization of neonatal seizures based on neural networks

This experimental study evaluated the performance of FFNNs trained to recognize and characterize the types of neonatal seizures by using a set of 240 video recordings of 43 patients exhibiting myoclonic seizures (80 cases), focal clonic seizures (80 cases), and random movements (80 cases). Each of the training and testing sets contained 120 video recordings (40 cases of myoclonic seizures, 40 cases of focal clonic seizures, and 40 cases of random movements). The inputs used for training the FFNNs were formed in terms of (a) features extracted from temporal motion-strength signals, (b) features extracted from temporal motor-activity signals, and (c) features extracted from temporal motion-strength and motor-activity signals. Each FFNN was trained and tested in 50 trials by using a different initial set of weights in each trial. The results of the 50 trials provided the basis for computing the sample mean μ and standard deviation σ for the sensitivity and specificity. These values were used to obtain the 95% confidence intervals shown in Tables 5–7.

Table 5 shows the sensitivity and specificity for myoclonic seizures and focal clonic seizures on the training and testing sets by the FFNN trained to recognize and characterize the types of neonatal seizures by using quantitative features selected from motion-strength signals. On average, the sensitivity and specificity of the FFNN exceeded 95% on the training set. When the FFNN was tested on the testing set, the average sensitivity reduced to $\sim$90% with a standard deviation $\sim$2%. The specificity of the FFNN on the testing set was on average $>$90%, whereas its standard deviation was considerably lower.

Table 6 shows the sensitivity and specificity for myoclonic seizures and focal clonic seizures on the training and testing sets by the FFNN trained to recognize and characterize the types of neonatal seizures by using quantitative features selected from motor-activity signals. When the FFNN was tested on the training set, the average sensitivity and specificity were both $>$90%. When the FFNN was tested on the testing set, the average sensitivity was slightly $<$90% with a standard deviation $\sim$2%. Compared with the FFNN trained by using quantitative features obtained from motion-strength signals, the FFNN trained by using quantitative features obtained from motor-activity signals exhibited lower sensitivity. However, training the FFNN by using quantitative features obtained from

TABLE 4. *Fisher ratio and generalized Fisher ratio computed for three features selected from motor-activity signals*

Class separability measure	Classes	Variance of time intervals	Energy ratio	Maximal spike duration
Fisher ratio	Focal clonic seizure/myoclonic seizure	10.016	3.894	3.423
Fisher ratio	Myoclonic seizure/random movement	4.786	2.044	1.969
Fisher ratio	Focal clonic/random movement	3.617	1.200	0.448
Generalized Fisher ratio	All three classes	1.029	0.397	0.324

The motor-activity signals were extracted from video recordings of 80 myoclonic seizures, 80 focal clonic seizures, and 80 random infant movements by the robust block motion tracking method.

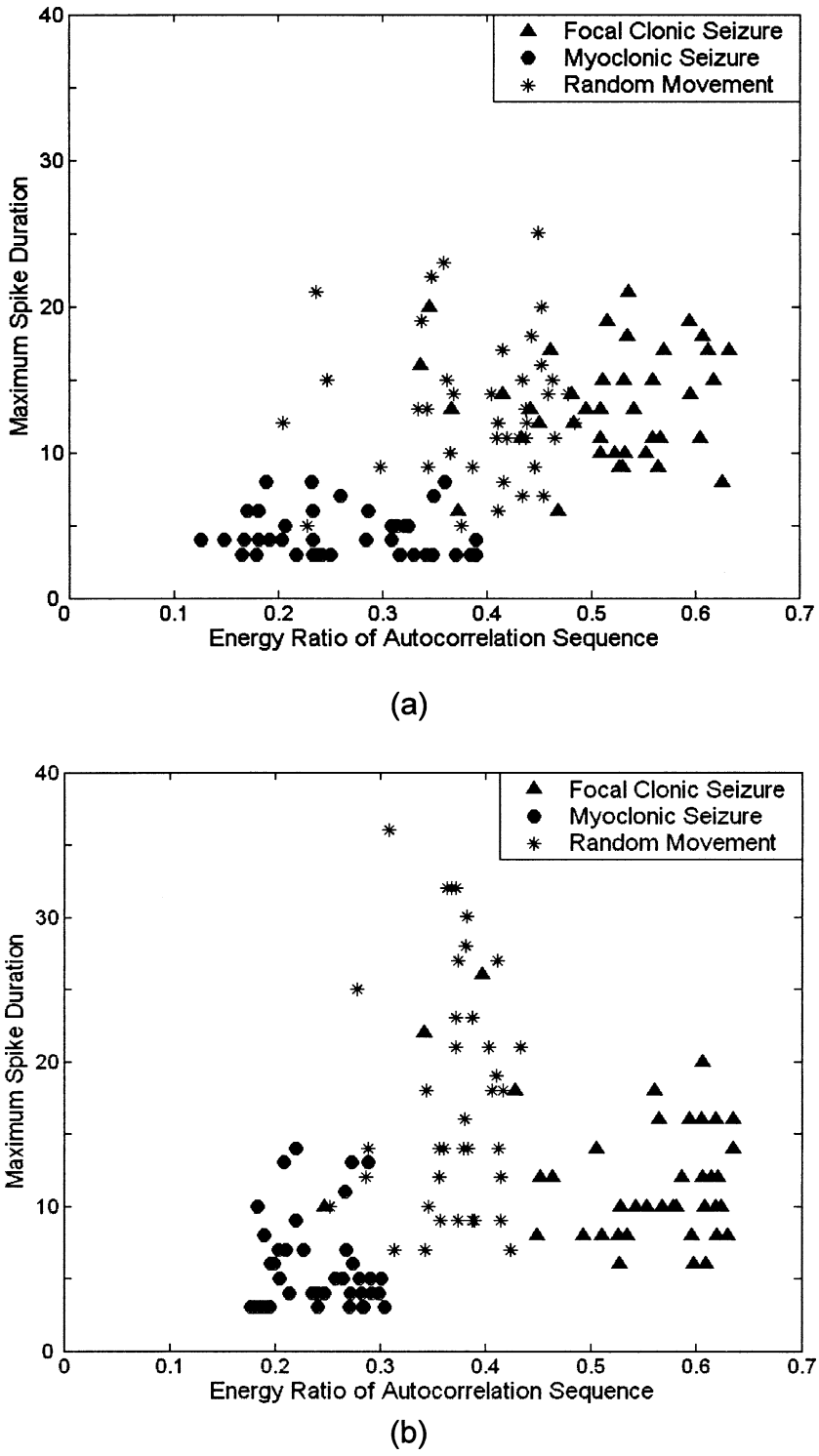

FIG. 7. Scatterplot of the energy ratio and the maximum spike duration obtained for motor-activity signals extracted from video recordings of myoclonic seizures, focal clonic seizures, and random infant movements by (a) the predictive block-matching method and (b) the robust block motion-tracking method.

motor-activity signals led to specificity values >90%. The sensitivity for myoclonic seizures was higher than that of the FFNN trained by using quantitative features obtained from motion-strength signals.

Table 7 shows the sensitivity and specificity for myoclonic seizures and focal clonic seizures on the training and testing sets by the FFNN trained to recognize and characterize the types of neonatal seizures by using quantitative features selected from motion-strength and motor-activity signals. Training the FFNN by using quantitative features obtained from both motion-strength and motor-activity signals led to sensitivity and specificity values >95% on the training set. This training strategy also increased the average sensitivity values obtained on the testing set, with the sensitivity for myoclonic seizures reaching values well above 90% and specificity values >95%.

TABLE 5. *Recognition and characterization of neonatal seizures based on three features extracted from motion-strength signals (variance of time intervals, energy ratio, and maximum spike duration)*

	Training set		Testing set	
	Sensitivity (%)	Specificity (%)	Sensitivity (%)	Specificity (%)
Myoclonic seizure	94.6 ± 1.9	99.1 ± 2.2	92.5 ± 1.7	92.5 ± 0.8
Focal clonic seizure	92.5 ± 1.2	96.8 ± 1.7	89.4 ± 2.4	96.3 ± 0.4

Sensitivity and specificity (95% confidence intervals) produced for the training and testing sets by a feed-forward neural networks trained to recognize myoclonic seizures, focal clonic seizures, and random infant movements.

Compared with the FFNNs trained by using quantitative features obtained from either motion-strength or motor-activity signals, the FFNN trained in these experiments exhibited a lower sensitivity for focal clonic seizures (∼85%) but higher sensitivity for myoclonic seizures (∼95%). The specificity values shown in Table 7 for the testing set are higher than those of the FFNNs trained by using quantitative features obtained from either motion-strength or motor-activity signals.

DISCUSSION

In the study outlined here, we developed and evaluated a variety of computational tools and procedures that may be used to carry out the essential tasks involved in the development of a computerized video system for monitoring infants at risk for seizures; these tasks include the extraction of quantitative motion information from video recordings of neonatal seizures in the form of motion-strength and motor-activity signals, the selection of quantitative features that convey some unique behavioral characteristics of neonatal seizures, and the training of neural networks to recognize and characterize the types of neonatal seizures. These three tasks were carried out by relying on short video segments containing either neonatal seizures or random infant movements not associated with seizures. The computational tools and procedures developed to carry out each of the three tasks were tested and evaluated separately by using as a sole criterion the objective of each task. To achieve the long-term goals of this project, we plan to upgrade the procedures developed during the ongoing project by automating their operation, enhancing their accuracy, and improving their robustness and reliability. The upgraded computational tools and procedures will be used to enhance the diagnostic value of video recordings of infants monitored for seizures. This will be accomplished by developing automated quantification procedures and visualization tools designed to assist physicians during retrospective review. The same computational tools and procedures will be integrated to develop an automated system trained to recognize and characterize the types of neonatal seizures in long recordings that may contain neonatal seizures. The remainder of this section discusses some open problems revealed by our experimental study and outlines some of our future research plans.

Extraction of quantitative motion information from video

The signals produced by the optical-flow method contain spikes that are wider than those produced for the same movements by the motion-segmentation method based on clustering and morphological filtering. This is an indication that the motion-segmentation method based on clustering and morphological filtering underestimated the duration of most of the infants' movements because it missed the beginnings and the ends of those movements. This experimental study indicated that the motion-strength signals produced by the best regularized optical-flow methods captured and quantified the defining characteristics of focal clonic and myoclonic seizures.

The experiments indicated that predictive block matching failed on some occasions to track the anatomical site selected on the moving body part throughout the frame sequence. Tracking motion based on block motion models appeared to be a more reliable approach. Block motion estimation improved considerably from the introduction of fractional block-motion models, which outperformed

TABLE 6. *Recognition and characterization of neonatal seizures based on three features extracted from motor-activity signals (energy ratio, maximum spike duration, and variance of time intervals)*

	Training set		Testing set	
	Sensitivity (%)	Specificity (%)	Sensitivity (%)	Specificity (%)
Myoclonic seizure	90.6 ± 2.5	98.4 ± 1.1	89.2 ± 4.9	95.7 ± 2.5
Focal clonic seizure	95.4 ± 3.6	94.0 ± 2.1	88.7 ± 3.9	93.5 ± 2.2

Extracted from motor-activity signals (energy ratio, maximal spike duration, and variance of time intervals). Sensitivity and specificity (95% confidence intervals) produced for the training and testing sets by an FFNN trained to recognize myoclonic seizures, focal clonic seizures, and random infant movements.

TABLE 7. *Recognition and characterization of neonatal seizures. Based on three features extracted from motion-strength signals (variance of time intervals, energy ratio, and maximum spike duration) and three features extracted from motor-activity signals (energy ratio, maximal spike duration, and variance of time intervals)*

	Training set		Testing set	
	Sensitivity (%)	Specificity (%)	Sensitivity (%)	Specificity (%)
Myoclonic seizure	100.0 ± 0.0	100.0 ± 0.0	94.4 ± 2.0	96.1 ± 0.8
Focal clonic seizure	95.0 ± 1.0	98.4 ± 1.2	85.5 ± 1.3	97.9 ± 1.2

Sensitivity and specificity (95% confidence intervals) produced for the training and testing sets by a feed-forward neural network with three output units trained to recognize and characterize neonatal seizures.

considerably a pure translation model and an affine block-motion model. The experimental results verified that the robust motion trackers developed in this study are resistant to noise and other recording imperfections.

Selection of quantitative features from video

The Fisher ratio measure used in this experimental study provided the basis for evaluating the quantitative features obtained from motion-strength and motor-activity signals using as a criterion the class separability. This evaluation is of critical importance given the long-tem goals of this project. The outcome of these experiments verified that optical-flow methods are more reliable than the method based on clustering and morphological filtering for quantifying neonatal seizures from video recordings in the form of motion-strength signals. Even when the motion-segmentation method based on clustering and morphological filtering managed to quantify motion, the optical-flow method produced motion-strength signals that constitute a more accurate representation of the infants' movements. The experimental results also verified that the robust motion trackers developed in this study outperformed considerably the motion trackers based on predictive block matching in terms of both reliability and accuracy.

The quantitative features selected from motion-strength and motor-activity signals constitute a satisfactory representation of neonatal seizures and random infant movements. Nevertheless, the set of quantitative features extracted in this study is not unique. Other features may exist whose combination provides a more effective representation of neonatal seizures and random infant movements. Thus the search for the best quantitative features from motion-strength and motor-activity signals is still an open problem worthy of further investigation.

Recognition and characterization of neonatal seizures based on neural networks

The outcome of this experimental study provides evidence suggesting that it is feasible to develop an automated system for the recognition and characterization of the types of neonatal seizures based on video recordings. This will be accomplished by enhancing the accuracy and improving the reliability of the computational tools and methods developed during the course of the ongoing study. In the next phase of this project, we plan to evaluate the available computational tools and procedures when they become the ingredients of the proposed seizure-recognition system. This evaluation will be carried out at three levels:

Level 1

Can the system recognize most of the true seizures while minimizing the proportion of true seizures classified as nonseizure behaviors? This measures sensitivity, the goal of the next phase of this project being ≥90%.

Level 2

Can the system recognize most of the nonseizure infant behaviors while minimizing the proportion of nonseizure infant behaviors classified as seizures? This measures specificity, the goal of the next phase of this project being ≥95%.

Level 3

Can the system assign a degree of certainty to seizure classification that is consistent with the evaluation of human experts? This assessment will investigate whether the response of the trained neural networks provides a reliable basis for identifying and quantifying uncertainty.

The ongoing study revealed that the performance of neural network models trained to perform seizure recognition and characterization is affected mainly by the existence of uncertain events. One source of uncertainty is the lack of contextual information. In the case of electroclinical seizures, the physicians who classified the video segments of the CRCNS database were able to observe simultaneous EEG recordings over multiple channels. These EEG recordings provided the physicians with numerous hints and clues that were critical for seizure recognition. However, such contextual information is not readily available to a classifier trained by examples to recognize neonatal seizures from video recordings.

Seizure recognition and characterization was performed during the ongoing study by training conventional FFNNs (36,37). However, despite their advantages, FFNNs are not capable of effectively dealing with the uncertainty typically involved in pattern-classification tasks. The inability of FFNNs to deal effectively with uncertainty

motivated the development of a class of inherently fuzzy neural networks known as quantum neural networks (QNNs) (40,41). QNNs use multilevel hidden units that produce a better structured representation of the input space by identifying overlapping between different classes of data. As a result, QNNs can identify and quantify the uncertainty typically associated with pattern-classification tasks. The superior performance of QNNs in the presence of uncertainty was revealed by a recent study that relied on FFNNs and QNNs to improve the detection of epileptic segments from neonatal EEG (42,43).

Combination of video with EEG analysis

One of our future goals is to enhance the overall accuracy and improve the reliability of automated seizure recognition by merging the video-analysis procedures and tools developed in this project with complementary techniques and procedures developed to analyze neonatal EEGs (42–46). Although recognition of seizures in the intensive care environment is still largely dependent on human observation, this mode is ineffective in the case of therapeutically paralyzed or restrained infants and does not identify patients experiencing purely EEG events. On the other hand, clinical seizures that have no electrographic correlate cannot be detected by EEG analysis. Consequently, an appropriate combination of automated video and EEG analytic approaches would be expected to result in a significant improvement in the ability to detect promptly the occurrence of all seizure types in this population.

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