ADVANCING VIDEOMETRY THROUGH APPLICATIONS: QUANTIFICATION OF NEONATAL SEIZURES FROM VIDEO RECORDINGS

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Abstract: This paper presents some recent advances in videometry that resulted from the development of video processing and analysis procedures designed to facilitate the quantification of neonatal seizures. This paper presents two automated procedures developed to extract temporal information from video recordings of neonatal seizures in the form of temporal motion strength and motor activity signals. These signals constitute an effective representation of videotaped clinical events and can be used in the development of an intelligent system for seizure recognition and characterization.

1. INTRODUCTION

Videometry [*video* + *metron* (Greek for measure)] can be defined as a collection of automated procedures and techniques developed in an attempt to extract, process, and analyze quantitative information from video recordings. Videometry is expected to flourish and gain significance in an era where video is becoming a necessary tool in many facets of human activity. This expectation is supported by the fact that the majority of scientific disciplines were developed in an attempt to satisfy certain human needs. This is especially true for disciplines developed to empower people with the ability to measure the world around them. A typical example is geometry, which was developed to provide a standard and undisputable methodology for measuring and redistributing the land after floods. The advancement of videometry is not really a choice but a necessity created by the transition from analog to digital video. A historical analogy can only be found in the revolutionary technological developments that were motivated by the advent of digital computers some decades ago.

Video is a rather unique imaging modality in the sense that it contains both temporal information (also contained in 1-D signals that vary with time) and spatial information (also contained in 2-D still images). This implies that the extraction of quantitative information from video cannot be accomplished by simply borrowing or even by extending techniques and procedures developed for 1-D and 2-D signals. Another challenge associated with videometry is that the extraction of quantitative information from video essentially involves intelligent abstraction. More specifically, the automated procedures developed for videometry must focus on regions of the frames containing time-varying information while ignoring the redundancy that is typically present in image sequences. Such an operation requires some *a priori* knowledge of the specific information that must be extracted from video. This implies that automated techniques and procedures developed for videometry are essentially application-dependent. It is apparent from the above discussion that videometry cannot be developed in a vacuum but only in the context of practical applications. Such an application is the quantification of neonatal seizures from their video recordings, which will be the main focus of the research outlined in this paper.

2. NEONATAL SEIZURES

Seizures occur in approximately 2-5/1000 live births, depending upon studied populations and methodology (Eriksson and Zetterstrom, 1979; Holden et al., 1982; Bergman et al., 1983; Ellenberg et al., 1984; Spellacy et al., 1987; Lanska et al., 1995; Ronen and Penney, 1995; Saliba et al., 1999). In addition, there may be different clinical manifestations and different consequences of neonatal seizures depending upon the conceptional age of the infant (Scher et al., 1993; Volpe, 1995; Lanska et al., 1995). This is particularly true for premature infants and those infants who are critically ill in intensive care nurseries. In fact, the incidence of seizures in infants weighing less than 1500 grams is 57.5/1000 live births compared to 3.5/1000 live births for all birthweights (Lanska et al, 1995). Similarly, Scher et al. (1993) reported that seizures occurred in approximately 4% of premature infants less than 30 weeks conceptional age, although some have reported the incidence in this population reaching as high as 20% (Seay and Bray, 1977). These studies indicate that seizure occurrence represents the most frequent clinical sign of central nervous system disorders in the newborn (Fenichel, 1990; Volpe, 1995; Mizrahi and Kellaway, 1998). These disturbances in cerebral function may result in significant long-term adverse sequelae such as neurological handicaps, mental retardation, and postnatal epilepsy (Holden, et al., 1982; Mellitis et al., 1982; Bergman et al., 1983; Ellenberg et al., 1984; Clancy and Legido, 1991; Scher et al., 1993; Volpe, 1995; Bye et al., 1997; Mizrahi, 1999). The prompt identification of clinical seizures when they occur in the newborn, the subsequent evaluation of their etiology, and the institution of etiology-specific therapy may significantly reduce associated morbidity. In some situations, antiepileptic medication is provided to diminish the likelihood of recurrent seizures, and to lower the risk of physiologic instability during seizures. Thus, prompt recognition of seizures by nursery personnel is very important with regard to diagnosis and management of underlying neurological problems.

Despite the importance of seizure recognition, most neonatal intensive care units and nurseries have limited

resources for seizure identification. Neonatal seizures are currently detected in clinical settings only if a physician or a trained nurse is present while the seizures are occurring, which is not guaranteed. The attention of nursing personnel is distributed across a large number of infants, who are ill and require continuous bedside care. Neonatal seizures are often brief and may not be recognized since nurses and physicians cannot provide continuous surveillance of all infants at risk for clinical seizures. 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 brief EEG recordings. The development of portable EEG/video/polygraphic monitoring techniques allows investigators to assess and characterize neonatal seizures at the bedside and permits retrospective review (Penry et al., 1975; Ives and Gloor, 1978; Kellaway et al., 1978; Binnie et al., 1981; Luther et al., 1982; Mizrahi and Kellaway, 1984; Kellaway and Frost, 1985; Mizrahi, 1986; Mizrahi and Kellaway, 1987; Pierelli et al., 1989; Bye et al., 1990; Ives et al., 1991; Oguni et al., 1992; Rector et al., 1993). These techniques are relatively expensive, are generally used for only a few hours of monitoring, and are not routinely available in many centers. The linkage of computer-based processing and analysis of video signals with seizure detection and characterization is an innovative approach that has never been used before. Automated 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: 1) develop automated mechanisms capable of detecting the beginning of clinical seizures, 2) refine the characterization of repetitive motor behaviors, and 3) facilitate the differentiation of certain clinical seizures from other abnormal paroxysmal behaviors not due to seizures. A video system based upon automated analysis potentially offers a number of advantages. Infants who are at risk for seizures could be monitored continuously using relatively inexpensive and noninvasive video techniques that supplement direct observation by nursery personnel. This would represent a major advance in seizure surveillance and offers the possibility for earlier identification of potential neurological problems and subsequent intervention.

3. EXTRACTION OF QUANTITATIVE INFORMATION FROM VIDEO

The extraction of quantitative information from videotaped seizures must focus only on the moving parts of the infant's body that are relevant to the seizure. This can be accomplished by two different but complementary procedures we briefly describe below (Karayiannis et al., 2001).

3.1 Extraction of Temporal Motion Strength Signals

The extraction from video recordings of visual information that is relevant only to the seizure can be accomplished by performing spatiotemporal subband decomposition of the image sequences that compose the video recording in order to identify the infant's moving body parts. Subband decomposition allows the processing and analysis of signals, images, and image sequences (i.e., video) at different resolutions from a set of frequency-selective subbands (Mallat, 1989; Daubechies, 1992; Tekalp, 1995). Wavelets became a popular tool for subband decomposition of images and video because of their good localization in both time and frequency (Mallat, 1989; Daubechies, 1992).

Spatiotemporal decomposition of an image sequence begins with temporal decomposition, which is followed by spatial decomposition of the resulting temporal subbands. In the temporal decomposition phase, the frames of the image sequence are passed block-by-block through a filter bank containing a low-pass temporal filter and a high-pass temporal filter. If temporal decomposition is performed by a filter of length 2, each block contains two consecutive frames of the sequence and temporal filtering results in two subbands: the low-pass temporal (LPT) subband and the high-pass temporal (HPT) subband. In the spatial decomposition phase, each of the LPT and HPT subbands is passed through a filter bank that performs low-pass and high-pass filtering along the horizontal dimension, followed by downsampling by a factor of 2. Each of the resulting subbands is passed through a filter bank that performs low-pass and high-pass filtering along the vertical dimension, followed once again by downsampling by a factor of 2. This sequence of operations completes one level of spatial decomposition of the LPT and HPT subbands. If necessary, the resulting subbands can be further decomposed. In Figure 1, the LPT subband has undergone two levels of spatial decomposition, which produced subbands 1-7. Subbands 8-11 were produced by one level of spatial decomposition of the HPT subband. Subband 8 contains the low frequency components of the HPT subband in both horizontal and vertical dimensions. As a result, subband 8 is often used as a *motion detector* instead of the HPT subband since it contains most of the information carried by the HPT subband and is reduced in size by a factor of 1/4 (Karayiannis and Li, 2001, Karayiannis et al., 2001).

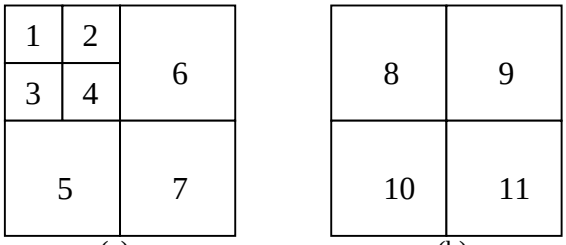


Figure 1: Spatiotemporal subband decomposition of image sequences based on wavelets: (a) two-level decomposition of the LPT subband, and (b) one-level decomposition of the HPT subband.

In this study, temporal decomposition was performed by the Haar filter of length 2 while spatial decomposition was performed by the Daubechies wavelet filter of length 20 (Daubechies, 1992). Motion was detected and measured on subband 8. Figure 2(b) shows subband 8 computed on the four frames of the videotaped myoclonic seizure shown in Figure 2(a). Subband 8 corresponding to frame 14 shows clearly the infant's left leg, which moves to the right and toward the top of the frame between frames 10 and 16 (Figure 2 shows only frame 14). The infant's left leg is not visible in subband 8 computed on frames 100 and 200 since there was no motion in these frames.

The experiments indicated that subband 8 contains the moving body parts but it is also corrupted by spiky noise, probably due to camera jitter and other recording imperfections. The noise appears as spurious patches (i.e., spikes) that occupy very small areas in comparison with those of the moving body parts. Most of these patches were removed from subband 8 by a 2-D median filter of size 3 x 3 pixels, which was found to be a particularly effective nonlinear operator for this kind of noise. Figure 2(c) shows the frames shown in Figure 2(b) after median filtering. Median filtering eliminated most of the spurious patches appearing in Figure 2(b). As a result, the infant's left leg is clearly traced in frame 14. However, frame 100 contains some spurious clusters of pixels even after median filtering. Following median filtering, the time sequence formed by subband 8 was segmented in order to isolate the moving body parts from background noise and other irrelevant clusters of pixels. Segmentation was performed by an adaptive version of the *c*-means (or *k*-means) algorithm, which clustered all pixels of each frame from the sequence formed by subband 8 in $c = 3$ clusters. Following the clustering process, one of the three clusters produced for each frame contained the pixels belonging to moving body parts, while the other two clusters contained background pixels as well as pixels that are not relevant to the seizure. The segmentation process was completed by assigning to all pixels belonging to the cluster of the highest intensities the same intensity value of 255 (corresponding to white color). All other pixels were assigned the intensity value of 0 (corresponding to black color). Thus, the segmentation process produced a sequence of black-and-white frames that display the moving body parts as white areas in a black background. Figure 2(d) shows the four frames produced by segmenting the frames shown in Figure 2(c). Segmentation eliminated all spurious clusters of pixels in frames 0, 100, and 200, which contained no moving body parts. Segmentation also eliminated the low intensity clusters of pixels from frame 14, which led to a better definition of the moving body part. The traces of the infant's left leg are shown in frame 14 as white patches in a black background.

The experimental results indicated that the segmented frames may still contain a few spurious bright patches due to noise in the original video recording. The contribution of such spurious patches to the measurements extracted from video recordings was prevented in this study by tracking the centroids of the bright patches in the frame sequence produced by the segmentation process. Tracking was performed by considering only those areas whose centroids were present within a small radius between successive frames. Averaging all such areas over successive frames produced the temporal signal $A_{av}(t)$, which measures the average area occupied by the moving body parts over time. The experiments indicated that seizure quantification may benefit by a scaling scheme that can magnify fast motion of small body parts while suppressing slow motion of bigger body parts that may not be caused by a seizure. Scaling was performed in this study by multiplying the areas of the moving parts by the distance covered by them between adjacent frames. This scheme produced the temporal signal $A_{sc}(t)$, which depends rather heavily on motion speed and can potentially facilitate the quantification of seizures involving small body parts.

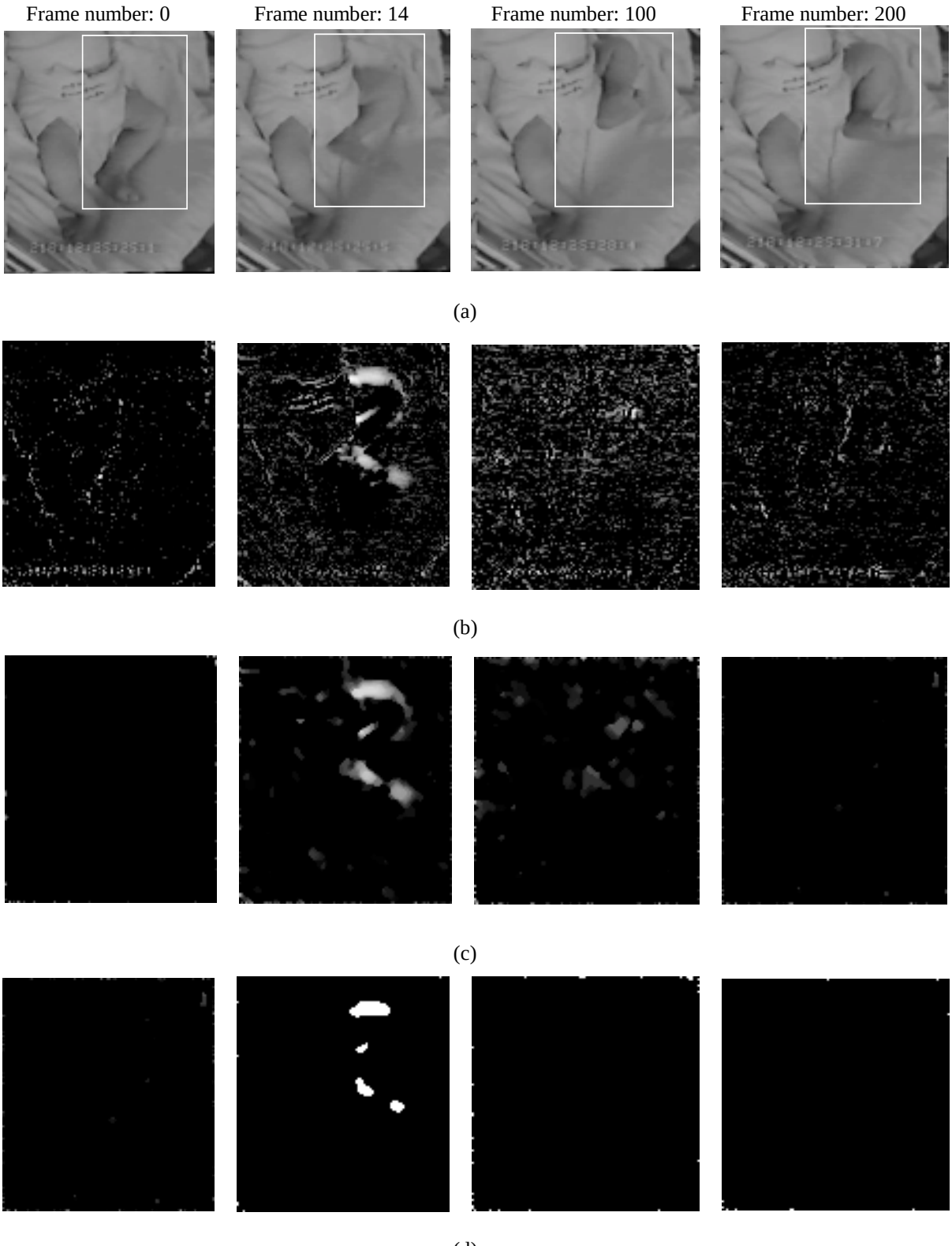


Figure 2: Extraction of temporal motion strength signals: (a) selected frames from a videotaped myoclonic seizure; (b) frames produced by computing subband 8 using spatiotemporal decomposition; (c) frames produced by applying median filtering on subband 8; (d) frames produced by segmenting the filtered version of subband 8.

3.2 Extraction of Temporal Motor Activity Signals

Neonatal seizures occur in a 3-D space but infants viewed in bed by a video system are confined in a 2-D plane. In this application, data reduction can be accomplished by projecting the location of selected anatomical sites to the horizontal and vertical axes. As the seizure progresses in time, these projections will produce temporal signals recording motor activity of the body parts of interest.

Figure 3 illustrates the mechanism that can be used for generating temporal signals tracking the movements of different parts of the infant's body during focal clonic and myoclonic seizures. Figure 3 depicts a single frame containing the sketch of an infant's body with four selected anatomical sites. In this particular configuration, X_{LL} and Y_{LL} represent the projections of the site located at the left leg to the horizontal and vertical axes, respectively. The projections of the sites located at the right leg, left hand, and right hand are denoted by X_{RL} and Y_{RL}, X_{LH} and Y_{LH}, and X_{RH} and Y_{RH}, respectively. As the infant moves its extremities, the locations of the sites in the frame will change, as will the projections of the sites to the horizontal and vertical axes. Recording the values of the projections from frame to frame of the videotaped seizure will generate four pairs of temporal signals, namely the signals $X_{LL}(t)$ and $Y_{LL}(t)$ for the left leg, the signals $X_{RL}(t)$ and $Y_{RL}(t)$ for the right leg, the signals $X_{LH}(t)$ and $Y_{LH}(t)$ for the left hand, and the signals $X_{RH}(t)$ and $Y_{RH}(t)$ for the right hand. For a given set of anatomical sites, each seizure will produce signature signals depending on its type and location.

The main objective of this study was the development of an automated algorithm capable of tracking the site of interest in successive frames of the video recording. This was accomplished by employing the KLT algorithm, a feature-tracking procedure developed by Tomasi and Kanade (1991) based on earlier work by Lucas and Kanade (1981). The KLT algorithm automatically selects "good features" from the first frame of an image sequence. A good feature is one that can be tracked well throughout the entire image sequence (Tomasi and Kanade, 1991; Shi and Tomasi, 1994).

The latest version of the KLT algorithm was utilized in this study to track moving body parts in videotaped neonatal seizures and non-seizure infant behaviors. Figure 4(b) shows the location of 400 features selected and tracked by the KLT algorithm in the four frames of the videotaped myoclonic seizure shown in Figure 4(a). It is clear from Figure 4(b) that the features selected by the KLT algorithm in the first frame of the sequence (i.e., frame 0) were almost uniformly distributed over the entire frame area. However, the KLT algorithm became increasingly selective as the seizure progressed. In frames 14, 100, and 200, the KLT algorithm tracked features located at the frame area occupied by the infant's body (including the moving body part) and the textured and non-homogeneous areas of the background. In contrast, the KLT algorithm did not track throughout the entire sequence the features located at the homogeneous area between the infant's legs at the lower-right quadrant of the frames.

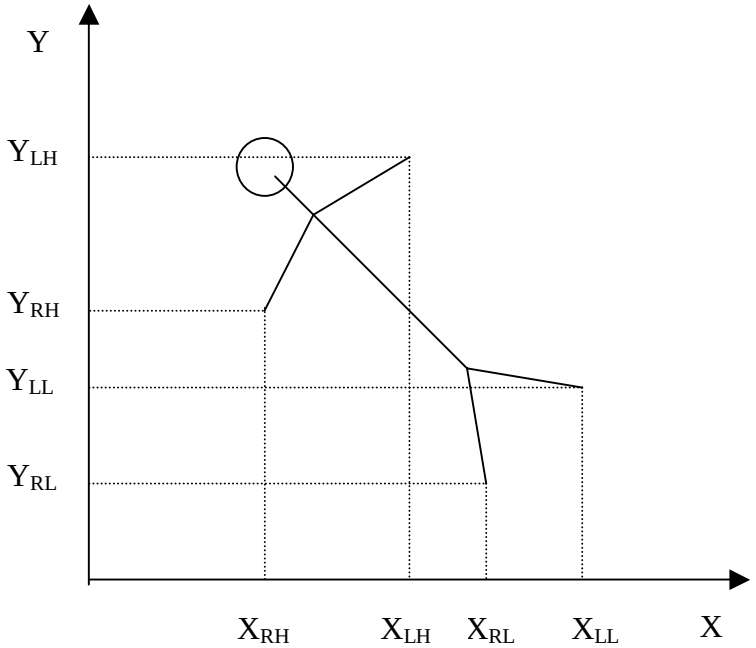


Figure 3: Extraction of temporal signals by projecting four selected anatomical sites to the horizontal and vertical axes.

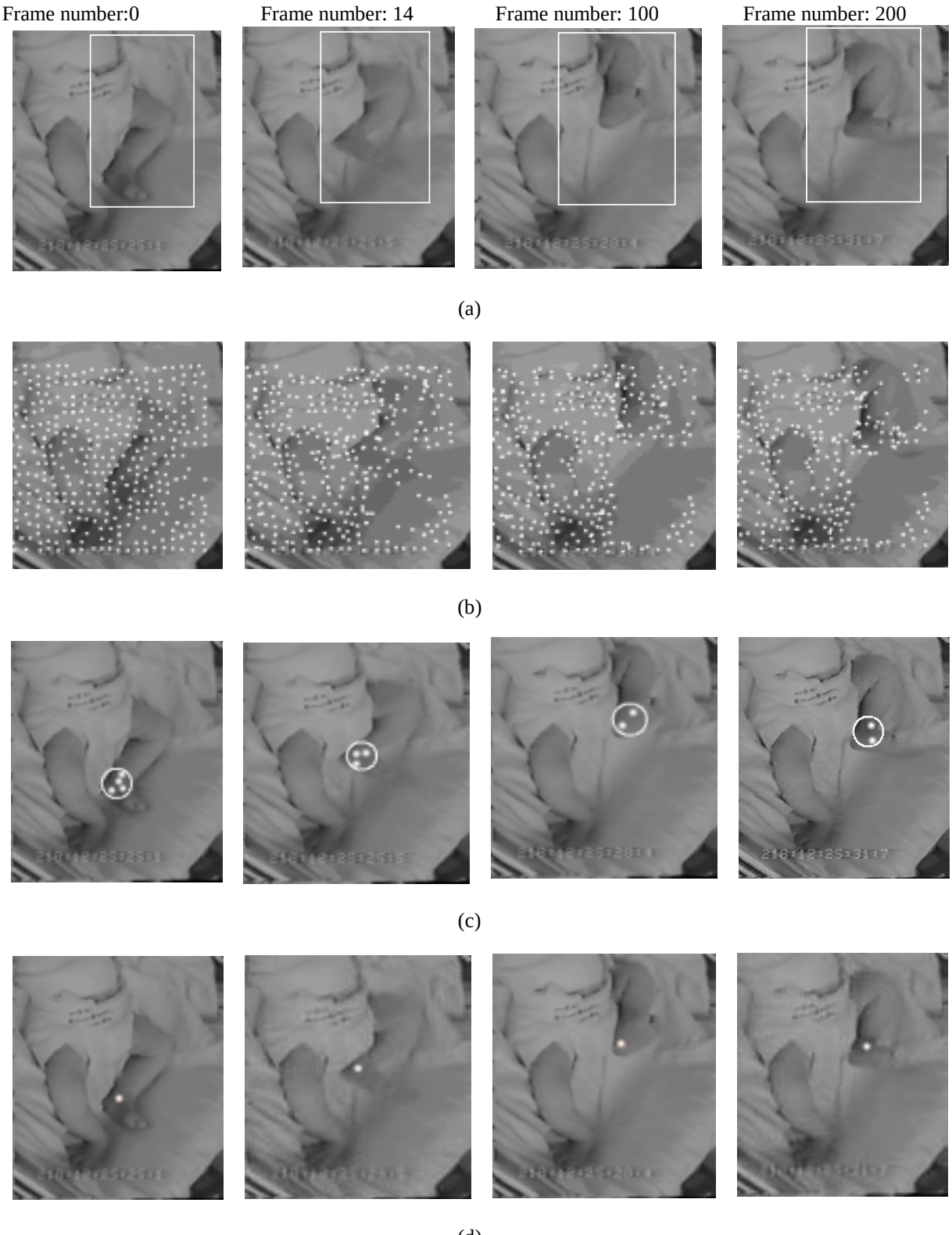


Figure 4: Extraction of temporal motor activity signals: (a) selected frames from a videotaped myoclonic seizure; (b) frames containing the features tracked by the KLT algorithm; (c) frames containing the features within a close neighborhood of the site; (d) frames containing the feature whose projections to the horizontal and vertical axes produced the motor activity signals.

Although the KLT algorithm was generally successful, in some cases the algorithm lost some features that were located at moving body parts tracked throughout the image sequence. The susceptibility of the KLT algorithm to "lost features" motivated the tracking of a sufficiently large number of features within a predetermined radius from the selected anatomical site in the frame sequence. Figure 4(c) shows the features tracked by the KLT algorithm within a predetermined radius from the site in the infant's left foot. In the first frame of the sequence (i.e., frame 0), the KLT algorithm selected four features within the neighborhood of the site indicated by a circle. It is apparent from Figure 4(c) that one of the original features has been lost in frame 14. Only two of the features in the neighborhood of the site were tracked by the KLT algorithm in subsequent frames of the sequence. One of these features provided the reference for tracking the site through the entire sequence. The strategy described above allowed the tracking of the site through the frame sequence even in cases where some of the features in its close neighborhood were lost by the KLT algorithm at some point in time. When the radius was sufficiently small, there were no noticeable differences between the ideal temporal signals (i.e., the signals corresponding to projections of the site) and the resulting temporal signals (i.e., the signals corresponding to the projections of the features tracked by the algorithm). The experiments indicated that the selection of a small radius improved the accuracy of the tracking process but also increased the likelihood of losing all features close to the site. The trade-off typically associated with the selection of the radius motivated an extension of the KLT algorithm that improved its ability to recover the site even if all features in its close neighborhood are lost. The location of the site in the next frame was predicted in this study through a linear model based on the history of its motion in the previous frames. After the site was recovered by the method used for prediction, the KLT algorithm was used to track a new set of features in its close neighborhood.

4. EXPERIMENTAL RESULTS

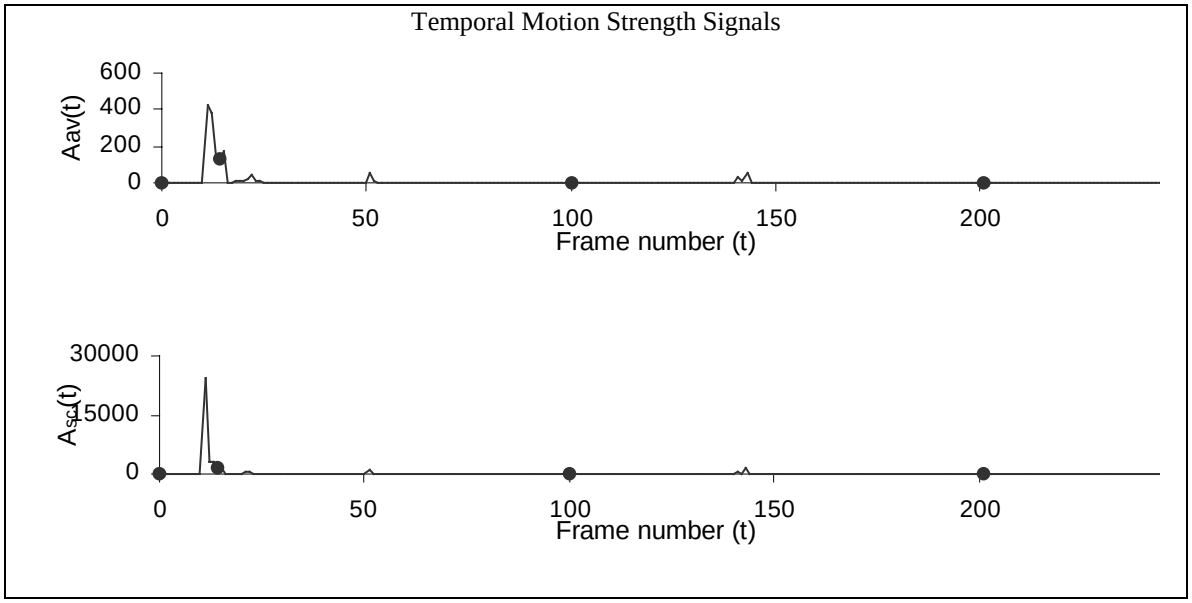
The two procedures described above were evaluated on the video recordings of neonatal seizures and other clinical events representing normal and abnormal infant behaviors not due to seizures (Karayiannis et al., 2001). Figures 5 and 6 show the four temporal signals extracted from video recordings of a myoclonic seizure and a focal clonic seizure, respectively. 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 Figures 5 and 6 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 bottom of each figure are indicated by dots, while the moving body part in each video recording is shown within a box.

In the myoclonic seizure shown in Figure 5, the infant's left leg moves to the right of the frame between frames 10 and 16 (Figure 5 shows only frame 14). This movement was captured by the temporal signal obtained as the projection of the moving part to the horizontal axis. The temporal signal obtained as the projection of the moving part to the vertical axis indicates that the left leg also moves toward the top of the frame, which can be verified by comparing frames 0 and 14 of the sequence. The motor activity observed between frames 10 and 16 was also captured by the temporal motion strength signals measuring the area and scaled area of the moving part, as is clearly indicated by their spikes between frames 10 and 16. The infant's left leg remains at an almost fixed position between frames 50 and 150. In this time interval, the temporal motor activity signals are almost flat. Figure 6 indicates that the temporal signals produced by the two proposed procedures capture and quantify the differences between myoclonic and focal clonic seizures. In the case of myoclonic seizures, the temporal motor activity signals are consistent with the "jerky" movements that are the typical signatures of such events. The temporal motion strength signals contain a significant spike and a few weaker spikes. In the case of focal clonic seizures, the temporal motor activity signals captured and quantified the rhythmicity that characterizes the movements of such clinical events. The temporal motion strength signals contain multiple spikes that correspond very well with their rhythmic movements.

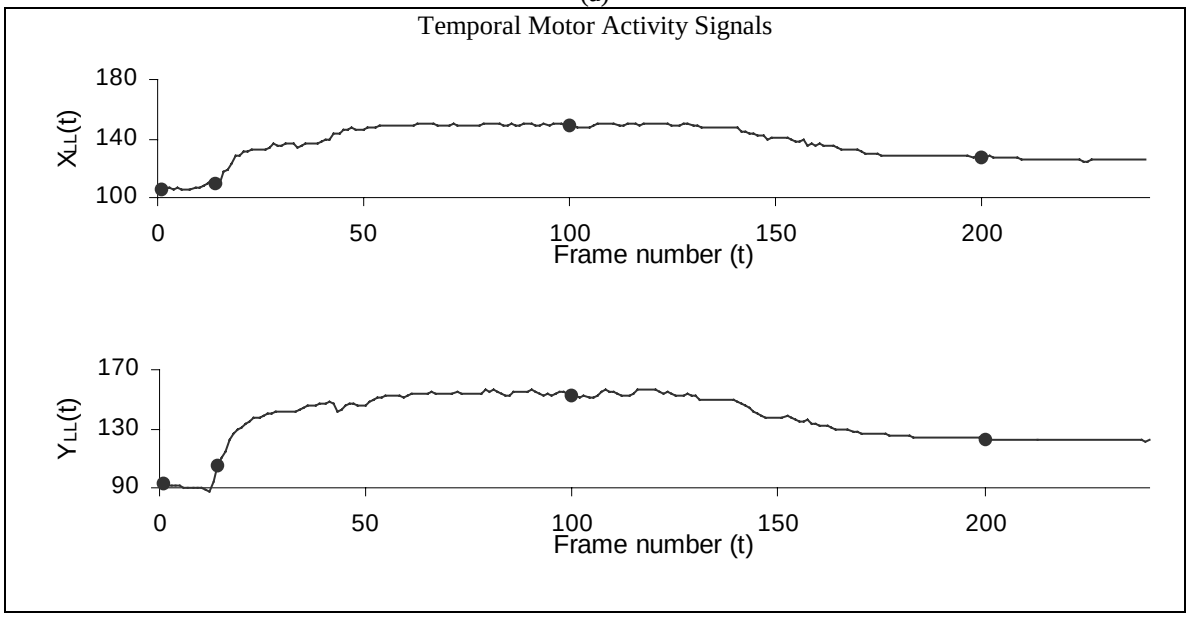
5. CONCLUSIONS AND FUTURE RESEARCH

The experiments conducted in this study proved the feasibility of the procedures proposed for extracting quantitative information from video recordings of neonatal seizures and other normal and abnormal infant behaviors. Further improvement and refinement of the procedures developed in this study can produce temporal motion strength and motor activity signals that constitute a consistent and effective representation of videotaped clinical events.

The robustness of the procedure developed to extract motion strength signals may be enhanced by employing a segmentation technique that relies on vector quantization. It is expected that the use of vector quantization will improve the segmentation results by exploiting the spatial correlation within each frame. The correlation among pixels in the same frame was ignored in the preliminary study, which relied on scalar quantization. The results of segmentation may also be improved by replacing the *c*-means algorithm by competitive learning vector quantization algorithms (Karayiannis and Pai, 1996; Karayiannis, 1997), which have been successfully tested on a variety of medical imaging applications (Karayiannis and Pai, 1999).



(a)



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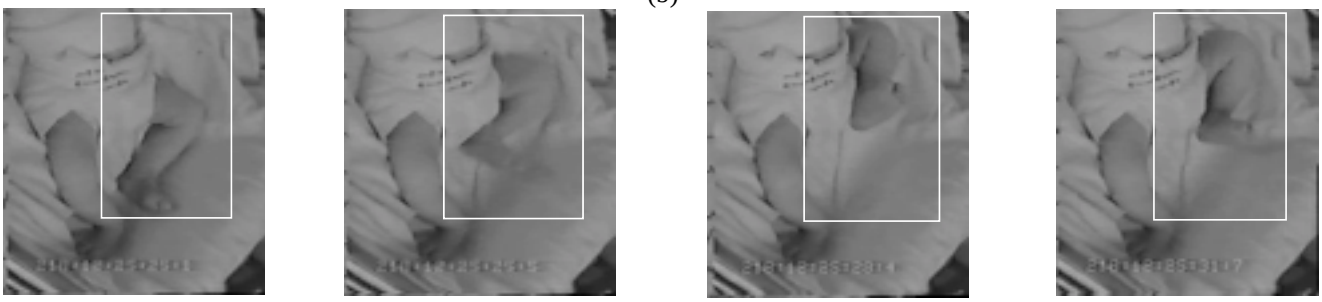
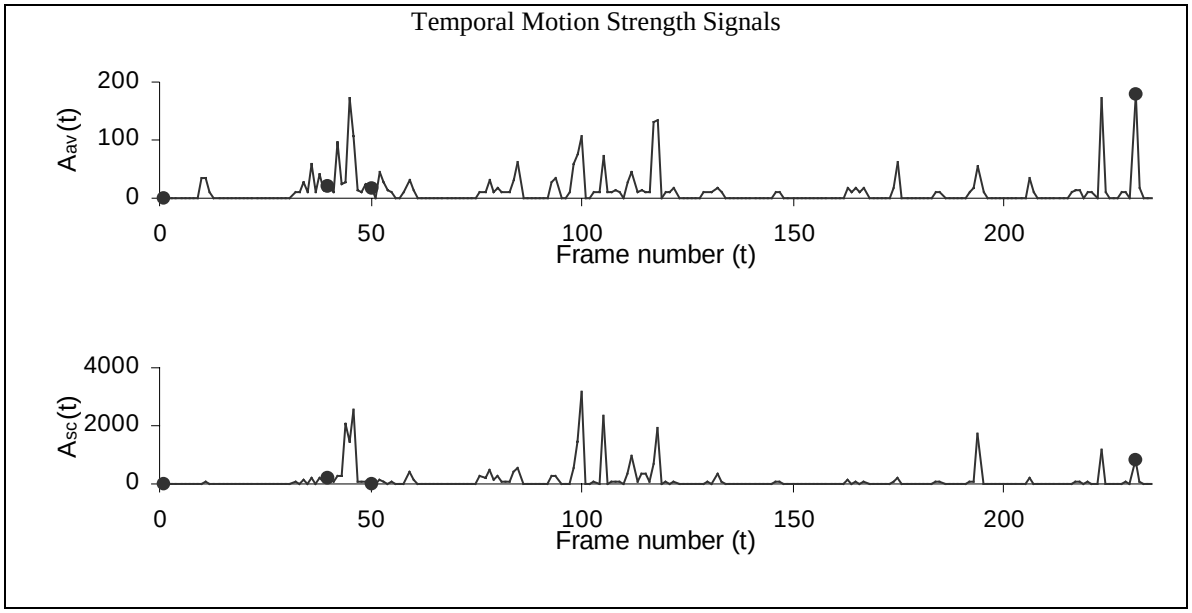


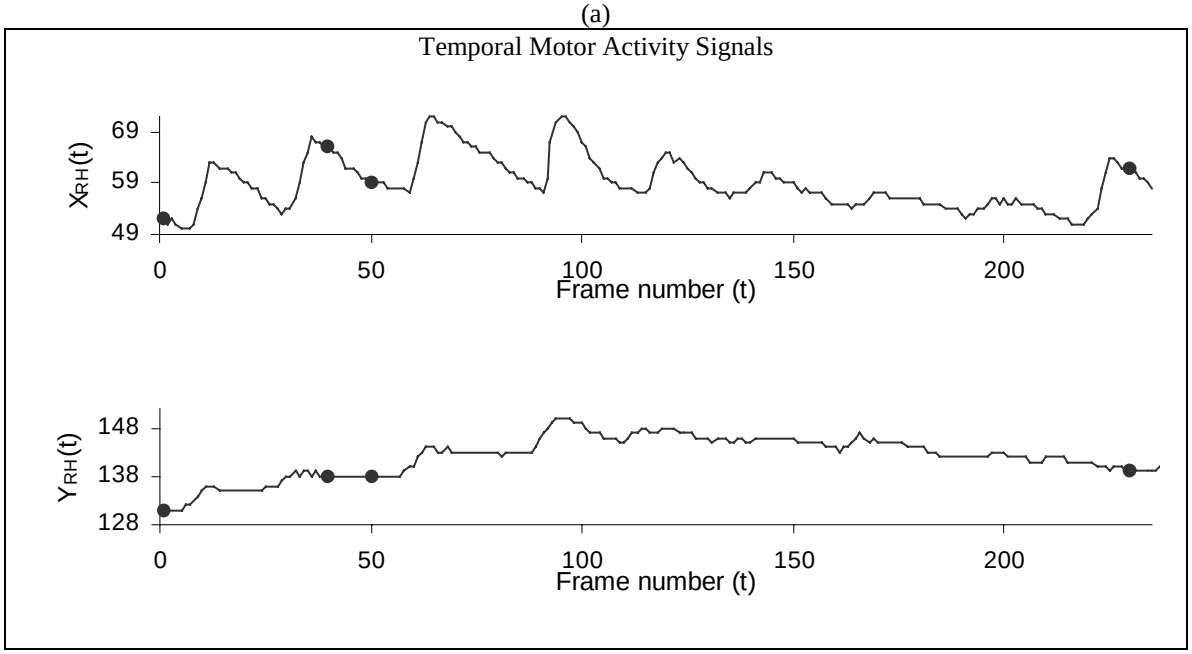
Frame number: 0 Frame number: 14 Frame number: 100 Frame number: 200

(c)

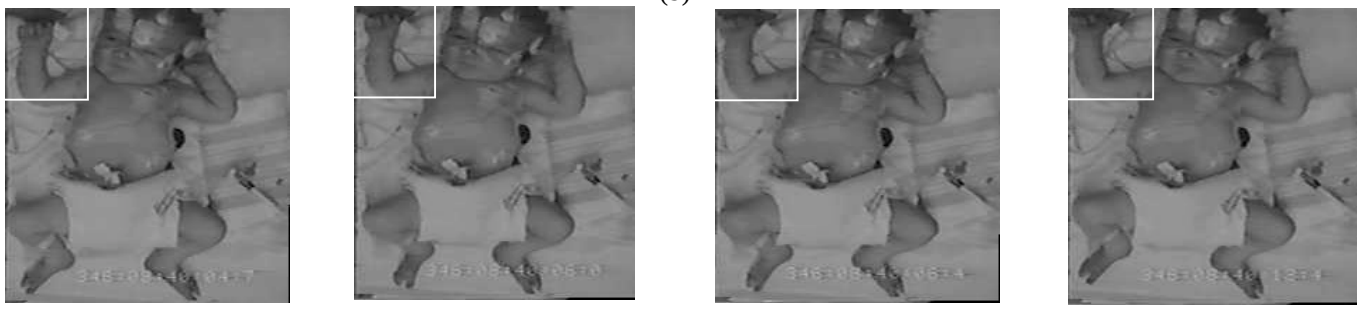
Figure 5: Temporal signals produced for a video recording of a focal myoclonic seizure affecting the infant's left leg: (a) temporal motion strength signals; (b) temporal motor activity signals; (c) selected frames of the sequence.



(a)



(b)



Frame number: 0 Frame number: 40 Frame number: 50 Frame number: 230

(c)

Figure 6: Temporal signals produced for a video recording of a focal clonic seizure affecting the infant's right hand: (a) temporal motion strength signals; (b) temporal motor activity signals; (c) selected frames of the sequence.

The extraction of temporal motor activity signals for clinical events involving movements of multiple body parts may be accomplished by extending and improving the existing procedure to make it capable of tracking multiple sites throughout each frame sequence. Tracking of multiple anatomical sites during the seizure also requires the development of an automated procedure for detecting the moving body part(s). These objectives may be accomplished by developing motion detection procedures and subsequently incorporating motion in the criteria used by the KLT algorithm for rejecting features throughout the frame sequence. More specifically, the KLT algorithm can be modified to track features located at moving body parts with higher priority. Such a strategy is expected to prevent the rejection of features located at moving body parts. This will essentially improve the procedure used for extracting temporal motor activity signals by minimizing the number of lost features located on the moving body part(s) tracked by the KLT algorithm.

The extraction of motion strength signals may also be accomplished by relying on *active geodesic region* models, which were developed for motion estimation and tracking of moving objects in video (Paragios and Deriche, 1999; 2000). Motion strength signals may be extracted by computing the area of the active geodesic region corresponding to moving body parts. The extraction of motor activity signals may also be accomplished by relying on *active contour* models, which are commonly referred to as "snakes" and were developed to simultaneously perform segmentation of noisy images and track objects that may deform and move in a plane (Kass et al., 1987; Williams and Shah, 1992; Blake and Isard, 1998). Motor activity signals may be extracted by projecting to the horizontal and vertical axes selected points of the contours of moving body parts.

The long-term goal of the proposed research is to integrate the computational procedures outlined in this paper into the development of a stand-alone automated system that could be used as a supplement in the neonatal intensive care unit to: 1) provide 24-hour a day noninvasive monitoring of infants at risk for seizures, and 2) facilitate the analysis and characterization of videotaped neonatal seizures by physicians during retrospective review. This goal will be accomplished by developing an intelligent system capable of recognizing focal clonic and myoclonic seizures and distinguishing them from videotaped clinical events characterized by increased motor activity of the infant's extremities. The development of a seizure recognition system will be attempted by: 1) training *static* neural networks (i.e., neural network models without memory) using features selected from the temporal signals extracted from video recordings, and 2) training *dynamic* neural networks (i.e., neural network models with memory) using directly the temporal signals extracted from video recordings. Neural networks provide a solid basis for the development of a seizure recognition system due to their versatility and flexibility (Bishop, 1995; Haykin, 1999; Karayiannis and Venetsanopoulos, 1993; Principe et al., 1999).

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