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A Framework for Fall Detection of Elderly People by Analyzing Environmental Sounds through Acoustic Local Ternary Patterns

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***Abstract*— The elderly people living alone or life of a patient face distress situations particularly in case of falling and becoming unable to ask for help. Fall in elderly people may result in head injury, broken hips, and bones that need immediate hospitalization to lower the mortality risk. During the last decade, several technological solutions were presented for early fall detection but most of them have critical limitations and are impeded by several environmental constraints. In this paper, we have analyzed the environmental sounds for early fall detection utilizing the fact that reflection of pain directly occurs through sound. The proposed framework first analyzes the environmental sounds by suppressing the silence zones in signals and distinguishing overlapping sound signals through hidden Markov model based component analysis (HMM-CA). The source separated components are then represented by acoustic local ternary patterns (acoustic-LTPs) by extending the existing ideas of acoustic local binary patterns (acoustic-LBPs). In the proposed work, we have also introduced the concept of rotation invariance through uniform patterns for audio signals that, arguably, is a fundamental requirement for an acoustic descriptor. Once the signal representation is completed, we classify the signals through SVM classifier. The performance of the proposed acoustic-LTP is evaluated against state-of-the-art methods and acoustic-LBP. Results clearly evince that proposed method is more powerful and reliable in terms of fall detection when compared against other methods.**

Keywords*— Acoustic-LTP; HMM-CA; Fall Classification

I. Introduction

Population of elderly people of age 65 and above is steadily increasing worldwide. As described in [1], the number of elderly people can touch the figure of 2 billion by 2050. The elderly people, living alone or life of a patient, face distress situations particularly when one falls and becomes unable to ask for help. Fall in elderly people may cause a life changing injury which may severely affect the quality of life. In US alone, almost 30% of about 13 million falls per year among elderly people result in broken hip and head trauma [2]. The delay of 24 hours in surgery of hip fracture may cause the rise of 30-day mortality risk from 7.3% to 8.7% [3]. Moreover, if extended time passes without any medication the mortality risk further increases [4]. Fall in elderly people can also result in the form of other critical diseases like rhabdomyolysis, dehydration, pressure sores or hypothermia [5]. The estimated cost for such hospitalization is more than $19 billion [6]. Hence, the early fall detection is necessary so that the essential help can be provided to avoid the critical situations and lowering the hospitalization cost.

In literature, the fall detection for elderly people is performed by either wearable devices that use sensing technologies mostly based on the accelerometer; or through environmental sensors on various locations of a building. The selection of the sensing technology has associated cost and usage constraint and is highly dependent on the target environment [7]. In [8] fall detection was carried-out using short-time Fourier transform based accelerometer attached on foot with a microphone. In [9] wearable microphone and Micro-Electro-Mechanical Systems (MEMS) accelerometer is used with a camera. In [10] a tri-axial accelerometer and barometric pressure sensors were attached with subject's waist for fall detection. The wearable devices used for fall detection become a cause of inconvenience and obtrusiveness for the patient. Moreover, the intrusion and fixed relative relations with person may also cause frequent disconnection of such sensors along with continuous battery recharge and vulnerability to break make these wearable devices less desirable choice for the elderly people.

To overcome these limitations of the wearable fall detection solutions, research also emphasized on the non-wearable solutions of fall detection. In [11] a Doppler radar-based fall detection method was proposed to recognize human activity. In [12] the fall detection was performed using Radar's effective non-intrusive sensing modality by detecting the human motion. In [13] Wavelet transform was used to detect human falls using a ceiling mounted Doppler range control radar. The major drawback of the Doppler radar based systems is their limited application due to the directional sensing capabilities. The radar based systems need the target in front range with static room settings [14]. The microwaves generated by the radars also have the severe health and behavioral hazards that make these methods less productive [15].

The acoustic analysis of environmental sounds provides an effective alternative to the drawbacks of both wearable and non-wearable solutions. Since non-wearable devices work as passive receivers with wider range, durability, and health related hazards, therefore, researchers have shown considerable interest in fall detection methods by monitoring patient's sounds which truly reflect pain. In [16] acoustic analysis was proposed for fall detection using the MFCC features and nearest neighbor (NN) classifier. In [17] daily sound recognition was performed using the MFCC, Linear Predictive Coding (LPCs) and non-spectral features. Main drawback of this technique is the selection of many irrelevant features which also negatively impact the classification results [18]. Another drawback is the inherent complexity that makes the combination less suitable for implementation of real-time systems. In [20], MFCC features were classified through NN, SVM, and Gaussian mixture classifiers for fall detection. The most common reasons to use MFCCs for fall detection are lower dimensional features and improved classification accuracy [21]. However, during the audio signal acquisition, several environmental factors affect this process and induce noise in the collected sound data. Various operating conditions also influence the extracted MFCC features by deteriorating its quality. These limitations can cause mismatch when MFCCs are used for classifier training and recognition of the fall event [19]. MFCC feature extraction is also a computationally complex process and consequently becomes difficult to implement on hardware devices. To increase the MFCC performance different feature extraction techniques are combined with MFCC that increase hardware implementation cost. Due to these reasons, more effective feature extraction techniques compared to MFCCs are required that ensure better classification performance for critical applications like fall detection, and also lower hardware implementation cost.

To address the limitations of MFCC based fall detection mechanisms, in this paper, we propose a novel feature extraction scheme for acoustic signals through acoustic Local Ternary Patterns (acoustic-LTP) and SVM classifier by suppressing low frequency signal periods through hidden Markov model based component analysis (HMM-CA). LTP feature descriptors were originally proposed for face recognition [22] and these features are never described for audio signal representation that is mainly 1-D in nature. Hence, our contribution through this research work is to present a novel audio representation scheme using acoustic-LTP for environmental sound classification and fall detection. In this paper, we have also introduced the concept of rotation invariance for audio signals as a novel concept by arguing that rotation invariance is also a fundamental requirement for audio descriptors. Therefore, the hypothesis for this research work is to evaluate the performance of the proposed acoustic-LTP based feature extraction scheme and to compare it against existing state-of-the-art audio representation mechanisms like MFCC, linear predictive coding (LPC), and acoustic-LBP for fall detection by classifying environmental sounds.

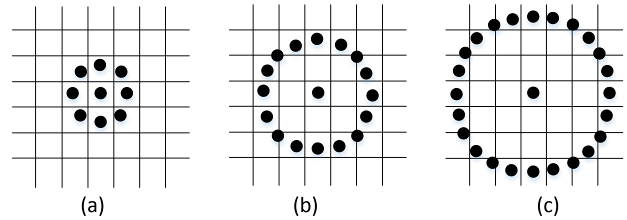

Fig. 1. Circular symmetric neighbor sets for different (P, R) (a) (P, R) = (8,1), (b) (P, R) = (16,2), (c) (P, R) = (24,3)

II. Proposed Method

In this paper, we have analyzed environmental sounds for possible fall detection. The key contribution of this paper comes in the form of feature extraction scheme through acoustic-LTP over the source separated components of the audio signals through HMM-CA. Proposal of a new audio signal representation scheme is entailed by the requirement of precision in classification, which has direct correlation with the reliability of the signal representation mechanism, particularly in case of critical applications like fall detection. Once the source signals are represented by the acoustic-LTP, classification of feature vectors is performed through SVM and if a signal is classified as a fall event or an event associated with fall, like scream, we conclude occurrence of fall. To perform the targeted acoustic analysis for fall detection, we have also proposed HMM-CA that suppresses the low frequency signals (e.g. silence periods) and ensures that learning algorithm never remains continuously busy. The architecture of the proposed method is presented in figure 1.

A. Problem Formulation

Given an audio signal $Y = \left\{ V^{(i)}[n] \right\}_{i=1}^{i=N_f}$ with N_f frames $V^{(i)}[n]$ of frame length L_f fall detection algorithm segments the audio signal into non-overlapping sources Y_S(described in (2)) with N_S frames where S represents distinct signal sources. For effective discrimination between different non-harmonic auditory environments, source signals are required to be represented effectively. Therefore, a more principled approach for environmental sound representation is required to effectively identify the human fall events through reliable classification.

B. Hidden Markov model based component analysis (HMM-CA)

Given the frame sequence Y , and to find frame sequences having acoustic events only, we find frame sequences that maximize posterior probability of frames $V = (V^{(1)}[n], V^{(2)}[n], \ldots, V^{(Nf)}[n])$ given the observations $O = (O^{1}[n], O^{2}[n], \ldots, O^{T}[n])$:

$$\tilde{V} = \arg\max_{V} P(V \mid O) = \arg\max_{V} P(V \mid O)\, P(V) \qquad (1)$$

Where $P(V \mid O)$ is the HMM model [23] for acoustic and silence events for given signal with left to right state transitions and 2 emission states. Observations O are composed of acoustic-LTP components. Baum-Welch algorithm [24] is used to train the model for silence and acoustic events as per O observations and the original HMM model. To compute the posterior probability of each observation, Viterbi algorithm is used [25]. For acoustic events posterior probability is larger than the posterior probability of silence period. Therefore, frames belonging to the acoustic event have higher posterior probability for acoustic state and are labeled as 1. The frames having higher posterior probability of the silence state represent silence frames and are labeled as 0. We detect the fall event in the frames that are labeled as acoustic event by first segmenting the overlapping sources through the FAST-ICA algorithm [26]. The FAST-ICA algorithm returns us segmented acoustic components as:

$$Y_s = \left\{ V_s^{(i)}[n] \right\}_{i=1}^{i=N_s} \qquad (2)$$

Where Y_s represents the segmented acoustic events that are further analyzed for possible fall detection.

C. Acoustic Local Binary Patterns (Acoustic-LBP)

As described in [27] acoustic-LBP is a fast and computationally inexpensive mechanism for signal representation that distinctively marks certain signal features. The signal features in the form of linear LBP codes can be adopted for signal segmentation and signal thumb-impression generation. The LBP examines the neighborhood of data samples from a signal and assigns an LBP code to each center sample after thresholding them against the neighboring samples [27]. Let $V_s^{(j)}[n]$ be the central sample in the samples window with $P+1$ elements in audio signal Y_s for $j = \left[\frac{P}{2} : N_s - \frac{P}{2}\right]$. The acoustic-LBP can be defined as:

$$LBP_P\left(V_s[j]\right) = \sum_{k=0}^{\frac{P}{2}-1} \left\{ \begin{array}{l} S\left[V_s[j+k-\frac{P}{2}] - V_s[j]\right] 2^k + \\ \ldots S\left[V_s[j+k+1] - V_s[j]\right] 2^{k+\frac{P}{2}} \end{array} \right\} \qquad (3)$$

Where sign function S[.] is given by:

Fig. 2. Architecture of the proposed fall detection framework

$$S[V_s] = \begin{cases} 1, & for\ V_s \geq 0 \\ 0, & for V_s < 0 \end{cases} \qquad (4)$$

In LBP, sample $V_s[j]$ serves as a threshold for the neighboring samples, and sign function S[.] transforms the difference between $V_s[j]$ and neighborhood as a P-bit binary code. The binomial weights are then multiplied to LBP code and summed to generate LBP value for the sample $V_s[j]$. The LBP locally describes a sample using neighborhood differences. For a constant signal these differences cluster near zero whereas at peaks and plateaus the difference is large. The LBP codes are used to described the local patterns as:

$$H_k = \sum_{\frac{P}{2} \leq j \leq N - \frac{P}{2}} \delta\left(LBP_P\left(V_s[j]\right), k\right) \qquad (5)$$

Where k=1…n, and n describes histogram bins corresponding to each LBP code and $\delta(i, j)$ is Kronecker delta function.

Acoustic-LBP features threshold exactly at the central sample, therefore, they are sensitive to noise. Particularly, at edges where the difference in some directions is larger than other directions [27]. Even exposure to small noise make results of acoustic-LBP descriptor unreliable. Another drawback of acoustic-LBP is its inability to address the concept of rotation for linear signals. Due to this reason, same expressions with different sounds have varying representations. Consider a scream that sounds “AAAH” against “HAAA”, acoustic-LBP generates different representations for both sounds. The foremost reason behind this disagreement is the signal representation mechanism for linear signals that do not consider the concept of circularity that serves as a basis for 2D-LBPs [28]. In this paper, we argue that rotation invariance is an equally important concept for linear signals as that of 2D counterparts to represent various forms of similar events. The feature extraction scheme we introduce is immune to noise and is based on the concept of circularity with uniform patterns that make it rotation invariant as well. Hence, signal representation occurs in a much precise way that significantly improves classifier performance for fall detection.

1) Circular Mapping for Linear Signals

For central sample $V_s\ [j]$ in the samples window with $P+1$ elements in audio signal Y_S and $j=\left[\frac{P}{2}:N_S-\frac{P}{2}\right]$; circular-wedge can be defined by first converting linear signal pattern into squared pattern with respect to the order $\sqrt{P+1}$ elements. Suppose coordinate of the sample $V_s\ [j]$ is (0,0), coordinates of local neighborhood U_P (p= 1,…,P) is given by (−R · sin (2πp/P), R · cos (2πp/P)) [29]. Figure 2 shows three examples of circularly symmetric neighbor sets for different configurations of (P, R).

D. Acoustic-Local Ternary Patterns (Acoustic-LTP)

Once the circular representation of signal with respect to $V_s\ [j]$ is generated, a three-valued code called acoustic-LTP is defined. For this, we compute signal magnitude difference between $V_s\ [j]$ and its surrounding neighbors U_P. Signal values in the range of width $\pm t_h$ around $V_s\ [j]$ are quantized to zero. Values above $V_s\ [j]+t_h$ are quantized to 1 and below $V_s\ [j]-t_h$ are quantized to -1. Hence, a three-valued function S' is given by:

$$S'\left(U_P,V_s\ [j],t_h\right)=\begin{cases}+1, & \left[U_P-\left(V_s\ [j]+t_h\right)\right]\geq 0\\ 0, & \left[V_s\ [j]-t_h\right]<U_P<\left[V_s\ [j]+t_h\right]\\ -1, & \left[U_P-\left(V_s\ [j]-t_h\right)\right]\leq 0\end{cases} \tag{6}$$

$S'\left(U_P,V_s\ [j],t_h\right)$ operator (6) represents acoustic signal by three valued ternary pattern that is further split into S'_{upper} and S'_{lower}. In S'_{upper} only +1 values are retained and all other values are replaced with zero as described in (7):

$$S'_{upper}\left(U_P,V_s\ [j],t_h\right)=\begin{cases}1, & for\left[S'(U_P,V_S\ [j],t_h=+1\right]\\ 0, & otherwise\end{cases} \tag{7}$$

Similarly, in $S'_{lower}\left(U_P,V_s\ [j],t_h\right)$, -1 values are retained as 1 and all other values are replaced with zero as described in (8):

$$S'_{lower}\left(U_P,V_s\ [j],t_h\right)=\begin{cases}1, & for\left[S'(U_P,V_S\ [j],t_h=-1\right]\\ 0, & otherwise\end{cases} \tag{8}$$

Hence, acoustic-LTP can be represented as (9):

$$Acoustic-LTP_P\left(V_s\ [j]\right)=\begin{bmatrix}\sum_{i=-1}^{i=1}\sum_{k=-1}^{k=1}S'_{upper}\left[V_s\ [i,k]-V_s\ [j]\right]2^l\ ||\\ \ldots\sum_{i=-1}^{i=1}\sum_{k=-1}^{k=1}S'_{lower}\left[V_s\ [i,k]-V_s\ [j]\right]2^l\end{bmatrix} \tag{9}$$

For rotation invariant audio signal representations, we obtain uniform patterns by obtaining the U value of acoustic-LTP as:

$$U\left(Acoustic-LTP_P\right)=\begin{bmatrix}\left|S'\left(U_P-V_S[j]\right)-S'\left(U_1-V_S[j]\right)\right|+\\ \ldots\sum_{P=1}^{P-1}\left|S'\left(U_P-V_S[j]\right)-S'\left(U_{P-1}-V_S[j]\right)\right|\end{bmatrix} \tag{10}$$

Where S' is the representation of both S'_{upper} and S'_{lower}. The U value of an acoustic-LTP can be defined as the number of bitwise transitions in the pattern and refers to uniform appearance i.e. with minimal discontinuities [30]. It is well established in research that uniform patterns with (U≤ 2) are the only fundamental patterns that contain rotation invariant attribute [30]. For signal representation, we consider uniform patterns as specific bins with P(P-1) +3 possible entries [30] and all non-uniform patterns are grouped under a "miscellaneous" label. So, a locally rotation invariant pattern can be described as:

$$Acoustic-LTP_P^{riu}=\begin{cases}\sum_{P=1}^{P-1}S'\left(U_P-V_S[j]\right) & if\ U\left(Acoustic-LTP_p\right)\leq 2\\ P+1 & otherwise\end{cases} \tag{11}$$

After identifying rotation invariant acoustic-LTPs local patterns are described as:

$$H_k=\sum_{\frac{P}{2}\leq j\leq N-\frac{P}{2}}\delta(Acoustic-LTP_P^{riu}(V_S[j]),k) \tag{12}$$

Where k={1,…,n}, and n describes histogram bins corresponding to rotation invariant acoustic-LTP codes and $\delta(i,j)$ is Kronecker delta function.

E. Classification

Once signal representation is done, we classify signal as fall or non-fall event by training SVM classifier.

III. Experiments and Results

The system evaluation experiments are performed on two standard benchmarks: a) real world computing partnership (RWCP) sound scene dataset [31], and b) daily sound dataset [32].

RWCP dataset contains environmental sounds that were recorded in an anechoic chamber through microphone and DAT recorder at 48 kHz [31]. The sounds were later down-sampled to 16 kHz. RWCP dataset contains a total of 9722 instances and 105 different non-speech dry source sounds. The dry source sounds are the sounds that are free from room acoustics [31]. Daily sound dataset contains all non-speech sound files in WAV format with sampling frequency of 16 KHz [32]. The sound files present in the dataset were downloaded from internet or recorded using a microphone [32]. The dataset comprises of 1049 sound files grouped into 18 different sound classes.

For fall detection experiments, we have recorded 100 fall sounds through human subjects with associated events e.g. screaming and object falling like cup breaking etc. The fall events were recorded in a rectangular room measuring 7m x 2m with carpeted floor. We have particularly selected night time for experiments, so that recorded sounds have minimum amount of external interventions. The fall events were performed at a distance spanning from 1m to 6m from the microphones with different angles in order to reproduce realistically different fall patterns. The fall events comprise of falls on hands, sides, back, and knees. The fall sounds were then merged with sound files present in RWCP and daily sound repositories using Audacity software to mimic real world environments. The isolated sound files were used for classifier training purposes whereas merged sound files were used for evaluation purposes of proposed framework. For evaluation of this work precision, recall, F1-score, accuracy, and error rates are used.

A. Fall Detection Evaluation

As aforementioned, for fall detection evaluation we have extended two standard repositories i.e. RWCP dataset, and daily sound dataset with fall events. Therefore, for validation of this work, we have written a computer simulation that randomly draws fall and non-fall classes for 50 times. Due to severe imbalance between number of samples in both classes, SVM hyperplane biases towards non-fall class due to more training examples. Therefore, in all 50 runs, fall class contains all 100 audio samples whereas random selection is applied only over non-fall class to also have 100 samples to represent various environmental events. Once training set is generated we randomly select 70% of the data for training purposes and remaining 30% of the data for testing purposes. For implementation of this work and acoustic-LTP based feature extraction, we have used threshold value of 0.0005. The evaluation criteria described earlier is then applied over classification output to measure efficacy of the system by reporting average results.

B. Fall Detection Results

For fall detection evaluation, we have compared our method against state-of-the-art audio representation schemes i.e. MFCC [19], acoustic-LBP [27], and LPC [33]. From results presented in figure 3 and 4, it can be observed that the proposed method has highest recall, accuracy, F1-score rates, and lowest error rate against comparative schemes.

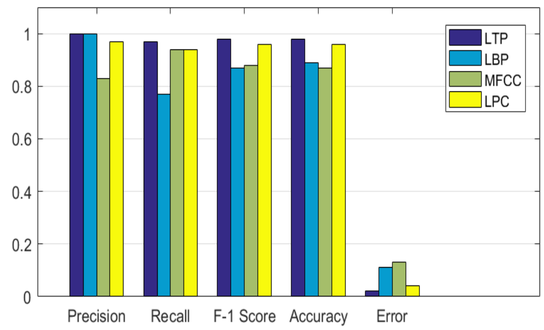

Fig. 3. Fall detection evaluation over RWCP dataset

C. Multiclass Evaluation

To unveil the capabilities of the proposed acoustic-LTP as a reliable audio descriptor, we have broadened evaluation scope by performing feature descriptor validation over multi-category problems. So that classification results over multiclass problems confirm robustness of the proposed feature descriptor. As shown in figure 5 proposed methodology achieves 97.41% accuracy on RWCP dataset with one-against-all classification settings for SVM classifier. Whereas, with similar experimental settings MFCC achieves 83.9% accuracy on RWCP dataset,

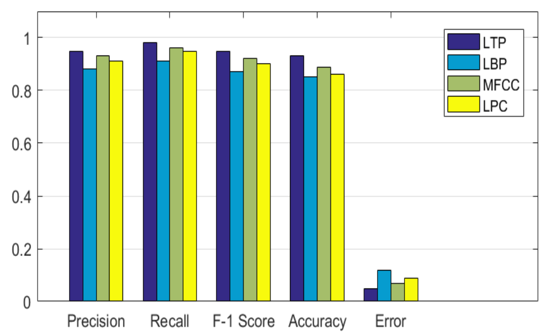

Fig. 4. Fall detection evaluation over Daily sounds dataset

IV. CONCLUSION

In this paper, we have provided a framework for automatic fall detection for elderly people by analyzing the environmental sounds. Our fall detection framework has attributes of powerful audio extraction and representation mechanisms through HMM-CA, and acoustic-LTP. The proposed novel audio representation mechanism is robust against rotation attacks that we have investigated in this paper. Performance comparison against state-of-the-art methods reveals the reliability of the proposed method in terms of fall

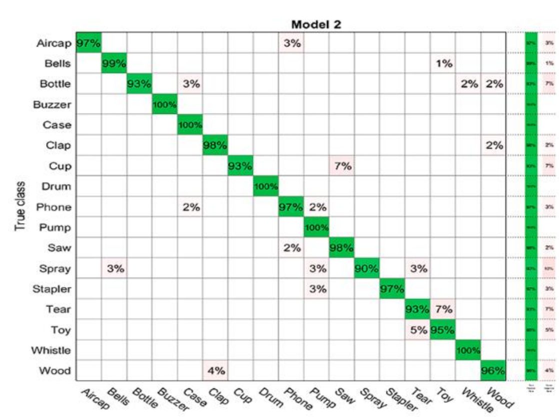

Fig. 5. Confusion matrix analysis over RWCP

detection to enhance the quality of life for elderly people living an independent life.

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