A Low Cost Scheme for Tracking the Lives Buried in Landslides

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ABSTRACT

The landslides cause several casualties and economic losses all over the world. Studies show that most casualties happen within the first *18-35* minutes after the burial. This demands life-detecting systems to be available immediately on the spot after the disaster. A suggested approach is deploying multiple units of these instruments across the country. Main constraint in developing countries for multiple deployments is the cost of the gadget. A scheme for detection and localization of lives buried in landslides based on a statistical and computational technique, called independent component analysis (ICA) and the Sound Source localisation using time delay of arrival (TDOA) and Cross-Correlation method is proposed.

General Terms

Audio processing, Landslides , Life detecting system, Signal processing, Statistical technique

Keywords

FastICA, Sound Localisation, Independent Component Analysis, Source Separation**,** Time delay of arrival

1. INTRODUCTION

Landslides cause massive casualties and severe economic losses worldwide The survival chances for persons caught in landslides are dependent on several factors. Chance of survival over time in a complete landslide burial is not linear. A high risk to die is in the first *18 to 35* minutes of burial.This demands life-detecting systems to be available immediately on the spot after the disaster. Transporting the life detecting systems from far places cause adverse delay in rescue operations. Our approach is based on capture the ground noise using a sensor array and separating the heart beats or human body sounds to identify the lives buried under the earth. This mixed sound signals can be separated to individual components using Independent Component Analysis, a Blind Source Separation (BSS) [1] methods followed by post processing will lead to prediction of lives buried. We also investigate the possibility of locating the buried lives by identifying depth and distance of burial by finding the angle of arrival of sound. This scheme can be used to build low cost life saving equipment.

2. NEED FOR THE SYSETM

The survival chances for persons caught in landslides are dependent on several factors. Survival chances after the landslide depends on whether the victim is able to breath and how fast the victim is dug out (in the case of critical burial; head and upper part of the body is under earth). If the airway of the buried person is not clear and if there is no air pocket round the victim, after *30-40* minutes the chances of survival is negligible [3].Chance of survival over time in a complete landslide burial is not linear (Figure 1). Transporting the life detecting systems from far places is not an effective solution. So a better solution is many units of this instrument make available across the states. The major limiting factor in procuring the high technology instrument like radars using ultra wideband (UWB) technology is the capital involved and the skilled technicians required for operation and maintenance [4].

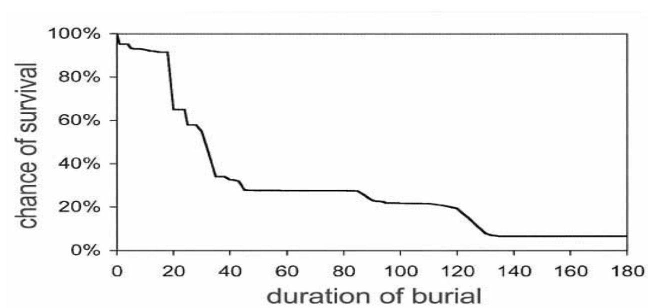

Figure 1. Survival chance of persons buried completely due to landslides [3]

3. INDEPENDENT COMPONENT ANALYSIS

Independent Component Analysis or ICA is a Blind source separation (BSS) method which aims to separate a set of *unknown* component signals, or sources, from a set of *known* mixtures (known as Cocktail Party Problem in speech processing [2,18]) BSS model make use of only mutual statistical independence between the source signals and no priori information about the characteristics of the source signals, the mixing matrix or the arrangement of the sensors is needed [6]. This makes ICA most suitable model for our application.

The recorded sound using two microphones can be expressed as a linear equation:

$x_1(t) = a_{11}s_1 + a_{12}s_2$ (1)

$x_2(t) = a_{21}s_1 + a_{22}s_2$ (2)

where $x_1(t)$ and $x_2(t)$ are recorded signals and a_{11}, a_{12}, a_{21}, and a_{22} are some parameters that depend on the distances of the sensors or microphones from the audio source. We have to estimate signals $s_1(t)$ and $s_2(t)$ from $x_1(t)$ and $x_2(t)$, which are recorded signals. We neglect any time delays, echoes, reverberation etc from this model. The problem becomes difficult because the parameter a_{ij} is unknown [7, 8].

We can adopt a statistical method to solve this problem. For using statistical procedures we assume that $s_1(t)$ and $s_2(t)$, at each time instant t, are *statistically independent[9,10]*. The procedure of Independent Component Analysis, or ICA, can be used to estimate the a_{ij} based on the information of their independence, which allows us to separate the s_1 *and* s_2 from the mixtures x_1 *and* x_2 [6,7,8,9,10,11]. ICA can be defined using statistical "latent variables" model [13], Assume that n linear mixtures $x_1, ..., x_n$ of n independent components $x_j = a_{j1}s_1 + a_{j2}s_2 + ... + a_{jn}s_n$ (3), for all j. These mixtures are observed signals. Assume x_j *and* s_k are random variables.

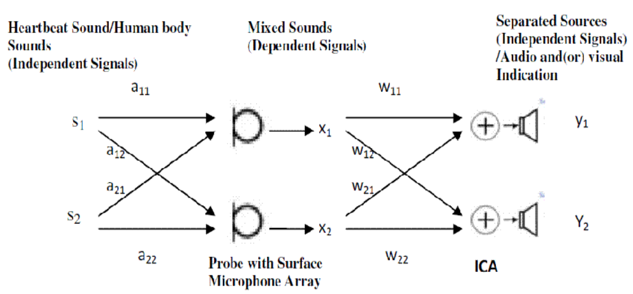

Figure 2. Ground signals are recorded using two sensors (Surface microphone arrays) and the mixture x_1&x_2 is separated to recover the component signals y_1& y_2.

Let both the mixture variables and the independent components have zero mean or *can* always make it zero mean by subtracting the sample mean (Centering process).

The above mixing model without taking into account the noise is written as

$\mathbf{x} = \mathbf{As}$. (4)

where **x** the random vector whose elements are the mixtures $x_1, ..., x_n$, and **s** the random vector with elements $s_1, ..., s_n$. Let us denote by **A** the matrix with elements a_{ij} .

The statistical model in Eq. 4 is called independent component analysis, or ICA model [7]. Assume zero-mean and uncorrelated Gaussian noise , $n \sim N(0, diag(\Sigma))$, ICA model can be given as;

$\mathbf{x} = \mathbf{As} + n$ (5);

For simplicity, assume that the unknown mixing matrix is square. Then, after estimating the matrix **A**, compute **W**, which is the inverse of A and obtain the independent component by:

$\mathbf{s} = \mathbf{Wx}$. (6) this is equivalent to finding a linear transformation given by matrix W, so that the random variables s_i, i= 1,..,n are independent as possible. In the ICA model in Eq. (4), the following ambiguities will hold [7] but are irrelevant to our case: It is difficult to determine the variances (energies) of the independent components and the order of the independent components.

4. PRINCIPLE OF ICA ESTIMATION

ICA minimizes both second-order and higher-order dependencies in the input. Two random variables ***y1*** and y2 are said to be uncorrelated, if their covariance is zero:

$E\{y1y2\} - E\{y1\}E\{y2\} = 0$ (6)

If the variables are independent, they are uncorrelated; but uncorrelatedness does *not* imply independence. Uncorrelatedness can be considered only as weaker form of independence The key to estimating the ICA model is nongaussianity. We can see that without nongaussianity the estimation is not possible. That is, for estimating the independent components by ICA technique, components must be nongaussian [6,7,10,11].

The Central Limit Theorem, a classical result in probability theory, tells that under certain conditions, the distribution of a sum of independent random variables tends toward a Gaussian distribution; generally, sum of two independent random variables has a distribution that is closer to Gaussian than any of the two original component random variables [7].

To use nongaussianity in ICA estimation, a quantitative measure of nongaussianity of a random variable, say y is to be used. Assume that y is centered (zero-mean) and has variance equal to one. We use preprocessing in ICA algorithms, to make this simplification possible. The pre processing make y centered and make variance equals to unity. The classical measure of nongaussianity is kurtosis or the fourth-order cumulant. The kurtosis of y can be defined as $\text{kurt}(y) = E\{y4\} - 3(E\{y2\})$ (7)

Since by assumption y is of unit variance, we can write $\text{kurt}(y) = E\{y4\} - 3$. This shows that kurtosis is simply a normalized version of the fourth moment $E\{y4\}$. For a Gaussian y, the fourth moment equals $(E\{y2\})$. The kurtosis is zero for a Gaussian random variable. Random variables that have a negative kurtosis are called subgaussian and those with positive kurtosis are called supergaussian [7,8,12].

5. THE FAST ICA ALGORITHM

The FastICA algorithm is a very efficient and popular algorithm. The algorithm is based on a fixed-point iteration scheme. It maximizes non-Gaussianity as a measure of statistical independence. It can be also derived as an approximate Newton iteration. The data is preprocessed by centering and whitening. The FastICA algorithm for one unit is given below [7,13,14]. By a "unit" in Fast ICA refer to a computational unit, eventually an artificial neuron, having a weight vector **w** that the neuron is able to update by a learning rule. The FastICA learning rule finds a direction, i.e. a unit vector **w** such that the projection $\mathbf{w}^T\mathbf{x}$ maximizes nongaussianity. The FastICA is based on a fixed-point iteration scheme for finding a maximum of the nongaussianity of $\mathbf{w}^T \mathbf{x}$,

The standard basic form is as follows:

Step 1. Choose an initial (e.g. random) weight vector **w**.

Step 2. Let $\mathbf{w}+ = E\{\mathbf{x}g(\mathbf{w}^T \mathbf{x})\} - E\{g0(\mathbf{w}^T \mathbf{x})\}\mathbf{w}$

Step 3. Let $\mathbf{w} = \mathbf{w}+/k\mathbf{w}+k$

Step 4. If not converged, go back to Step 2.

if the old and new values of **w** point in the same direction, we can say convergence happened. It is not necessary that the vector converges to a single point, since **w** and −**w** define the same direction. This is again because the independent components can be defined only up to a multiplicative sign.

6. SOUND LOCALISATION

The angle (Azimuth) at which the sound-source is located with respect to our unidirectional sensors is determined by computing the time delay of arrival (TDOA) of the wave front at the two sensors (microphones). The lag of the wave at a specific point received at both microphones is calculated to determine the angle of incidence of sound waves. This is calculated by finding two identical points along the waveform (have maximum correlation) Signals *f (t)* and *g (t)* recorded at the microphones are passed to the cross-correlation function which is used to compare the signals for similarity. The basic method is presented in [5].

The cross-correlation function is defined as

$$(f * g)_n (t) \stackrel{\text{def}}{=} \sum_{k=0}^{N-1} f_{j+k}\, g_k \quad (8)$$

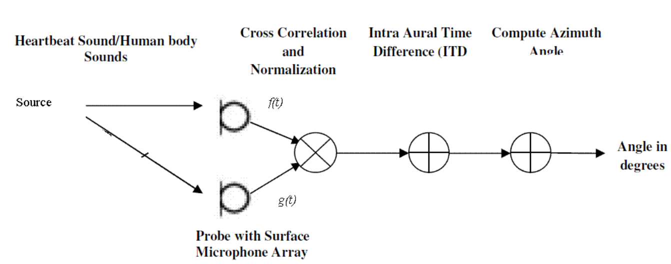

Figure 3. The sensor arrangement to capture the sound and Steps for localisation using TDOA

Cross-correlation value is maximum at some point in time (t_n) when the function *f(t)* is shifted in time across the function *g(t).* We use the cross-correlation in this instance is used to compare two vectors A and B (which contain the values for the signals *f(t)* and *g(t)* respectively) for similarity. The signals are then slid across each other at all points to give a product vector C whose length is shown as;

(length (A) + length (B))-1 (9)

The maximum value in the returned vector C represents the position of maximum correlation between the two signals f(t) and g(t) with a time delay σ.

Detect the delay (σ) offset of the highest correlation point in vector C and use this to find the angle the source make with our sensors as explained. Assume that normal to the line joining the sensors as 0^0 and towards Clock Wise (CW) direction as positive and Counter Clock Wise (CCW) as negative. The σ of the maximum correlation point is found by moving to the mid-point of C as this is 0^o. Counting the number of locations to the highest position gives the σ. This delay is then used to calculate the TDOA.

Time increment between sampling, $\Delta = 1/44.1 \times 10^3$ S (10).

From the Figure.4 the side;

$$a = t \times V_{sound} = (\Delta \times \sigma) \times V_{sound} \quad (11)$$

and

$$\theta = \sin^{-1}(\Delta \times \sigma) \times V_{sound}/c \quad (12)$$

where t time required for the sound to traverse line 'a', Δ = time between sound sampling, and σ = the number of delay samples returned from the cross-correlation function.

To find the approximate depth of burial we can use the following procedure. The unidirectional sensors are placed on the earth surface pointing downwards and the angle of arrival of the high-flying sound is detect as θ_1 using the method discussed above. Then the sensors repositioned in such a way that the first sensor occupies the midpoint of line connecting the two sensors in the first arrangement. The sensors are rotated to make the line connecting the sensors normal to the line connecting midpoint of sensors in the first arrangement and the sound source. (Fig. 5) The angle of arrival θ_2 with respect to new position is determined by the earlier procedure.

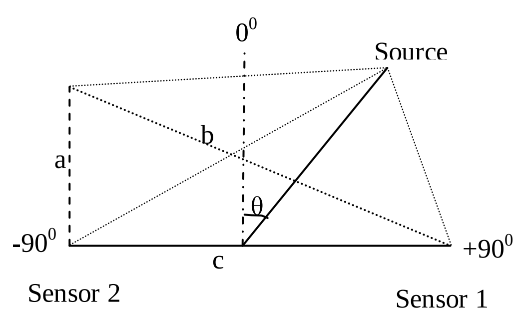

Figure 4. The sound waves reach the sensor1 and sensor 2 in different time

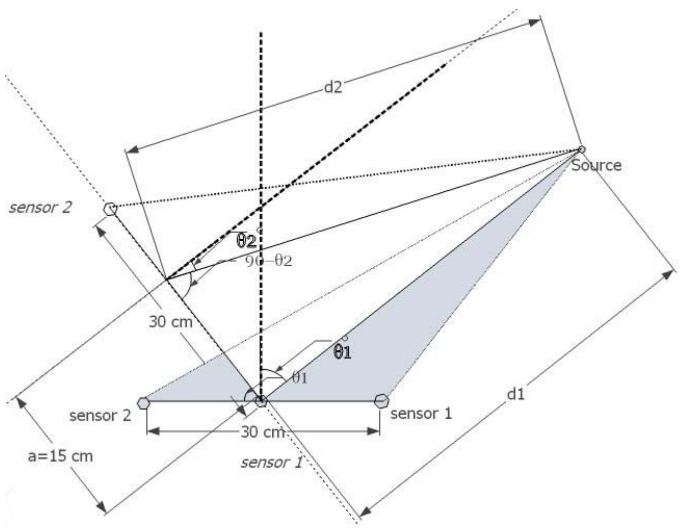

Figure 5. Repositioning the sensors to find the distance between source and sensors.

We can see that tan $\theta_2 = a/d1$ (13) and we know the distance between sensors; here we took as 30 cm , so a=15 cm. Substituting we get the distance between sensor 1 and the source $d_1 = 15 \cot \theta_2$ (14) and angle of arrival as θ_1. We can compute the other unknowns very easily if required.

The distance of burial can be find using the same procedure but the sensors orientation should be parallel to the earth surface. The new position might be in a plane orthogonal to the first.

7. EXPERIMENT RESULTS

Human body produces a variety of sounds[19]. We consider only heart sounds for the present study and other sounds we consider as noises.

We studied separations of many samples. Three cases are discussed here. Heart beats of three persons with different age and gender - Heart beat of a 34 year old male (s_1), 28 year old female (s_2) and a 5 year old girl child (s_3) are recorded using contact microphones. The first two recordings are in similar environment and third one is recorded in a noisier environment. In addition to the centering and whitening steps in the algorithm, a preprocessing step- the noise reduction is done based on the noise profile obtained. The obtained noise profile is subtracted from the signal. This additional step is because of the low SNR of the recorded signal.

The separation using FastICA, a computationally efficient algorithm[13,14,15] for the linear mixtures of $s_1$and s_2 , $s_1$and s_3 and s_2 and s_3 are experimented. The scatter plot and the joint density plot of the recordings s_1& s_2 showing the independence and non-Gaussian behavior of the two signals[17] (Figure 6). The scatter plot and the joint density plot of the linear mixtures s_1& s_2 showing the dependence and a more Gaussian behavior (Figure 7). The scatter plot and the histogram of the separated components (Independent components) from the mixtures showing the independence and non-Gaussian behavior (Figure 8).

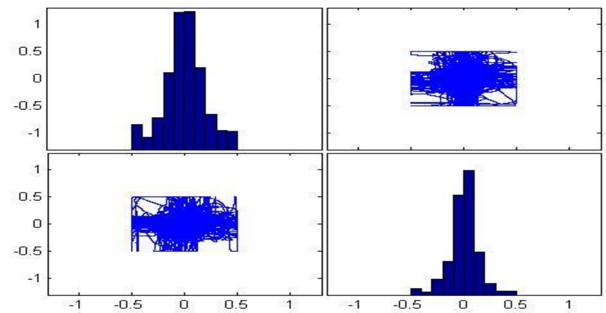

Figure 6. The scatter plot and the histogram of the recordings s1 and s2 showing the independence and non-Gaussian behavior of the two signals

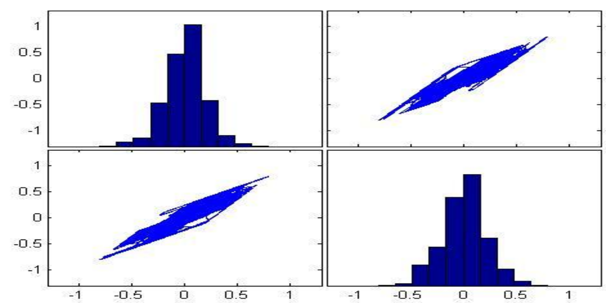

Figure 7 . The scatter plot and the histogram of the linear mixture of s1 and s2 showing the dependence and more Gaussian behavior

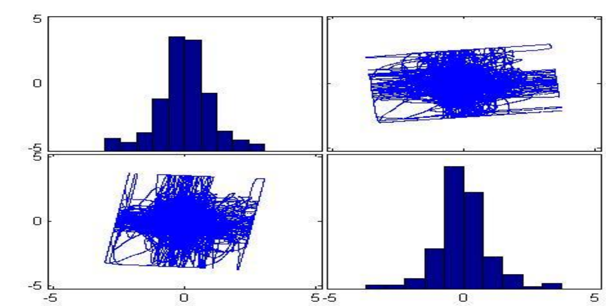

Figure 8 . The scatter plot and the histogram of the separated components (Independent components) from the mixture of s1 and s2 showing the independence and non-Gaussian behavior of the two signals.

The buried lives can be localized using TDOA and Cross-Correlation methods [5] discussed in the preceding sections. A schematic of this method is given in Figure 3. A proto type system consist two electrets microphones as sensors and MAYA 44 USB sound card is used in the study. We recorded the sound to be localised signals for 20-30 seconds slice. The experiments are performed in room conditions. We took different measurements by varying the distance and angle between the microphones and the sound source. The prototype system gives accuracy above 96 % in finding the angle of arrival (Table 3). Figure 9 shows the plot of actual angle and measured angle for the source placed at distance 15 cm from the midpoint of the line join the sensors. The deviation from the actual is shown by plotting the actual value. Plotted is the worst case we came across. The distance of the source is computed as discussed early.

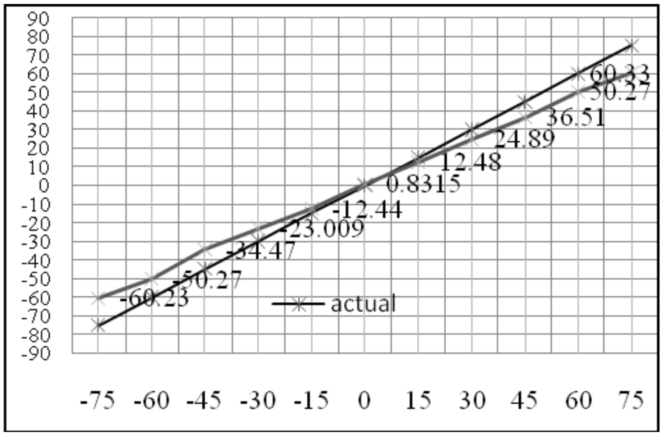

Figure 9. The Plot of the measured angle (Y-axis) Vs Actual angle (X-axis).The distance of the source is 15 cm. Deviations from the expected curve is also shown. The accuracy in this case is 81.35%

8. DISCUSSIONS

We consider human body sounds other than heartbeat as noise and the real condition recordings is also affected by other surrounding noises[16,20].

Noise is subtracted from the signal in a preprocessing step outside the FastICA procedure. Scatter plots and the histograms shows a more Gaussian behavior in the mixed signal and non Gaussian behavior [12] in the separated signal. This is supported by the plots and data presented in the tables. We measured kurtosis (Table1) and correlation coefficients (Table 2). The difference in the kurtosis of separated signals and the independent signals shows only small variations. The higher kurtosis of separated signal implies the non Gaussian behavior or peaky nature of the signal. The result shows that source separation is possible for the specimen signals. The direction of arrival is calculated based TDOA and Cross-Correlation methods gives accuracy over 96% under test conditions (Table 3).The experiment give more accurate results for larger distance between the sensor and source.

Table 3 Accuracy of the measurements obtained for various distance of the sources to the midpoint of the line connecting the two sensors

Distance of the Source	**Accuracy of the measurements obtained in percentage**
15	81.35
30	96.36
45	96.38
60	96.68

Table 1 Shows the comparison of kurtosis of recorded signals, mixed signals, whitened signals and separated signals.

Component Heartbeat Signals with Kurtosis	**Component heartbeat Signals with Kurtosis**	**Mixed Heart Beat Signals**	**Kurtosis of Signals**	**Kurtosis of Whitened Signals**	**Kurtosis of Separated Signals**
s_1 (3.7196)	**s_2 (5.6992)**	**s_{12} A**	***4.1239***	***3.9997***	***3.8034 5.7009***
		s_{12} B	***3.4134***	***3.6166***	
s_1 (3.7196)	**s_3 (16.5064)**	**S_{13} A**	***3.5881***	***13.9657***	***15.3712 3.7192***
		S_{13} B	***3.6158***	***3.5751***	
s_2 (5.6992)	**s_3 (16.5064)**	**S_{23} A**	***5.2036***	***12.7764***	***15.3731 5.6985***
		S_{23} B	***5.4145***	***5.2660***	

Table 2 Shows the correlation of recorded signals, mixed signals, whitened signals and separated signals.

Component heartbeat Signals	**Correlation Coefficient**	**Mixed Heart Beat Signals**	**Correlation Coefficient**	**Correlation Coefficient Whitened Signals ($x10^{-8}$)**	**Correlation Coefficient of Separated Signals ($x10^{-8}$)**
s_1	***0.050136***	**s_{12} A**	***0.939664***	***-7.51975***	***20.0112***
s_2		**s_{12} B**			
s_1	***0.011522***	**S_{13} A**	***0.959860***	***-5.47922***	***.996523***
s_3		**s_{13} B**			
s_2	***0.01427***	**s_{23} A**	***0.980618***	***-3.89508***	***2.58379***
s_3		s_{23} B			

9. CONCLUSION

A low cost life tracking system based on Independent Component Analysis which can be used to detect lives buried in landslides is proposed. The blind source separation (BSS) of heartbeat sound mixtures was examined. Source signals are extracted only from observed mixed signals. The statistical technique of independent component analysis (ICA) was studied from the audio signal processing point of view. Localizing sound using TDOA and Cross-Correlation methods is found to be very efficient. A new simple method for finding the distance of the source from only using angle of arrival is proposed.

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