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A Supporting Uncertainty Decision Making Processes based on Fusion of Audio - Vision Evidence

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***Abstract:*-This paper presents a new method for decision making based on the fusion of audio-visual evidences. Evidences fusion is characterized that the decision will be more accurate and specific because it does not depend on one evidence's alone as in the probabilistic approach.**

The decision-making process depends on decisional separation of conflict conditionally between contributions of several independent sources of information represented by audio and images.

In order to provide effective of evidence fusion, one must employ an analytical framework that can capture the uncertainty inherent in audio and visual data. In particular, feature extraction of audio and visual data results in propositions that inherently possess significant semantic ambiguity. An evidence fusion must be able to exploit the respective advantages of audio and visual data while mitigating their particular weaknesses.

Keywords: Evidence fusion, Evidence measures, decision making.

1. INTRODUCTION

Decision making (DM) is the study that identifying and choosing from a nonempty set of alternatives (A) probabilities based on a given set of criteria (C) and preferences of the decision maker i.e.:

$$\begin{aligned} DM &= f(A,C) \\ &= f : A \times C \to A,\ A \subseteq U, A \neq \phi \end{aligned}$$

The outcomes of a DM process are determined by the decision making strategies selected by decision makers when a set of alternative decisions has been identified. There is a great variation of DM strategies developed in traditional decision as well as cognitive science, system science, management science, and economics. Decision making is one of the fundamental cognitive processes modeled in the layered reference model of the brain (LRMB) [1, 2]. Modeling for decision making involves two distinct parties one is the decision maker and the other is the model builder known as the analyst [3]. There are three most widely types of decision models that help to analyze depending on the amount and degree of knowledge namely decision making by buying information [4], decision making under risk [5] and decision making under pure uncertainty[6]. In decision making under pure uncertainty, the decision-maker has no knowledge regarding any of the states of nature outcomes, and/or it is costly to obtain the needed information.

In the environment of uncertainty, more than one type of event can take place and the decision maker is completely in dark regarding the event that is likely to take place. The decision maker is not in a position, even to assign the probabilities of happening of the events as shown in figure 1.

In most decision whose outcomes depend on uncertain events are contain implicitly degree of belief. Belief function is used to determine degree of belief which can be defined as a function satisfying three axioms which can be viewed as a weakening of the Kolmogorov axioms that characterize probability functions [7]. The view of belief function as a generalization probability theory is quit different from a representation of a body of evidence [8].

Evidence theory [9] has often been promoted as an alternative approach for fusion information when the hypotheses for Bayesian approach cannot be precisely stated.

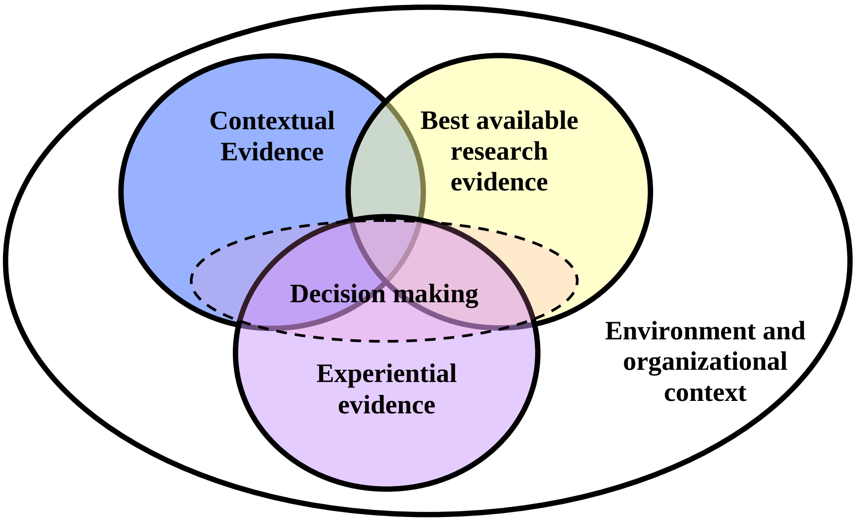


Fig. 1: Evidence based decision making environment

The evidence alone is not enough to make the decision because its calculation method depends on randomized trials and other quantifiable methods. So evidence alone is considered an only one key component in the decision-making process but its have high probability of being affected by noisy data and lack of distinctiveness which contributes to the inability of decision maker in making the right decision.

Fusion of evidence should actually be used to contribute to the decision by predicting the performance of the fused evidence and comparing it with the corresponding belief function of the best expert. In the recent literature [13] there has been a large amount of work devoted to the definition of new rules. For example, Dempster-Shafer theory [14] which based on belief functions [15] and combines different pieces of evidences into a single value that approximates the probability of an event. And there are theoretical framework [16] is developed for combining multiple experts and the most usual classifiers combinations schemes, such as the product, sum, min, max and median rules.

Subsequently, this paper is illustrated by implementing two well known audio and visual evidences. Typically, these evidences take into account a consensual evaluation of the sources by invalidating irrelevant sources of information on the basis of a majority decision. The remainder of this paper is organized as follows: Section 2 basic notation. Section 3 proposed method. Section 4 experimental and results Finally, Section 5 concludes.

2. BASIC NOTATION

General formula which represents the knowledge base is $K = \langle f, R \rangle$ where (f) represents facts and (R) is inference engine that can reason about those facts. Each of (f) and (R) are associated with some supporting evidence as $f = \{\langle h, E \rangle\}$ and $R = \{\langle \delta, E \rangle\}$ respectively. An evidence argument is a pair $\langle h, E \rangle$, where (h) is a formula in (K) and $E = \{e_1, e_2, \ldots, e_n\}$ is a set of formula in (K) denoted by $E(h)$. An element $e_i \in E(h)$ represents an indivisible chunk of information serving as evidence called a focal element of the evidence for (h). A focal element is an element of the power set to which a non-zero belief is assigned. It is possible that $\{\langle h, E_1 \rangle, \langle h, E_2 \rangle\} \subseteq f$, such that $E_1 \neq E_2$. For every pair $\langle h, E \rangle$:

1. $h = \varpi \in K \text{ or } h = \delta \in \Delta; \text{ and}$
2. $E = \{e_1, e_2, \ldots, e_n\}$ is a set of evidence for (h) such that $e_i \neq e_j$ for any $i \neq j$.

For every set of evidence E there are constituent members have a probability mass function denoted by

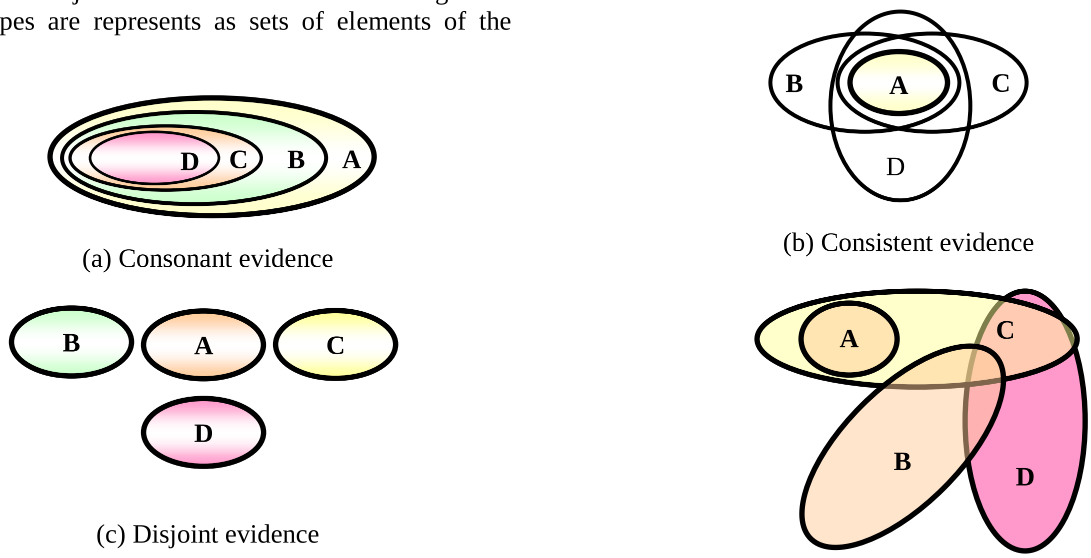
$m(E,.) : E \rightarrow [0,1]$ and satisfies the constraint:

$$m(E, e_1) + m(E, e_2) + \ldots + m(E, e_n) = 1$$

$$m(E, \phi) = 0 \quad \text{for all } \phi \notin E$$

a. Evidence Types:

Evidence can be divided into four type's [17] namely consonant evidence, consistent evidence, arbitrary evidence, and disjoint evidence. As shown in figure 2 evidence types are represents as sets of elements of the frame of discernment for where there are non-zero basic probability assignments.



(a) Consonant evidence

(b) Consistent evidence

(c) Disjoint evidence

(d) Arbitrary evidence

Fig. 2. Four types of evidence

Consonant evidence can be represented as nested structure of subsets, where smallest subset elements are included in the next larger subset. This can correspond to the situation where information is obtained over time that increasingly narrows or refines the size of the evidentiary set. While, consistent evidence means that there is at least one element that is common to all subsets. But arbitrary evidence corresponds to the situation where there is no element common to all subsets, though some subsets may have elements in common. Whereas disjoint evidence implies that any two subsets have no elements in common with any other subset.

b. Evidence Combining:

Evidence combining can be stated in the context of information fusion. Depending on the type of information that is fused, the fusion scheme can be classified as sensor level, feature level, score level and decision level fusion. Feature level fusion refers to combining deferent feature sets that are extracted from multiple biometric sources. When the feature sets are dependences a single resultant feature set can be calculated as a weighted average of the individual feature sets [18]. Whereas the feature sets are independents a single feature set form can be concatenated [19]. Concatenated feature set is demonstrating different properties of uncertainty about the evidence, generate different characterizations of the evidence as observed through the evidence they can obtain. The obtained evidence can be characterized by the basic probability assignments to the frame of discernment of evidence.

c. Evidence measures:

By applying evidence combination rules there are several evidence measures (EM) can be created. An evidence belief function (EBF) is a numerical reasoning method represents the evidence in the form of generalized probabilities [20]. EBF a problem is described all possible values of element in an environment and provides a way to represents the hesitation and ignorance. The elements of the environment are mutually exclusive and exhaustive. The exhaustive set of mutually exclusive elements is referred to as a frame of discernment denoted as $\hbar$. Let Bel be such EBF that represents belief in the propositions that correspond to the elements of $2^{\hbar}$:

$$Bel : 2^{\hbar} \rightarrow [0,1]$$

$$A \rightarrow Bel(A) with \sum_{A \subseteq \hbar}(A) = 1$$

where, $Bel(A)$ is the total belief committed to A.

The counterpart of Bel is the plausibility measure (pl) :

$$2^{\hbar} \rightarrow [0,1] \quad with \quad pl(A) = \sum_{B \cap A \neq \phi} m(B)$$

The measure $pl(A)$ shall not be understood as a complement of $Bel(A)$. Only

$$\{A \subseteq \hbar \mid m(A) > 0\} \neq \phi \rightarrow Bel(A) \leq pl(A)$$

has to be fulfilled.

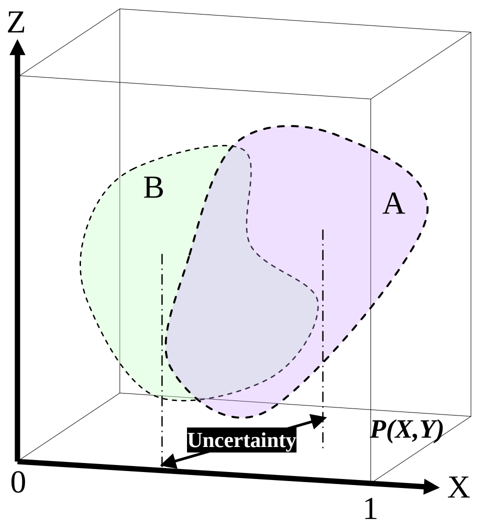
In addition to Bel and pl third evidence measure can be defined as commonality measure (cmn) [21]. With $cmn : 2^{\hbar} \rightarrow [0,1]$ and

$$cnm(A) = \sum_{B \supseteq A} m(B)$$

The complements to the measures Bel and pl are doubt and disbelief respectively. Doubt [22] can defined as complements to the plausibility measure it seems to make more sense to distinguish between doubt and disbelief. Lack of belief does not imply disbelief [23]. The disbelief of set A is the belief in the complement. There is

$$Bel(\neg A) = 1 - pl(A)$$
$$pl(\neg A) = 1 - Bel(A)$$
$$with$$
$$Bel(\neg A) \leq pl(\neg A)$$

The difference $pl(A) - Bel(A)$ describes the uncertainty concerning the hypothesis A represented by the evidential interval as shown in figure 3.



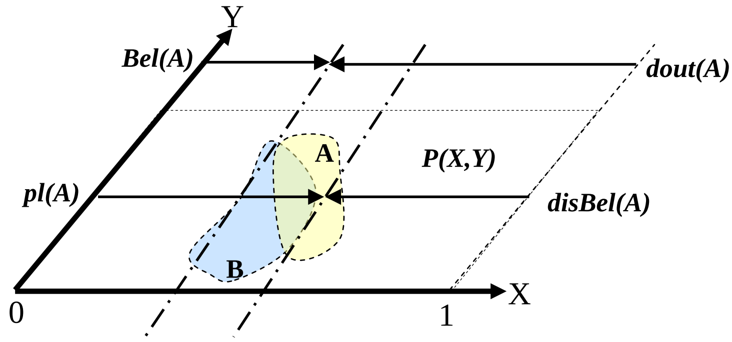


Fig 3. measures of belief and plausibility and its complements

3. PROPOSED METHOD

The proposed method presents new method for improving decision making based on the decision function, which adjudicate in a decisional dispute conditionally to basic decisions provided by the several sources of information. As shown in figure 4, there are three subsections which introduce evidence representation, evidence fusion and decision making.

a. Evidence representation:

We consider there are two different sources for evidence namely image evidence (Ev_{Im}) and sound evidence (Ev_{So}). Each of evidence detects a set of objects denoted by $Ev_{\mathrm{Im}} = \{ev_{im_1}, ev_{im_2}, ..., ev_{im_n}\}$ for (Ev_{Im}) and $Ev_{So} = \{ev_{so_1}, ev_{so_2}, ..., ev_{so_n}\}$ for (Ev_{So}). All evidence that has been obtained from the classifier that gives information on the actual class of a test pattern. This information can be represented by a belief mass function $m(.)$ after the presentation on the expert.

Let $\Phi = \{\varphi_1, \varphi_2, ..., \varphi_n\}$ be a frame of discernment of a decision making problem under consideration (n) distinct elements $\varphi_i, i = 1,2,...,n$. Evidence belief mass function defined as a mapping from the power set of Φ denoted by 2^{Φ} that must satisfy the two conditions. The first is mass of empty set which represent the impossible event is zero and the other is the mass of belief is normalized to one. An element $\beta \subseteq \Phi$ is called focal element if and only if $m(\beta) > 0$. Focal element represents a degree of belief attached to the proposition $\varphi \in \beta$ and to uncertainly proposition, based on some evidence.

Each normalized mass function $m_N(.)$ can represent by several function associated with belief function known as plausibility, commonality and disbelief. Plausibility function (pl) is the most important which represents the upper limits of uncertainty whereas the belief function (bel) represents the lower limits. Each of (pl) and (bel) functions are in one to one correspondence, they may be obtained from each other through linear transformation.

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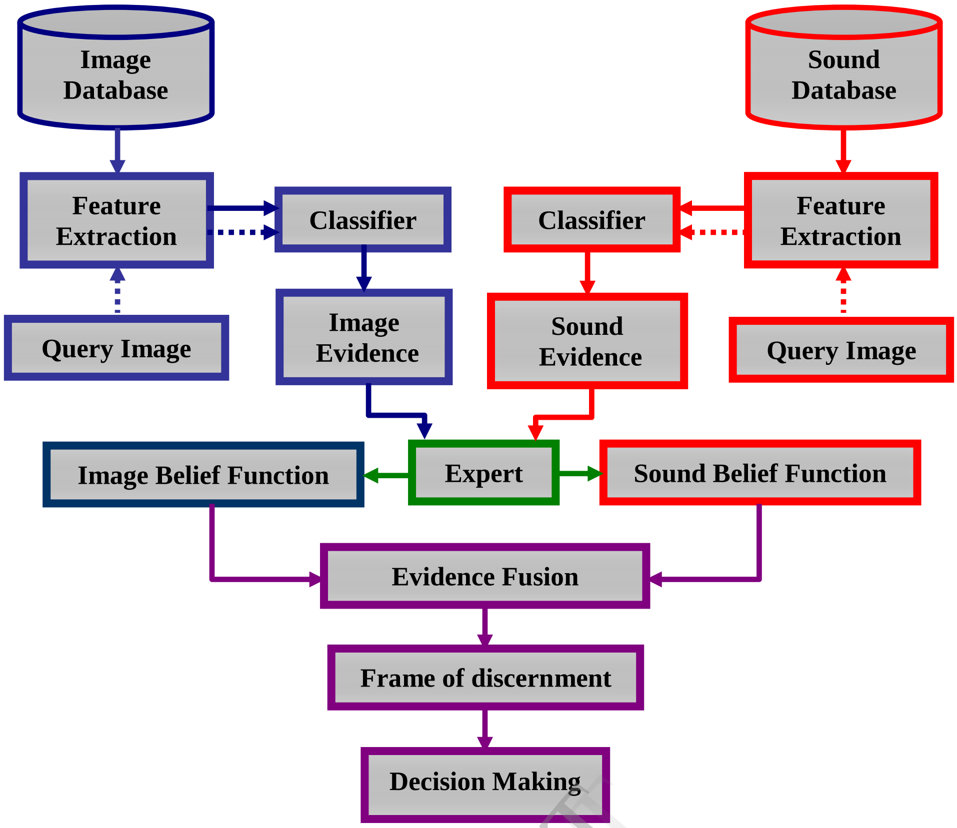

Fig 4: proposed method to improving decision making.

b. Evidence representing algorithm:

Let there are probability (p), $p \in [0,1]$ of two evidences $Ev_{\mathrm{Im}}, Ev_{So}$ and a partition $(\{Ev_{\mathrm{Im}_{1:n}}\}, \{Ev_{So_{1:m}}\})$ of $[1, s]$ such as:

$$E(X \mid Y_{1:s}; m_{1:s}) = pEv_{\mathrm{Im}}(X \mid Y_{Ev_{\mathrm{Im}_{1:n}}}; m_{Ev_{\mathrm{Im}_{1:n}}}) + (1-p)Ev_{So}(X \mid Y_{Ev_{1:m}}, m_{Ev_{So_{1:m}}})$$

Then, evidences of the fused belief function $\oplus[m_{1:s} \mid E]$ are generated by means of the sub arbitraments related to Ev_{Im} and Ev_{So}:

Evidence representing algorithm:

1- **Entries generation:**

For each $i \in [1, n]$, generates $\Phi \in 2^{\Phi}$ according to the basic belief function (m_i), considered as probabilistic distribution over the set 2^{Φ}.

2- **Conditional arbitrament:**

- Generate $\varphi \in 2^{\Phi}$ according to experts $E(\varphi \mid \Phi_{1:n}; m_{1:n})$ considered as a probabilistic distribution over the set 2^{Φ}.
- In case empty set $\Phi = \phi$ means impossible event. Otherwise event is focal element.

c. Evidence Fusion:

The purpose of aggregation of information is to meaningfully summarize and simplify information rationally obtained from an independent source or multiple sources. Hence the evidence fusion algorithm can be done by algorithm 1. Combination rules are the special types of aggregation methods for data obtained from multiple sources. From a set theoretic standpoint, the combination and disjunction of evidence is employed by AND (set intersection) and OR (set union) operation respectively. The combination rule is determined from the aggregation of two basic probability assignment of m1 and m2 in the following manner:

$$m_{12}(A) = \frac{\sum_{B \cap C = A} m_1(B) m_2(C)}{1-K} \quad where \;\; A \neq \phi \qquad (I)$$

$$m_{12}(\phi) = 0$$

$$K = \sum_{B \cap C = \phi} m_1(B) m_2(C)$$

The normalization factor (1-K) has the effect of completely ignoring conflict and attributing any probability mass associated with conflict to the null set [24]. The combination rule results which based on conjunctive pooled evidence can be measured by evidence measures.

Algorithm 1: Evidence Fusion

Data: Audio evidence: $Ev_{So} = \{ev_{so_1}, ev_{so_2}, ..., ev_{so_n}\}$, $Ev_{So}.bel$, $Ev_{So}.focal$

Visual evidence: $Ev_{\mathrm{Im}} = \{ev_{im_1}, ev_{im_2}, ..., ev_{im_n}\}$, $Ev_{\mathrm{Im}}.bel$, $Ev_{\mathrm{Im}}.focal$

$n - Experts\ (ex) : \{ex_1, ex_2 ..., ex_n\}$

$m(ev_{im_k}) = m(ev_{So_k}) \neq 0$

Results: Fusion of (Ev_{Im}) and (Ev_{Im}) : F_{ev}

```
for i = 1:n do
    fusion ← φ
    for Ev_So.focal in ex_i do
        for Ev_Im.focal in ex_i do
            K ← Ev_So.focal ∩ Ev_Im.focal
            fusion.focal ← K
            fusion.bel ← Ev_So.bel × Ev_Im.bel
    Concatenate same focal in fusion
    F_ev ← fusion
```

d. Decision Making:

A belief function has to be transformed into a probability function for decision making. The belief function that quantifies knowledge of the actual class of (x) is transformed into a pignistic probability distribution [25]. Each mass of belief $m(A)$ is divided equally between the elements of (A) for all $A \subseteq \Phi$. This leads to pignistic probability distribution of class (w) defined as [26]:

$$BetP(w_k) = \sum_{w_k \in A} \frac{m(A)}{|A|}, \quad \forall w_k \in \Phi \qquad (II)$$

4. EXPERIMENTAL AND RESULTS

The most important and immediate application of this proposed method is helping decision makers decide most appropriate in given situation as shown in figure 5. Such decisions are based on information from set of hypothesis (ς) consisting of basic hypotheses $\{c_1, c_2 ..., c_m\}$, pieces of evidence that get from two sources audio-visual evidences and decision maker opinion. Audio and visual sources, provided by the sound signal sensor and image processing specifying the sets of features and the probabilities conditional on the features and corresponding cases characteristics. Expert's opinion is provided by the case concerning his characteristics and preferences on the basis of which relevant utility functions are to be chosen.

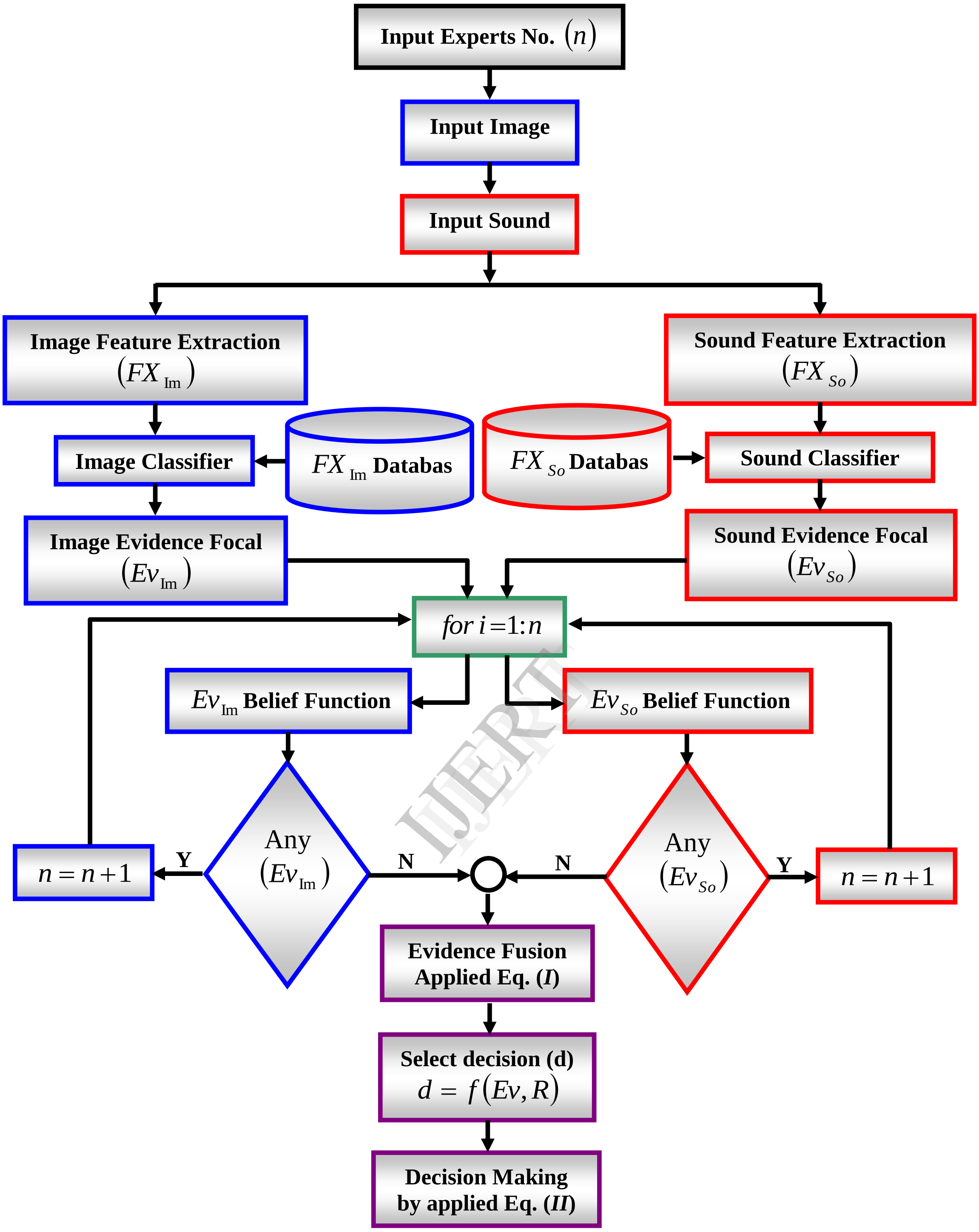

Fig. 5: Decision making based on audio-visual evidences.

For illustrates, the decisions can be determined to three precisely defined hypothesis represented by:

$$\varsigma = \{c_1, c_2, c_3\}$$

The corresponding power set of (ς) is:

$$2^{\varsigma} = \{\phi, \{c_1\}, \{c_2\}, \{c_3\}, \{c_1, c_2\}, \{c_1, c_3\}, \{c_2, c_3\}, \{c_1, c_2, c_3\}\}$$

Each case can be described by two major symptoms called audio (So) and visual (Im) evidences. The decision depends on the point of view of decision-makers, where his opinion depending on the evidence probability that affect in the hypothesis.

One of the decision makers mainly states that the hypothesis (c_1) or (c_2) are the reason for the problem. In other words, the piece of evidence three (ev_{Im_3}) might have occurred and resulted in the consequences (c_1)

or (c_2). Whereas, the second decision maker was focused on hypothesis (c_1) and (c_3). The complete survey of the qualitative evidences-hypothesis is given in Table 1.

Table 1: qualitative evidences-hypothesis

		Evidence	Degree of belief	Hypothesis
Decision makers	1st	ev_{Im_1}	$P(ev_{\mathrm{Im}_1})$	c_1
		ev_{Im_2}	$P(ev_{\mathrm{Im}_2})$	c_2
		ev_{Im_3}	$P(ev_{\mathrm{Im}_3})$	c_1, c_2
		ev_{Im_4}	$P(ev_{\mathrm{Im}_4})$	c_1, c_2, c_3
	2nd	ev_{So_1}	$P(ev_{So_1})$	c_1
		ev_{So_2}	$P(ev_{So_2})$	c_2
		ev_{So_3}	$P(ev_{So_3})$	c_1, c_3
		ev_{So_4}	$P(ev_{So_4})$	c_1, c_2, c_3

As shown from table 1, there are different evidences as ev_{Im_1}, ev_{Im_3} and ev_{Im_4} leads to a different set of consequences that contain same hypotheses as elements c_1. So, the possibility of decision making be very difficult because presence uncertainly area containing on degree of beliefs of evidences leads to which hypothesis is selected by the decision makers.

Degree of belief that effected on the hypothesis is determined for each evidence by experts and that is used by decision maker to take the appropriate decision as shown in table 2. Based on the degree of belief can be calculated belief and doubt, commonality, plausibility and disbelief measures that helping to define the uncertainty evidences area to decision-making as shown in table 3. From the lower boundary (belief) and higher boundary (plausibility) can fuses each of audio evidence with visual evidence to builds the fusion evidence as shown in table 4.

Table 2: relation of degree of belief for decision maker by power set (ς)

1st decision maker	2^{ς}	2nd decision maker
$m(ev_{\mathrm{Im}_1}) = 0.2$	$\{c_1\}$	$m(ev_{So_1}) = 0.2$
$m(ev_{\mathrm{Im}_2}) = 0.1$	$\{c_2\}$	$m(ev_{So_2}) = 0$
$m(ev_{\mathrm{Im}_3}) = 0$	$\{c_3\}$	$m(ev_{So_3}) = 0.2$
$m(ev_{\mathrm{Im}_4}) = 0.6$	$\{c_1 \cup c_2\}$	$m(ev_{So_4}) = 0$
$m(ev_{\mathrm{Im}_5}) = 0$	$\{c_1 \cup c_3\}$	$m(ev_{So_5}) = 0.4$
$m(ev_{\mathrm{Im}_6}) = 0$	$\{c_2 \cup c_3\}$	$m(ev_{So_6}) = 0$
$m(ev_{\mathrm{Im}_7}) = 0.1$	$\{c_1 \cup c_2 \cup c_3\}$	$m(ev_{So_7}) = 0.2$

Table 3: belief and plausibility measures for evidences

$m(ev_{\mathrm{Im}_K})$	$bel(ev_{\mathrm{Im}_K})$	$pl(ev_{\mathrm{Im}_K})$	2^{ς}	$m(ev_{So_K})$	$bel(ev_{So_K})$	$pl(ev_{So_K})$
0.2	0.2	0.9	$\{c_1\}$	0.2	0.2	0.8
0.1	0.1	0.8	$\{c_2\}$	0	0	0.2
0	0	0.1	$\{c_3\}$	0.2	0.2	0.8
0.6	0.9	1	$\{c_1 \cup c_2\}$	0	0.2	0.8
0	0.2	0.9	$\{c_1 \cup c_3\}$	0.4	0.8	1
0	0.1	0.8	$\{c_2 \cup c_3\}$	0	0.2	0.8
0.1	1	1	$\{c_1 \cup c_2 \cup c_3\}$	0.2	1	1

Table 4: the fusion table contains audio and visual evidences cut set.

$\cap$	ev_{Im_1}	ev_{Im_2}	ev_{Im_3}	ev_{Im_4}	ev_{Im_5}	ev_{Im_6}	ev_{Im_7}
ev_{So_1}	c_1	ϕ	ϕ	c_1	c_1	ϕ	c_1
ev_{So_2}	ϕ	c_2	ϕ	c_2	ϕ	c_2	c_2
ev_{So_3}	ϕ	ϕ	c_3	ϕ	c_3	c_3	c_3
ev_{So_4}	c_1	c_2	ϕ	$c_1 \cup c_2$	c_1	c_2	$c_1 \cup c_2$
ev_{So_5}	c_1	ϕ	c_3	c_1	$c_1 \cup c_3$	c_3	$c_1 \cup c_3$
ev_{So_6}	ϕ	c_2	c_3	c_2	c_3	$c_2 \cup c_3$	$c_2 \cup c_3$
ev_{So_7}	c_1	c_2	c_3	$c_1 \cup c_2$	$c_1 \cup c_3$	$c_2 \cup c_3$	ς

Information Lake represents a significant problem and influential in the decision. So reducing the size of information and reduce the time of the decision distinguishes the proposed system where the negligence of rows and columns relating to non focal elements $\left(\left(m(ev_{\mathrm{Im}_K}) = 0, m(ev_{So_K}) = 0\right)\right)$. In our example, columns Im_3, Im_5 and Im_6, and rows So_2, So_4 and So_6 are not applicable as shown in table 5:

Table 5: The reduced fusion evidences.

$\cap$	ev_{Im_1}	ev_{Im_2}	ev_{Im_4}	ev_{Im_7}
ev_{So_1}	c_1	ϕ	c_1	c_1
ev_{So_3}	ϕ	ϕ	ϕ	c_3
ev_{So_5}	c_1	ϕ	c_1	$c_1 \cup c_3$
ev_{So_7}	c_1	c_2	$c_1 \cup c_2$	ς

After reduction of information dimensionality the effect of both audio and visual evidences on the hypothesis available to the decision-making is calculated. Table 6 is illustrate the formal procedure by applied the equation (*I*). For each hypothesis can calculate the effect of both audio and visual evidence in them. While the sum over all calculated combination in table 6 is identical with the denominator of equation *(I)* to calculate the evidence measures of combined hypotheses as shown in table 7.

Table 6: effect o audio-visual evidences on decision hypothesis

$\otimes$	ev_{Im_1}	ev_{Im_2}	ev_{Im_4}	ev_{Im_7}
ev_{So_1}	0.04	$\times$	0.12	0.02
ev_{So_3}	$\times$	$\times$	$\times$	0.02
ev_{So_5}	0.08	$\times$	0.24	0.04
ev_{So_7}	0.04	0.02	0.12	0.02

Table 7: the evidence measures for fuses hypotheses.

2^{ς}	m	bel	cmn	pl
ς	0.0263	1	0.0263	1
$\{c_1 \cup c_2\}$	0.1579	0.8947	0.1842	0.9737
$\{c_1 \cup c_3\}$	0.0526	0.7895	0.0789	0.9737
$\{c_1\}$	0.7105	0.7105	0.9474	0.9471
$\{c_2\}$	0.0263	0.0263	0.2105	0.2105
$\{c_3\}$	0. 0263	0.0263	0.1053	0.1053

From the results shown in table 7, the decision maker should avoid hypotheses two (c_2) and three (c_3) due to the same low values of belief and (c_3) takes roughly half the range of uncertainty region of audio and visual evidences and plausibility that (c_2). Also, the first hypothesis (c_1) is excludes due to the wide range of audio and visual evidences uncertainty region $(\cong 0.24)$. The combination between first and third hypotheses $\{c_1 \cup c_3\}$ covers a smaller distance between lower boundary (belief) and higher boundary (plausibility) than first hypothesis (c_1) alone $(\cong 0.18)$. So the best decision is combination first and second hypotheses $\{c_1 \cup c_2\}$, where it is smallest range of uncertainty $(\cong 0.08)$ with the same (highest) plausibility as in case of the combination of first and third hypotheses $\{c_1 \cup c_3\}$.

5. CONCLUSION

The decision-making process is difficult and very stressful as it is assumed in the decision-maker should be familiar with the diagnosis knowledge, available procedures, their consequences, and the probabilities of the associated outcomes. The proposed method presents a new method to decision making based on audio and visual evidences which add a new precisely and reliability flavor compared to probabilistic approaches. The fusion of evidences may be responsible for the serious changes of the decision properties.

A decision function represents an arbitrament process conditionally to the contributions of several independent evidences. It has been shown that evidence fusions based on the concept of decision functions have a straightforward sampling based implementation.

The proposed method can be used in decision making based on the evidence as audio-visual equipment in the diagnosis of defects in the field of engineering and diagnosis of diseases in the medical field.

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